Glossary of Big Data, MapReduce, Spark

Prelude

- This glossary is written for my students taking Big Data Modeling & Analytics at Santa Clara University.
- This is not a regular glossary: it is a detailed glossary for my students to learn basics of key terms in big data, MapReduce, and PySpark (Python API for Apache Spark).
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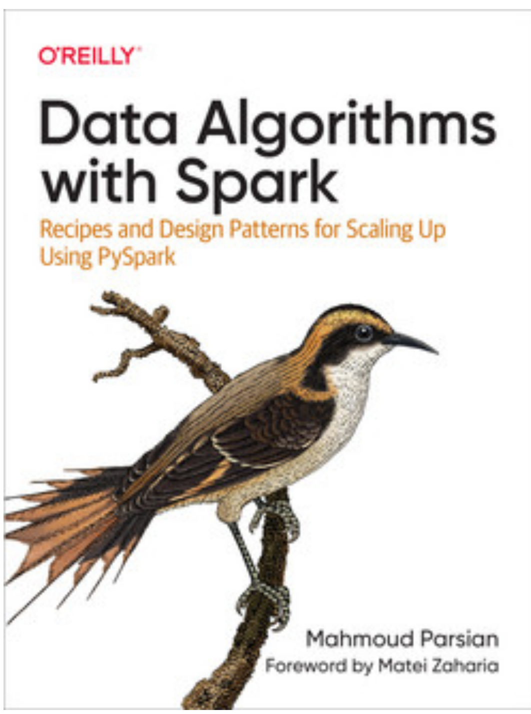
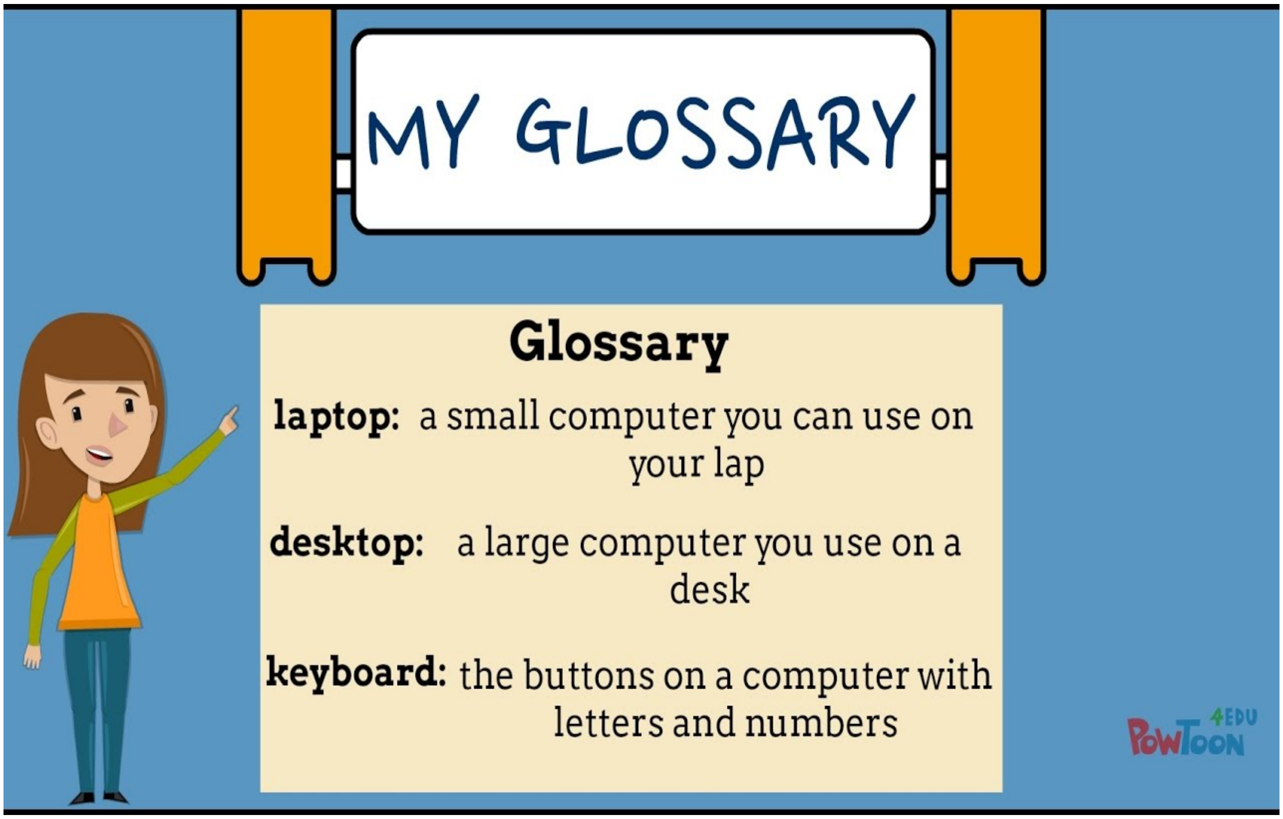
- Last updated date: 2/18/2023



"… This book will be a great resource for both readers looking to implement existing algorithms in a scalable fashion and readers who are developing new, custom algorithms using Spark. …"

Dr. Matei Zaharia
Original Creator of Apache Spark

FOREWORD by Dr. Matei Zaharia



Introduction

Big data is a vast and complex field that is constantly evolving, and for that reason, it's important to understand the basic common terms and the more technical vocabulary so that your understanding can evolve with it. The intention is to put these definitions and concepts in one single place for ease of exploring, searching and learning.

Big data environment involves many tools and technologies:

- Data preparation from multiple sources
- Engine for large-scale data analytics (such as Spark)
- ETL processes to analyze prepare data for Query engine
- Relational database systems
- Query engines such as Amazon Athena, Google BigQuery, Snowflake
- much more…

The purpose of this glossary is to shed some light on the fundamental definitions of big data, MapReduce, and Spark. This document is a list of terms, words, concepts, and examples found in or relating to big data, MapReduce, and Spark.

Algorithm

Mohammed Ibn Musa-al-Khwarizmi was a Persian mathematician and creator of the term: **algorithm**.

- An algorithm is a mathematical formula that can perform certain analyses on data
- An algorithm is a procedure used for solving a problem or performing a computation.
- An algorithm is a set of well-defined steps to solve a problem
- For example, given a set of words, sort them in ascending order
- For example, given a set of text documents, find frequecy of every unique word
- For example, given a set of numbers, find (minimum, maximum) of given numbers

An algorithm is a step-by-step set of operations which can be performed to solve a particular class of problem. The steps may involve calculation, processing, or reasoning. To be effective, an algorithm must reach a solution in finite space and time. As an example, Google uses algorithms extensively to rank page results and autocomplete user queries. Typically an algorithm is implemented using a programming language such as Python, Java, SQL, …

In big data world, an algorithm can be implemented using a compute engine such as MapReduce and Spark.

In The Art of Computer Programming, a famous computer scientist, Donald E. Knuth, defines an algorithm as a set of steps, or rules, with five basic properties:

> 1) **Finiteness**: an algorithm must always terminate after a finite number of steps.
>
> 2) **Definiteness**: each step of an algorithm must be precisely defined

> 3) **Input**: an algorithm has zero or more inputs
>
> 4) **Output**: an algorithm has one or more outputs
>
> 5) **Effectiveness**: an algorithm is also generally expected to be effective

List of Algorithms

Simple Algorithms (partial list):

- Sum of list of numbers
- Average of list of numbers
- Median of list of numbers
- Finding the standard deviation for a set of numbers
- Mode of list of numbers: the most frequent number-that is, the number that occurs the highest number of times.
- Minimum and Maximum of list of numbers
- Cartesian product of two sets
- Given a list of numbers, find (number-of-zeros, number-of-negatives, number-of-positives)
- Word Count: given a set of text documents, find frequency of every unique word in these documents
- Given a set of integer numbers, identify prime and non-prime numbers
- Anagrams Count: given a set of text documents, find frequency of every unique anagram in these documents
- Given users, movies, and ratings (1 to 5), what are the Top-10 movies rated higher than 2.
- DNA base count for FASTA and FASTQ files

Famous Algorithms (partial list):

- T-Test algorithm
- Tree traversal algorithms
- Suffix Tree Algorithms
- Red–Black tree algorithms
- Dijkstra’s Algorithm
- Merge Sort
- Quicksort
- Depth First Search
- Breadth-First Search
- Linear Search

- Binary Search
- Minimum Spanning Tree Algorithms
- Bloom Filter
- All-Pairs Shortest Paths – Floyd Warshall Algorithm
- Kmers for DNA sequences
- Huffman Coding Compression Algorithm
- Bioinformatics Algorithms
- The Knuth-Morris-Pratt algorithm
- Connected Components
- Finding Unique Triangles in a graph

Example of a Simple Algorithm

US Change Algorithm: Convert some amount of money (in cents/pennies) to fewest number of coins. Here we assume that the **penny**, **nickel**, **dime**, and **quarter** are the circulating coins that we use today.

FACTs on US Coins:

- One dollar = 4 quarters = 100 pennies
- One quarter = 25 pennies
- One dime = 10 pennies
- One nickle = 5 pennies

- **Input**: An amount of money, `M`, in pennies (as in integer)

- **Output**: The smallest number of quarters `q`, dimes `d`, nickles `n`, and pennies `p` whose value add to `M`: the following rules must be satisfied:

    - `25q +10d + 5n + p = M` and
    - `q + d + n + p` is as small as possible.

- **Algorithm**: Greedy algorithm: a greedy algorithm is any algorithm that follows the problem-solving heuristic of making the locally optimal choice at each stage. According to the National Institute of Standards and Technology (NIST), a greedy algorithm is one that always takes the best immediate, or local, solution while finding an answer. Greedy algorithms find the overall, or globally, optimal solution for some optimization problems, but may find less-than-optimal solutions for some instances of other problems.

  Greedy algorithm is designed to achieve optimum solution for a given problem (here US Change problem). In greedy algorithm approach, decisions are made from the given solution domain. As being greedy, the closest solution that seems to provide an optimum solution is chosen.

- **Algorithm Implementation**: The following is a basic US Change Algorithm in Python. In this algorithm, we use the `divmod(arg_1, arg_2)` built-in function which returns a tuple containing the **quotient** and the **remainder** when `arg_1` (dividend) is divided by `arg_2` (divisor). We are using Greedy algorithm, which finds the optimal solution: first find the number of quarters (x 25), then dimes (x 10), finally the number of nickles (x 5) and pennies (x 1).

```python
# M : number of pennies
# returns (q, d, n, p) where
#    q = number of quarters
#    d = number of dimes
#    n = number of nickle
#    p = number of pennies
# where
#   25q +10d + 5n + p = M and
#   q + d + n + p is as small as possible.
#
def change(M):
  # step-1: make sure that M is an integer
  if not(isinstance(M, int)):
    print('M is not an integer')
    return (0, 0, 0, 0)
  #end-if

  # here: M is an integer type
  # step-2: make sure M > 0
  if (M < 1):
    return (0, 0, 0, 0)
  #end-if

  # step-3: first, find quarters as q, since q > d > n > p
  q, p = divmod(M, 25)
  if (p == 0):
    return (q, 0, 0, 0)
  #end-if

  # step-4: find dimes, since d > n > p
  d, p = divmod(p, 10)
  if (p == 0):
    return (q, d, 0, 0)
  #end-if

  # step-5: find nickles and pennies
  n, p = divmod(p, 5)

  # step-6: return the final result
  return (q, d, n, p)
#end-def
```

Basic testing of the `change()` function:

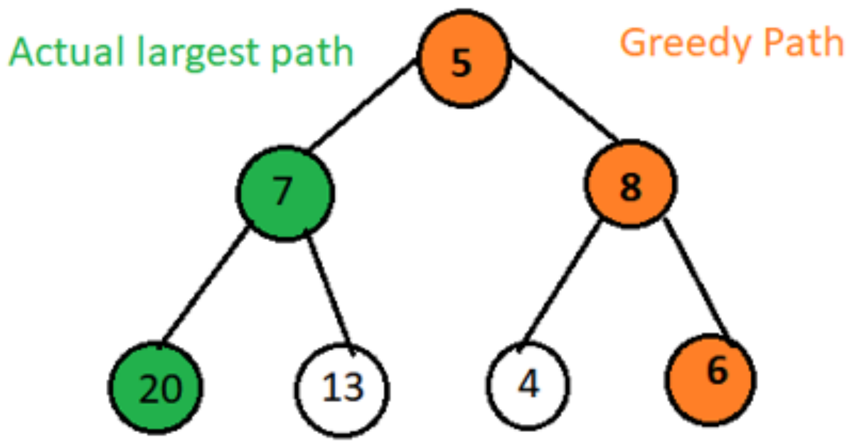
```
>>> change(None)
M is not an integer
(0, 0, 0, 0)
>>> change([1, 2, 3])
M is not an integer
(0, 0, 0, 0)
>>> change('x')
M is not an integer
(0, 0, 0, 0)
>>> change(2.4)
M is not an integer
(0, 0, 0, 0)
>>> change(0)
(0, 0, 0, 0)
>>> change(141)
(5, 1, 1, 1)
>>> change(30)
(1, 0, 1, 0)
>>> change(130)
(5, 0, 1, 0)
>>> change(55089)
(2203, 1, 0, 4)
>>> change(44)
(1, 1, 1, 4)
```

Types of Algorithms

- Sorting algorithms: Bubble Sort, insertion sort, and many more. These algorithms are used to sort the data in a particular format.
- Searching algorithms: Linear search, binary search, etc. These algorithms are used in finding a value or record that the user demands.
- Graph Algorithms: It is used to find solutions to problems like finding the shortest path between cities, and real-life problems like traveling salesman problems.
- Dynamic Programming Algorithms
- Greedy Algorithms: minimization and maximization

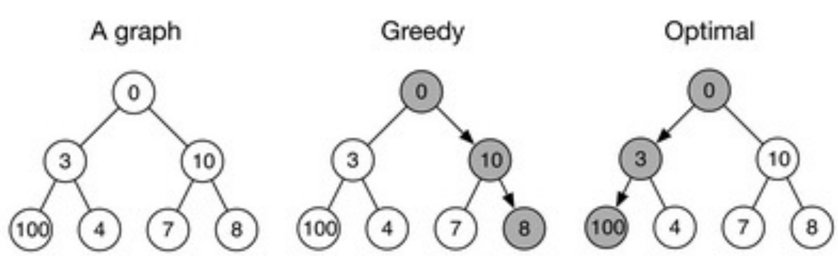
Greedy Algorithm

Greedy Algorithm is defined as a method for solving optimization problems by taking decisions that result in the most evident and immediate benefit irrespective of the final outcome. It works for cases where minimization or maximization leads to the required solution.



Characteristics of Greedy algorithm: For a problem to be solved using the Greedy approach, it must follow a few major characteristics:

- There is an ordered list of resources (profit, cost, value, etc.)
- Maximum of all the resources(max profit, max value, etc.) are taken.
- For example, in the fractional knapsack problem, the maximum value/weight is taken first according to available capacity.



A greedy algorithm fails to maximise the sum of nodes along a path from the top to the bottom because it lacks the foresight to choose suboptimal solutions in the current iteration that will allow for better solutions later

Storing Files on Tape is an example of [Greedy Algorithm](#).

Recursive Algorithms

In computer science, recursion is a method of solving a computational problem where the solution depends on solutions to smaller instances of the same problem. Recursion solves such recursive problems by using functions that call themselves from within their own code.

A recursive algorithm is an algorithm which calls itself with "smaller (or simpler)" input values, and which obtains the result for the current input by applying simple operations to the returned value for the smaller (or simpler) input. More generally if a problem can be solved utilizing solutions to smaller versions of the same problem, and the smaller versions reduce to easily solvable cases, then one can use a recursive algorithm to solve that problem. For example, the elements of a recursively defined set, or the value of a recursively defined function can be obtained by a recursive algorithm.

The classic example of recursive programming involves computing factorials. The factorial of a number is computed as that number times all of the numbers below it up to and including 1. For example, `factorial(5)` is the same as `5 * 4 * 3 * 2 * 1`, and `factorial(3)` is `3 * 2 * 1`.

An interesting property of a factorial is that the factorial of a number is equal to the starting number multiplied by the factorial of the number immediately below it. For example, `factorial(5)` is the same as `5 * factorial(4)`. You could almost write the factorial function simply as this:

```
factorial(n) = n * factorial(n - 1) for n > 0 (general definition)
factorial(n) = 1                    for n = 0 (base definition)
```

Factorial function can be expressed in a pseudo-code:

```
# assumption: n >= 0
int factorial(int n) {
   if (n == 0) {
      return 1;
   }
   else {
      return n * factorial(n - 1);
   }
}
```

Example of Recursive Algorithms:

1. Factorial of a Number
2. Greatest Common Divisor
3. Fibonacci Numbers
4. Recursive Binary Search
5. Linked List

6. Reversing a String
7. QuickSort Algorithm
8. Binary Tree Algorithms
9. Towers of Hanoi
10. Inorder/Preorder/Postorder Tree Traversals
11. DFS of Graph
12. File system traversal

Recursive definitions are often used to model the structure of expressions and statements in programming languages. Language designers often express grammars in a syntax such as Backus–Naur form; here is such a grammar, for a simple language of arithmetic expressions (denoted as an `<expr>`) with multiplication and addition:

```
    <expr> ::= <number>
             | (<expr> * <expr>)
             | (<expr> + <expr>)
```

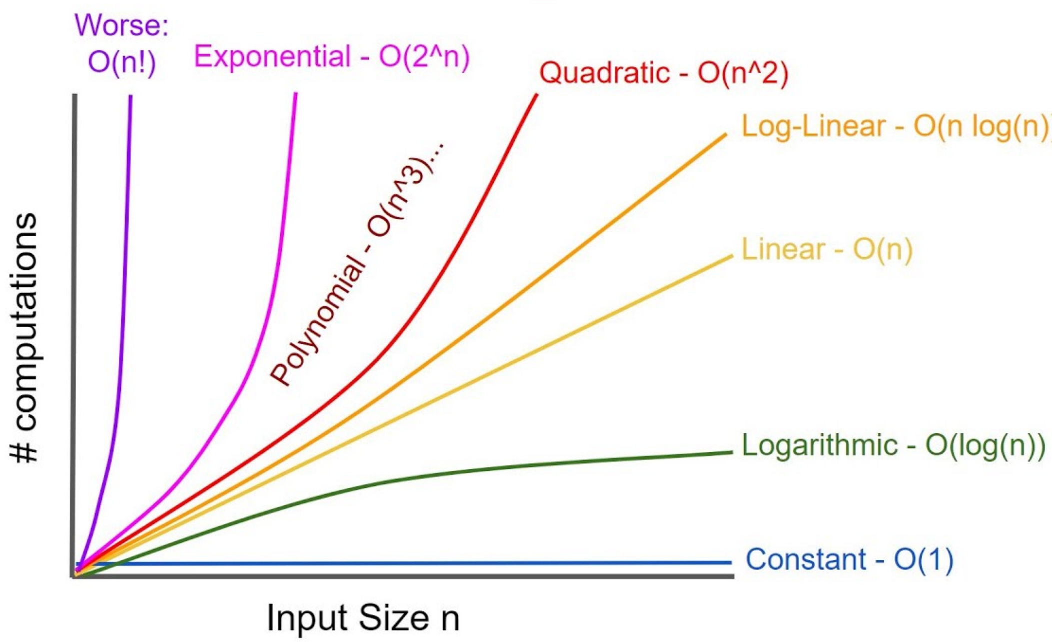
Algorithm Complexity

An algorithm is analyzed using Time Complexity and Space Complexity. Writing an efficient algorithm help to consume the minimum amount of time for processing the logic. For algorithm `A`, it is judged on the basis of two parameters for an input of size `n` :

- **Time Complexity**: Time taken by the algorithm to solve the problem. It is measured by calculating the iteration of loops, number of comparisons etc. In computer science, the time complexity is the computational complexity that describes the amount of computer time it takes to run an algorithm.

- **Space Complexity**: Space taken by the algorithm to solve the problem. It includes space used by necessary input variables and any extra space (excluding the space taken by inputs) that is used by the algorithm. For example, if we use a hash table (a kind of data structure), we need an array to store values so this is an extra space occupied, hence will count towards the space complexity of the algorithm. This extra space is known as Auxiliary Space.

  Computational Complexity of Algorithms:



Distributed Algorithm

A distributed algorithm is an algorithm designed to run on computer hardware constructed from interconnected processors. Distributed algorithms are used in different application areas of distributed computing, such as DNA analysis, telecommunications, scientific computing, distributed information processing, and real-time process control. Standard problems solved by distributed algorithms include leader election, consensus, distributed search, spanning tree generation, mutual exclusion, finding association of genes in DNA, and resource allocation. Distributed algorithms run in parallel/concurrent environments.

In implementing distributed algorithms, you have to make sure that your aggregations and reductions are semantically correct (since these are executed partition by partition) regardless of the number of partitions for your data. For example, you need to remember that average of an average is not an average.

Example of systems running distributed algorithms:

- Apache Spark can be used to implement and run distributed algorithms.
- MapReduce/Hadoop can be used to implement and run distributed algorithms.
- Amazon Athena
- Google BigQuery

- Snowflake

Access Control List (ACL)

In a nutshell, in computer security, an access-control-list (ACL) is a list of permissions associated with a system resource (object).

In a file system, ACL is a list of permissions associated with an object in a computer file system. An ACL specifies which users or processes are allowed to access an object, and what operations can be performed.

Apache Software Foundation (ASF)

ASF is a non-profit corporation that supports various open-source software products, including Apache Hadoop, Apache Spark, and Apache Maven. Apache projects are developed by teams of collaborators and protected by an ASF license that provides legal protection to volunteers who work on Apache products and protect the Apache brand name.

Apache projects are characterized by a collaborative, consensus-based development process and an open and pragmatic software license. Each project is managed by a self-selected team of technical experts who are active contributors to the project.

Partitioner

Partitioner is a program, which distributes the data across the cluster. The types of partitioners are

- Hash Partitioner
- Murmur3 Partitioner
- Random Partitioner

* Order Preserving Partitioner

For example, an Spark RDD of `480,000,000,000` elements might be partitioned in to `60,000` chunks (partitions), where each chunk/partition will have a bout `8,000,000` elements.

```
480,000,000,000 = 60,000 x 8,000,000
```

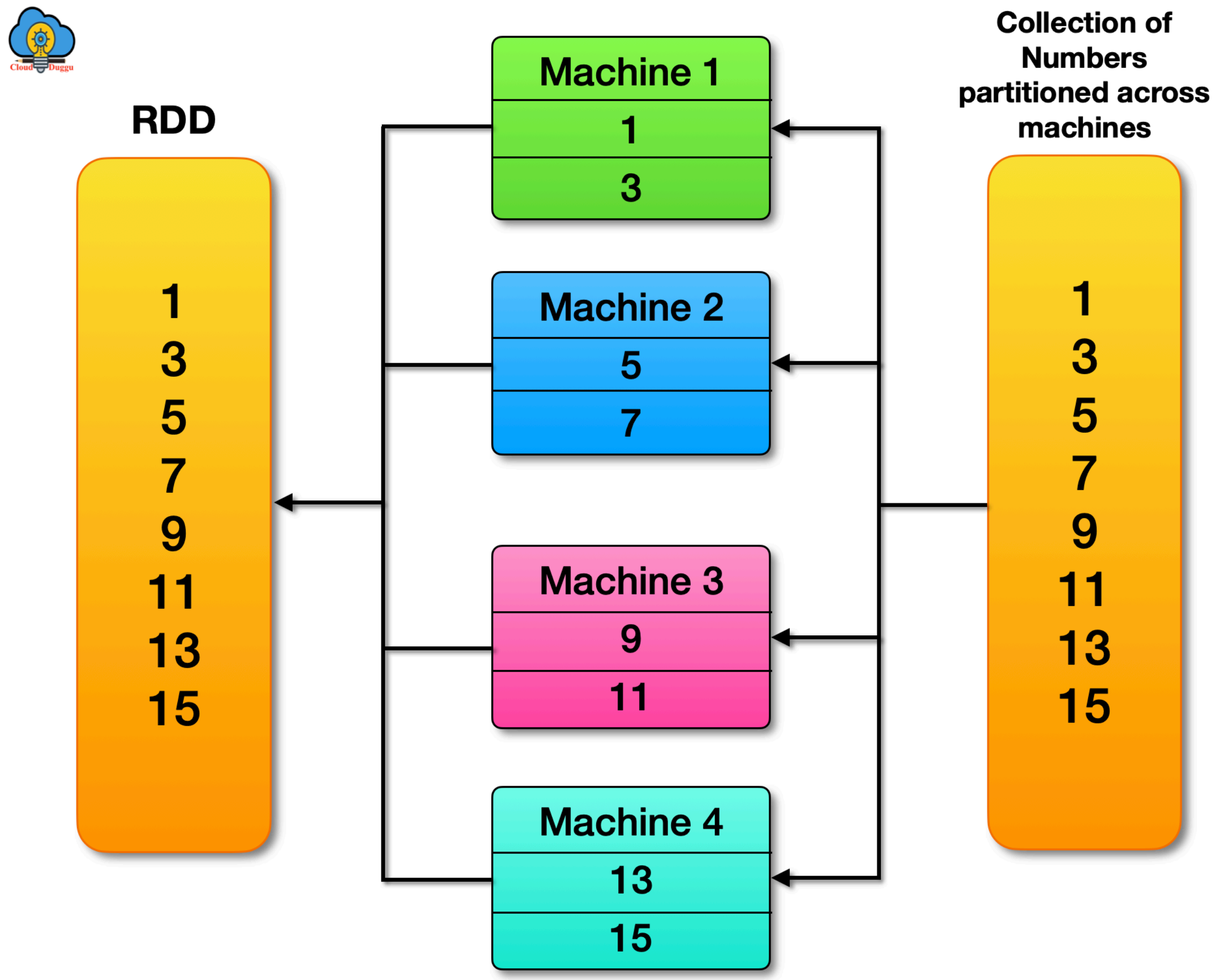
One of the main reasons of data partitioning is to process many small partitions in parallel (at the same time) to reduce the overall data processing time.

In Apache Spark, your data can be represented as an RDD, and Spark partitions (to enable parallelism of data transformations) your immutable RDD into chunks called partitions. The Partitions are the parts of RDD that allow Spark to execute in parallel on a cluster of nodes. It is distributed across the node of the cluster and logical division of data. In Spark, all input, intermediate, and output data is presented as partitions in which one task process one partitions at a time. RDD is a group of partitions.

In the following figure, the Spark RDD has `8` elements as `{1, 3, 5, 7, 9, 11, 13, 15}` and has `4` partitions as:

* `RDD = { Partition-1, Partition-2, Partition-3, Partition-4 }`
* `Partition-1` : `{ 1, 3 }`
* `Partition-2` : `{ 5, 7 }`
* `Partition-3` : `{ 9, 11 }`
* `Partition-4` : `{ 13, 15 }`

The main purpose of partitions is to enable independent and parallel execution of transformations (such as mappers, filters, and reducers). Partitions can be executed on different servers/nodes.



Aggregation

- A process of searching, gathering and presenting data.

- Data aggregation refers to the process of collecting data and presenting it in a summarised format. The data can be gathered from multiple sources to be combined for a summary.

Data Aggregation

Data aggregation refers to the collection of data from multiple sources to bring all the data together into a common athenaeum for the purpose of reporting and/or analysis.

- Data aggregation is the process of compiling typically some large amounts of information from a given database and organizing it into a more consumable and comprehensive medium.
- For example, find average age of customer by product

- For example, find median rating for movies rated last year

What is Data Aggregation? Data aggregators summarize data from multiple data sources. They provide capabilities for multiple aggregate measurements, such as sum, median, average and counting.

In a nutshell, we can say that data aggregation is the process of bringing together data from multiple sources and consolidating it in a storage solution for data analysis and reporting.

Analytics

- The discovery of insights in data, find interesting patterns in data
- For example, given a graph, find (identify) all of the triangles
- For example, given a DNA data, find genes, which are assocaited with each other
- For example, given a DNA data, find rare variants

What is Data Analytics? Data analytics helps individuals and organizations make sense of data. Data analysts typically analyze raw data for insights, patterns, and trends.

According to NIST: “analytics is the systematic processing and manipulation of data to uncover patterns, relationships between data, historical trends and attempts at predictions of future behaviors and events.”

Data Analytics

Data analytics helps individuals and organizations make sense of data. Data analysts typically analyze raw data for insights and trends.

Data analytics converts raw data into actionable insights. It includes a range of tools, technologies, and processes used to find trends and solve problems by using data. Data analytics can shape business processes, improve decision making, and foster business growth.

Data Analytics is the process of examining large data sets to uncover hidden patterns, unknown correlations, trends, customer preferences and other useful business insights. The end result might be a report, an indication of status or an action taken automatically based on the information received. Businesses typically use the following types of analytics:

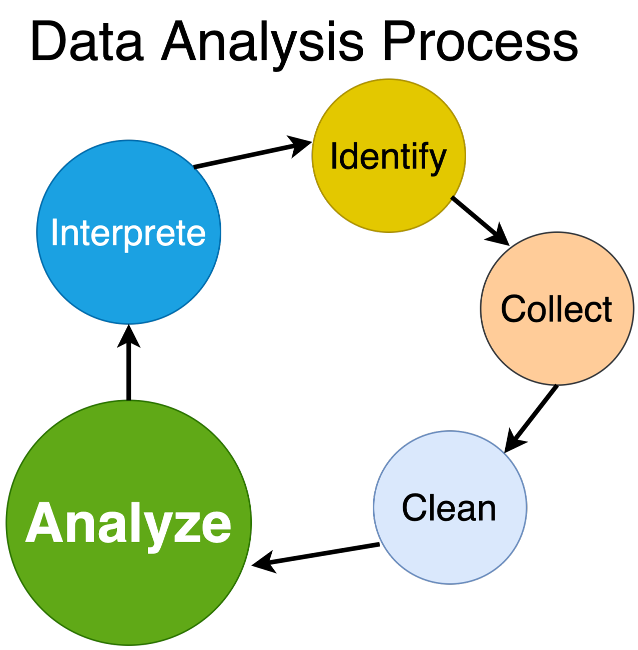
- **Behavioral Analytics:** Using data about people’s behavior to understand intent and predict future actions.

- **Descriptive Analytics:** Condensing big numbers into smaller pieces of information. This is similar to summarizing the data story. Rather than listing every single number and detail, there is a general thrust and narrative.

- **Diagnostic Analytics**: Reviewing past performance to determine what happened and why. Businesses use this type of analytics to complete root cause analysis.
- **Predictive Analytics:** Using statistical functions on one or more data sets to predict trends or future events. In big data predictive analytics, data scientists may use advanced techniques like data mining, machine learning and advanced statistical processes to study recent and historical data to make predictions about the future. It can be used to forecast weather, predict what people are likely to buy, visit, do or how they may behave in the near future.
- **Prescriptive Analytics:** Prescriptive analytics builds on predictive analytics by including actions and make data-driven decisions by looking at the impacts of various actions.

Data Analysis Process

The data analysis process consists of 5 key stages.



- **Identify**: you first need to identify why do you need this data and what is the purpose of it in the enterprise
- **Collect**: this is the stage where you start collecting the needed data. Here, you define which sources of information you will use and how you will use them. The collection of data

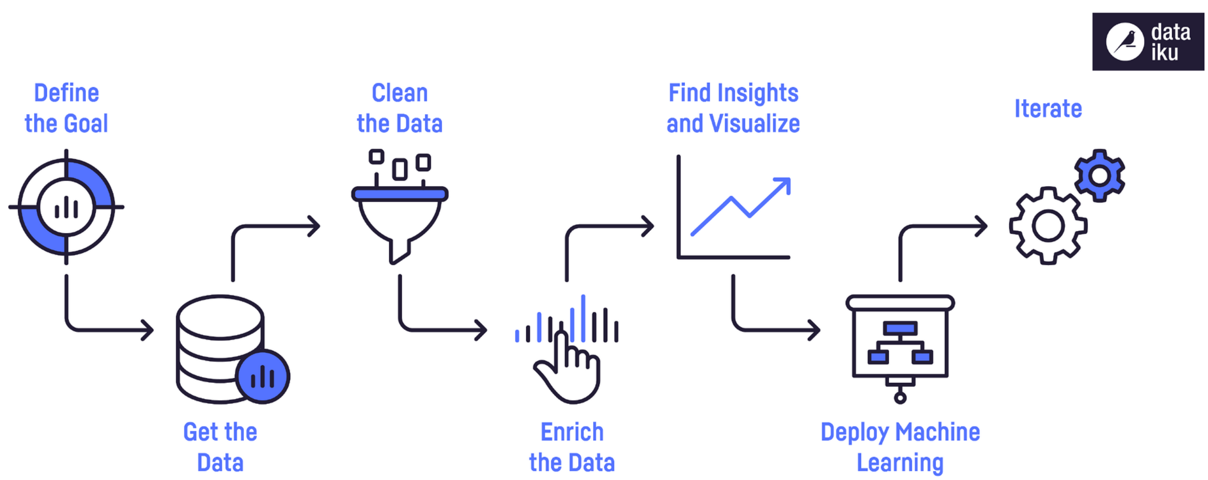
can come in different forms such as internal or external sources; you need to identify where the data will reside

- **Clean**: Once you have the necessary data it is time to clean it and leave it ready for analysis. Not all the data you collect will be useful, when collecting big amounts of information in different formats it is very likely that you will find yourself with duplicate or badly formatted data.

- **Analyze**: With the help of various tools and techniques such as statistical analysis, regressions, neural networks, text analysis, DNA analysis, and more, you can start analyzing and manipulating your data to extract relevant conclusions. At this stage, you find trends, correlations, variations, and patterns that can help you answer the questions you first thought of in the identify stage.

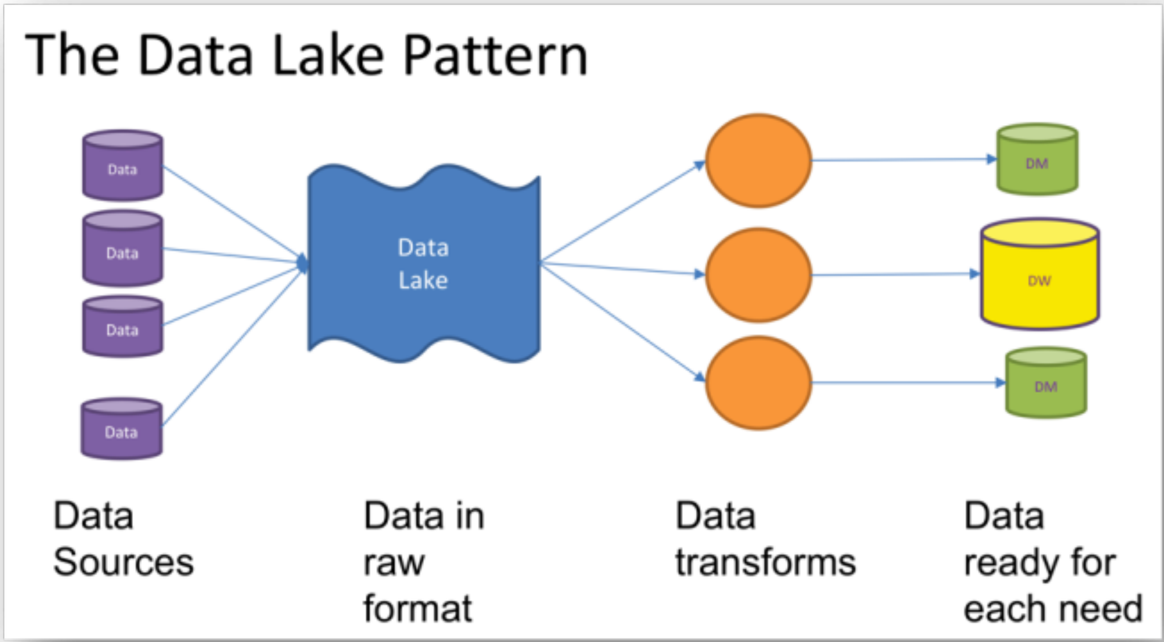
- **Interprete**: Last but not least you have one of the most important steps: it is time to interpret your results. This stage is where the researcher comes up with courses of action based on the findings.

[7 Fundamental Steps to Complete a Data Analytics Project:]



Data Lake

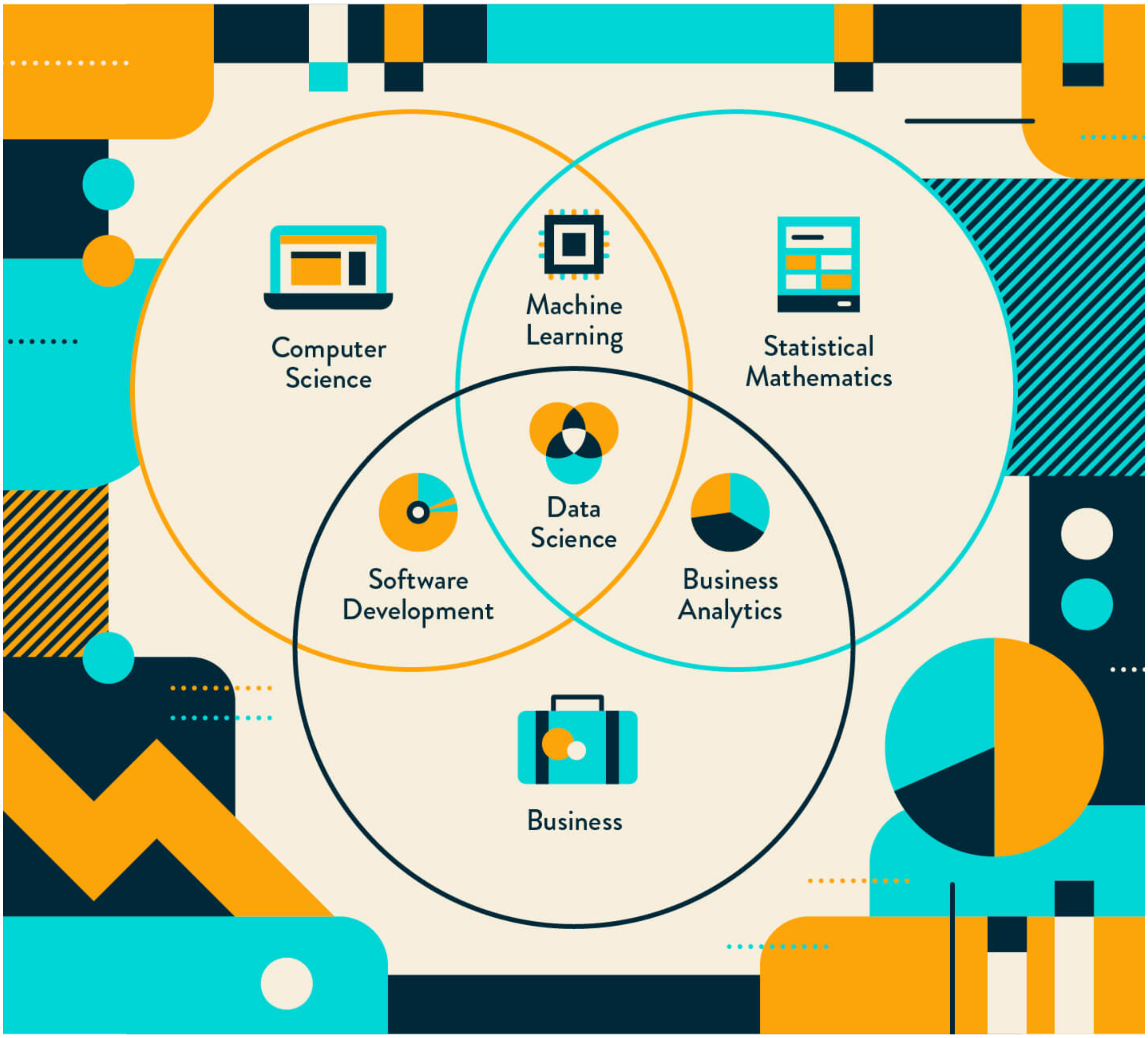
A data lake is a centralized repository that allows you to store all your structured and unstructured data at any scale.



A storage repository that holds a vast amount of raw data in its native format until it's required. Every data element within a data lake is assigned a unique identifier and set of extended metadata tags. When a business question arises, users can access the data lake to retrieve any relevant, supporting data.

Data Science

Data science is really the fusion of three disciplines: computer science, mathematics, and business.

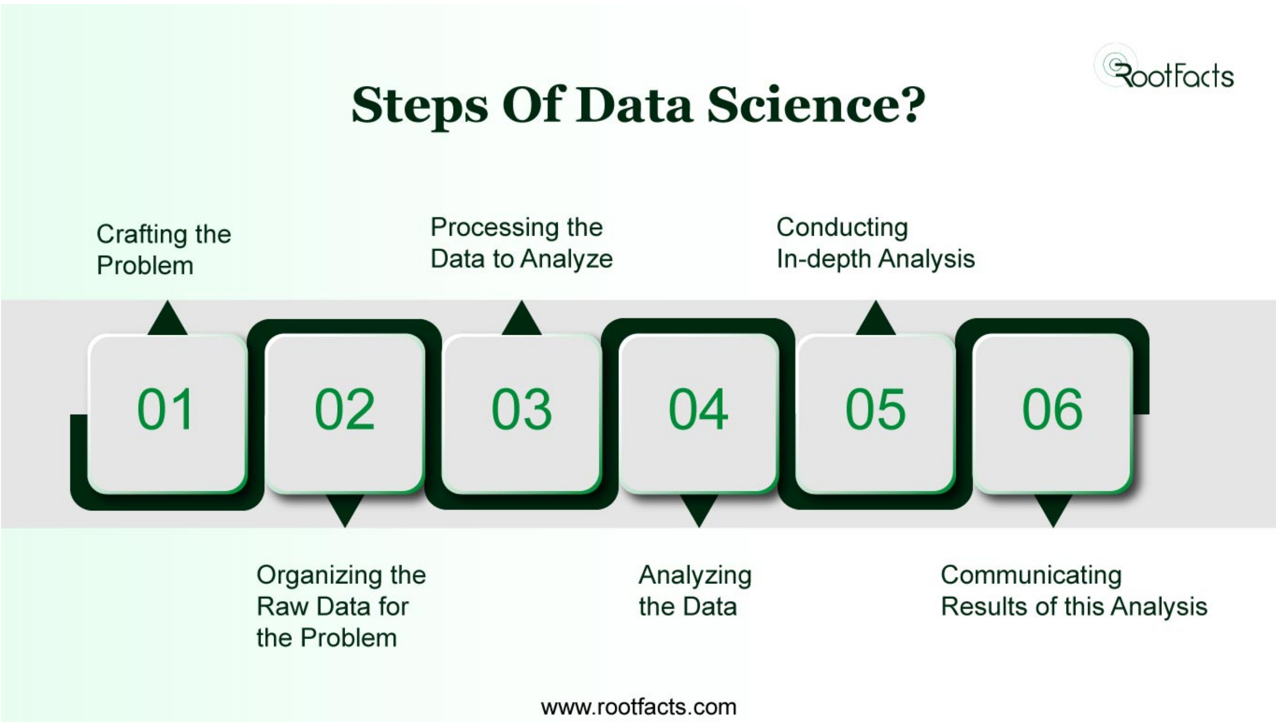


Data Science is the field of applying advanced analytics techniques and scientific principles to extract valuable information from data. Data science typically involves the use of statistics, data visualization and mining, computer programming, machine learning and database engineering to solve complex problems.

Data science is the methodology for the synthesis of useful knowledge directly from data through a process of discovery or of hypothesis formulation and hypothesis testing. Data science is tightly linked to the analysis of Big Data, and refers to the management and execution of the end-to-end data processes, including the behaviors of the components of the data system. As such, data science includes all of analytics as a step in the process. Data science contains different approaches to leveraging data to solve mission needs. While the term data science can be understood as the activities in any analytics pipeline that produces knowledge from data, the term is typically used in the context of Big Data.

Data Science Process

According to NIST, Data Science is focused on the end-to-end data processing life cycle of Big Data and related activities. The data science life cycle encompasses the data analytics life cycle (as described below) plus many more activities including policy and regulation, governance, operations, data security, master data management, meta-data management, and retention/destruction. The data analytics life cycle is focused on the processing of Big Data, from data capture to use of the analysis. The data analytics life cycle is the set of processes that is guided by the organizational need to transform raw data into actionable knowledge, which includes data collection, preparation, analytics, visualization, and access.



The end-to-end data science life cycle consists of five fundamental steps:

1. **Capture**: gathering and storing data, typically in its original form (i.e., raw data);
2. **Preparation**: processes that convert raw data into cleaned, organized information;
3. **Analysis**: techniques that produce synthesized knowledge from organized information;
4. **Visualization**: presentation of data or analytic results in a way that communicates to others;
5. **Action**: processes that use the synthesized knowledge to generate value for the enterprise.

Anonymization

- Making data anonymous; removing all data points that could lead to identify a person
- For example, replacing social security numbers with fake 18 digit numbers
- For example, replacing patient name with fake ID.

API

- An Application Programming Interface (API) is a set of function definitions, protocols, and tools for building application software. What Are APIs Used For? APIs are used to abstract the complexity of back-end logic in a variety of software systems.
- For example, MapReduce paradigm provides the following functions
    - mapper: `map()`
    - reducer: `reduce()`
    - combiner: `combine()` [optional]
- For example, Apache Spark provides
    - RDDs and DataFrames as Data Abstractions
    - mappers: `map()`, `flatMap()`, `mapPartitions()`
    - filters: `filter()`
    - reducers: `groupByKey()`, `reduceByKey()`, `combineByKey()`
    - SQL access to DataFrames
- For example, Google Maps API: The Google Maps API gives users the privilege of nearly limitless geographic aptitude at their fingertips. Search nearby restaurants, niche shops, and whatever else is in relative distance to your location.
- SQL API:
    - CREATE TABLE
    - DROP TABLE
    - INSERT row(s)
    - DELETE row(s)
    - UPDATE row(s)
    - …

Application

- An Application is a computer software that enables a computer to perform a certain task
- For example, a payroll application, which issues monthly checks to employees
- For example, a MapReduce application, which identifies and eliminates duplicate records
- For example, an Spark application, which finds close and related communities in a given graph
- For example, an Spark application, which finds rare variants for DNA samples

Data sizes

Short name	Full Name	Description
Bit	Bit	`0` or `1`
B	Byte	8 bits: (`00000000 .. 11111111`) : can represent 256 combinations (0 to 255)
KB	Kilo Byte	1,024 bytes = 2^{10} bytes ~ 1000 bytes
MB	Mega Byte	1,024 x 1,024 bytes = 1,048,576 bytes ~ 1000 KB
GB	Giga Byte	1,024 x 1,024 x 1,024 bytes = 1,073,741,824 bytes ~ 1000 MB
TB	Tera Byte	1,024 x 1,024 x 1,024 x 1024 bytes = 1,099,511,627,776 bytes ~ 1000 GB
PB	Peta Byte	1,024 x 1,024 x 1,024 x 1024 x 1024 bytes = 1,125,899,906,842,624 bytes ~ 1000 TB
EB	Exa Byte	1,152,921,504,606,846,976 (= 2^{60}) bytes ~ 1000 PB
ZB	Zetta Byte	1,208,925,819,614,629,174,706,176 bytes (= 2^{80}) bytes

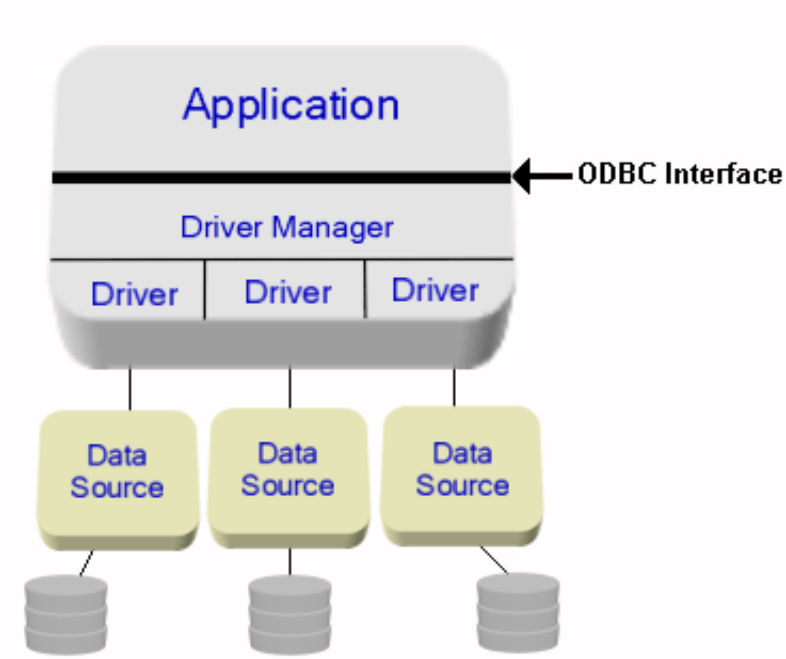
~ denotes “about”

Behavioural Analytics

Behavioural Analytics is a kind of analytics that informs about the how, why and what instead of just the who and when. It looks at humanized patterns in the data.

ODBC

Open Database Connectivity (ODBC) is a standard application programming interface (API) for accessing database management systems (DBMS). The designers of ODBC aimed to make it independent of database systems and operating systems. An application written using ODBC can be ported to other platforms, both on the client and server side, with few changes to the data access code.

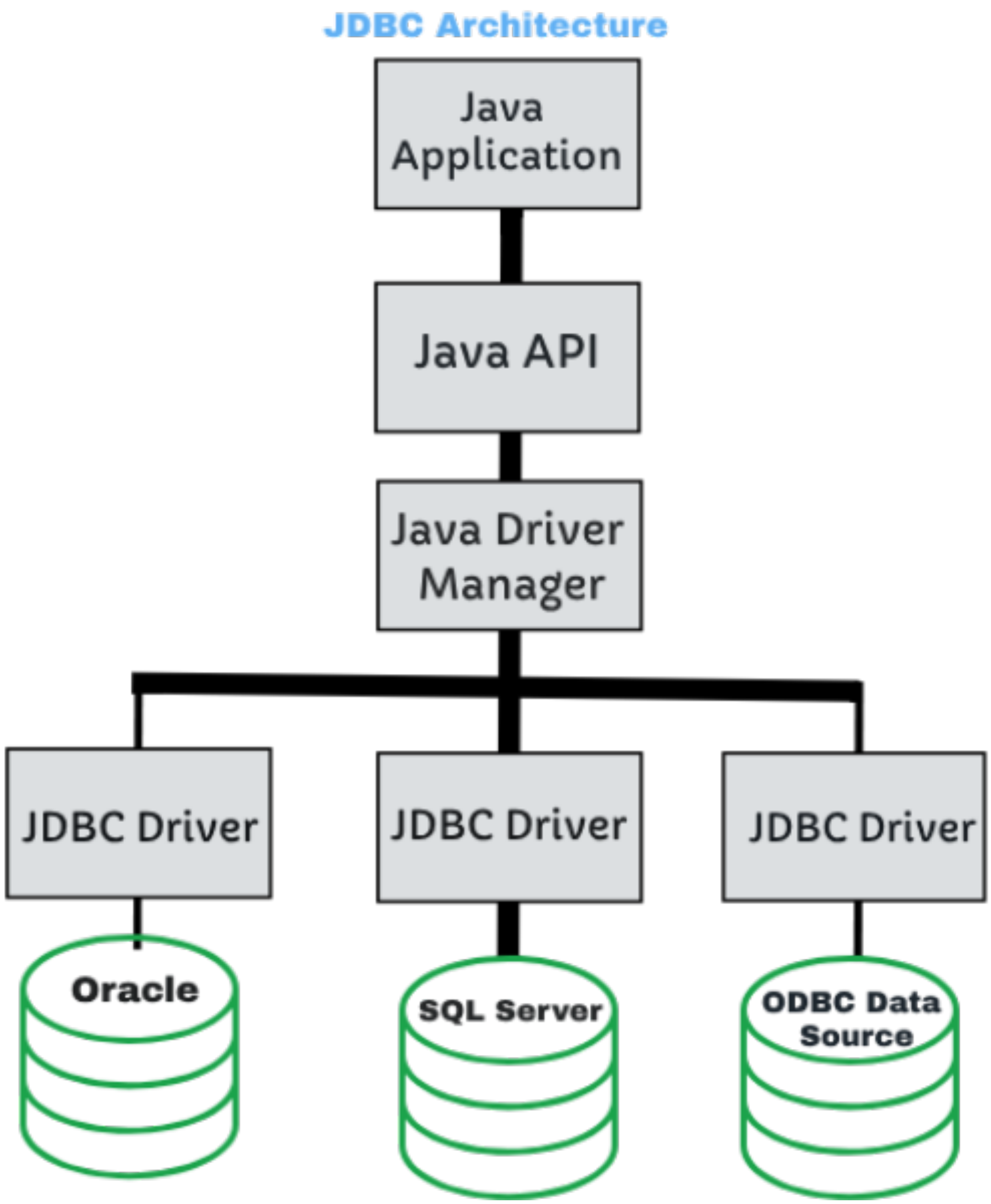


Open Database Connectivity (ODBC) is a protocol that you can use to connect a Microsoft Access database to an external data source such as Microsoft SQL Server.

JDBC

Java database connectivity (JDBC) is the specification of a standard application programming interface (API) that allows Java programs to access database management systems. The JDBC API consists of a set of interfaces and classes written in the Java programming language.

Using these standard interfaces and classes, programmers can write applications that connect to databases, send queries written in structured query language (SQL), and process the results.



Since JDBC is a standard specification, one Java program that uses the JDBC API can connect to any database management system (DBMS), as long as a driver exists for that particular DBMS.

Big Data

According to Gartner: “Big Data is high-volume, high-velocity and/or high-variety information assets that demand cost-effective, innovative forms of information processing that enable enhanced insight, decision making, and process automation.”

Big Data consists of extensive datasets – primarily in the characteristics of volume, velocity, variety, and/or variability – that require a scalable architecture for efficient storage, manipulation, and analysis.

Big data is an umbrella term for any collection of data sets so large or complex that it becomes difficult to process them using traditional data-processing applications. In a nutshell, big data refers to data that is so large, fast or complex that it's difficult or impossible to process using traditional methods. Also, big data deals with accessing and storing large amounts of information for analytics.

So, what is Big Data? Big Data is a large data set with increasing volume, variety and velocity.

Big data solutions may have many components (to mention some):

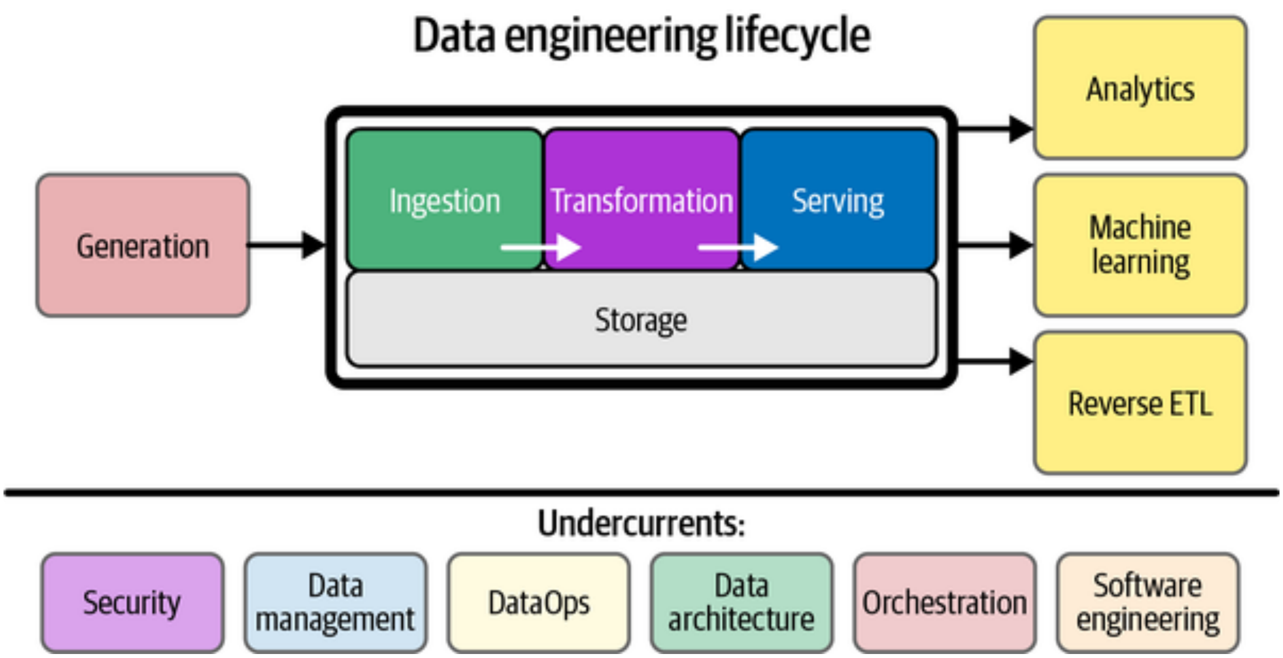
- Distributed File System (such as HDFS, Amazon S3)
- Analytics Engine (such as Spark)
- Query Engine (Such as Snowflake, Amazon Athena, Google BigQuery, …)
- ETL Support
- Relational database systems
- Search engine (sich as Apache Solr, Apache Lucene)
- …

Big Data Engineering

Big Data engineering is the discipline for engineering scalable systems for data-intensive processing.

Data collected from different sources are in a raw format, i.e., usually in a form that is not fit for Data Analysis. The idea behind what is Big Data Engineering is not only to collect Big Data but also to transform and store it in a dedicated database that can support insights generation or the creation of Machine Learning based solutions.

What is the Data Engineering Lifecycle? The data engineering lifecycle comprises stages that turn raw data ingredients into a useful end product, ready for consumption by analysts, data scientists, ML engineers, and others.



Data Engineers are the force behind Data Engineering that is focused on gathering information from disparate sources, transforming the data, devising schemas, storing data, and managing its flow.

Big Data Modeling

What is Big Data Modeling? Data modeling is the method of constructing a specification for the storage of data in a database. It is a theoretical representation of data objects and relationships between them. The process of formulating data in a structured format in an information system is known as data modeling.

In a practical sense, Big Data Modeling involves:

- **Queries**: understand queries and algorithms, which needs to be implemented using big data
- **Formalizing Queries**: understaning queries for big data (how big data will be accessed, what are the parameters to these queries): this is a very important step to understand queries before designing proper data model
- **Data Model**: once queries are understood, then design a data model, which optimally satisfies queries
- **Data Analytics Engine**: engine which distributed algorithms and ETL will run; for example: Apache Spark
- **ETL Processes**: design and implement ETL processes to build big data in a suitable format and environment
- **Scalability**: scalability needs to be understood and addressed at every level

Big Data Platforms/Solutions

- Apache Hadoop, which implements a MapReduce paradigm. Hadoop is slow and very complex (does not take advantage of RAM/memory). Hadoop's analytics API is limited to `map-then-reduce` functions.
- Apache Spark, which implements a superset of MapReduce paradigm: it is fast, and has a very simple and powerful API and works about 100 times faster than Hadoop. Spark takes advantage of memory and embraces in-memory computing. Spark can be used for ETL and implementing many types of distributed algorithms.
- Apache Tez
- Amazon Athena (mainly used as a query engine)
- Snowflake (mainly used as a query engine)
- Google BigQuery: is a serverless and multicloud data warehouse designed to help you turn big data into valuable business insights

Biometrics

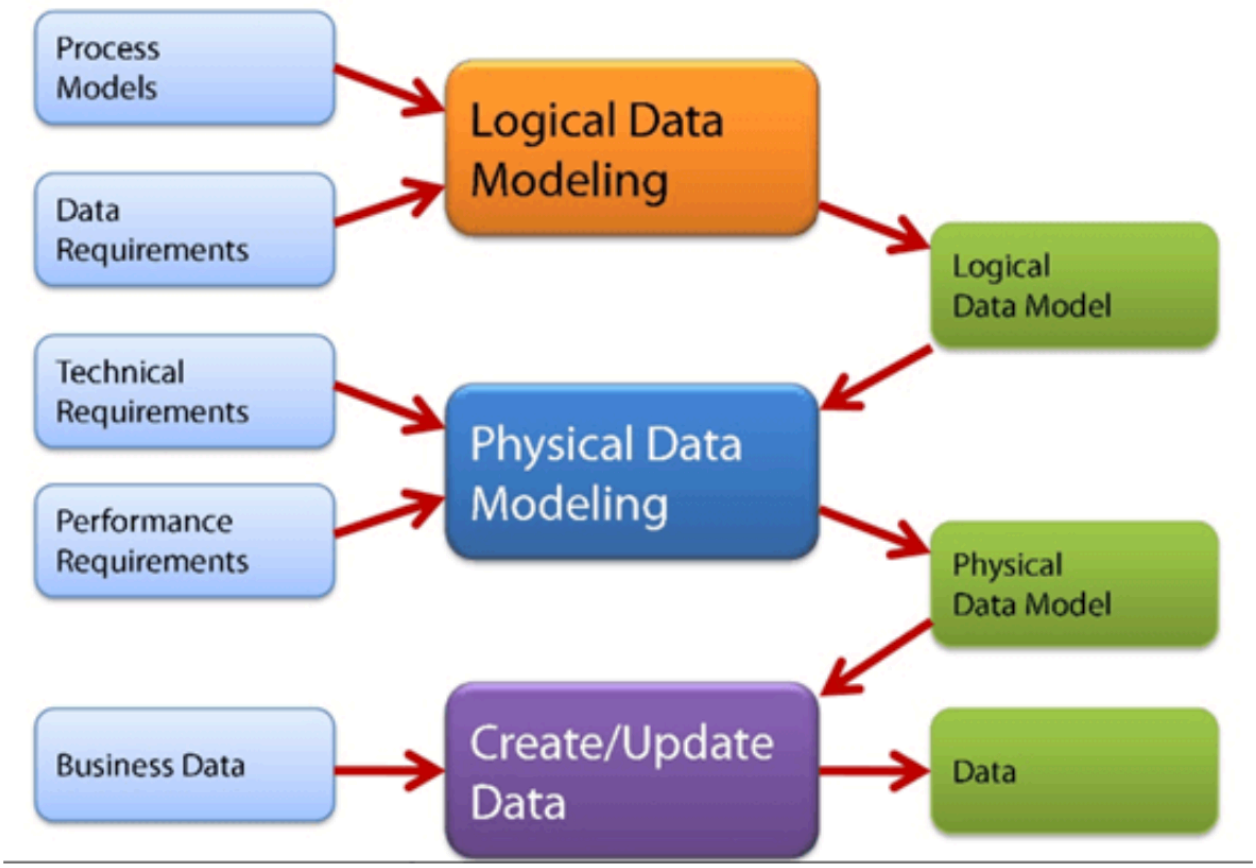
According to dictionary: the automated recognition of individuals by means of unique physical characteristics, typically for the purposes of security. Biometrics refers to the use of data and technology to identify people by one or more of their physical traits (for example, face recognition).

While there are many types of biometrics for authentication, the five most common types of biometric identifiers are: fingerprints, facial, voice, iris, and palm or finger vein patterns.

Data Modelling

Data modeling is the process of creating a data model for the data to be stored in a database. This data model is a conceptual representation of Data objects, the associations between different data objects, and the rules. The analysis of data sets using data modelling techniques to create insights from the data:

- data summarization,
- data aggregation,
- joining data



Types of Data Model

There are 5 different types of data models:

- **Hierarchical Data Model**: A hierarchical data model is a structure for organizing data into a tree-like hierarchy, otherwise known as a parent-child relationship.
- **Relational Data Model**: relational model represents the database as a collection of relations. A relation is nothing but a table of values (or rows and columns).
- **Entity-relationship (ER) Data Model**: an entity relationship diagram (ERD), also known as an entity relationship model, is a graphical representation that depicts relationships among people, objects, places, concepts or events within an information technology (IT) system.
- **Object-oriented Data Model**: the Object-Oriented Model in DBMS or OODM is the data model where data is stored in the form of objects. This model is used to represent real-world entities. The data and data relationship is stored together in a single entity known as an object in the Object Oriented Model.
- **Dimensional Data Model**: Dimensional Modeling (DM) is a data structure technique optimized for data storage in a Data warehouse. The purpose of dimensional modeling is to optimize the database for faster retrieval of data. The concept of Dimensional Modelling was developed by Ralph Kimball and consists of “fact” and “dimension” tables.

Design Patterns

What is a design pattern? In software engineering, a design pattern is a general repeatable solution to a commonly occurring problem in software design. In general, design patterns are categorized mainly into three categories:

- Creational Design Pattern
- Structural Design Pattern
- Behavioral Design Pattern

Gang of Four (Erich Gamma, Richard Helm, Ralph Johnson, and John Vlissides) Design Patterns is the collection of 23 design patterns from the book [Design Patterns: Elements of Reusable Object-Oriented Software].

What are **data design patterns**? Data Design Pattern is a general repeatable solution to a commonly occurring data problem in big data area.

The following are common **Data Design Patterns**:

- Summarization patterns
- Filtering patterns

- In-Mapper patterns
- Data Organization patterns
- Join patterns
- Meta patterns
- Input/Output patterns

The data design patterns can be implemented by MapReduce and Spark and other big data solutions.

Data Set

A collection of (structured, semi-structured, and unstructured) data.

Example of Data Sets:

- DNA data samples for 10,000 patients can be a data set.
- Daily log files for a search engine
- Weekly credit card transactions
- Monthly flight data for a country
- Twitter daily data
- Facebook daily messages

Data Type

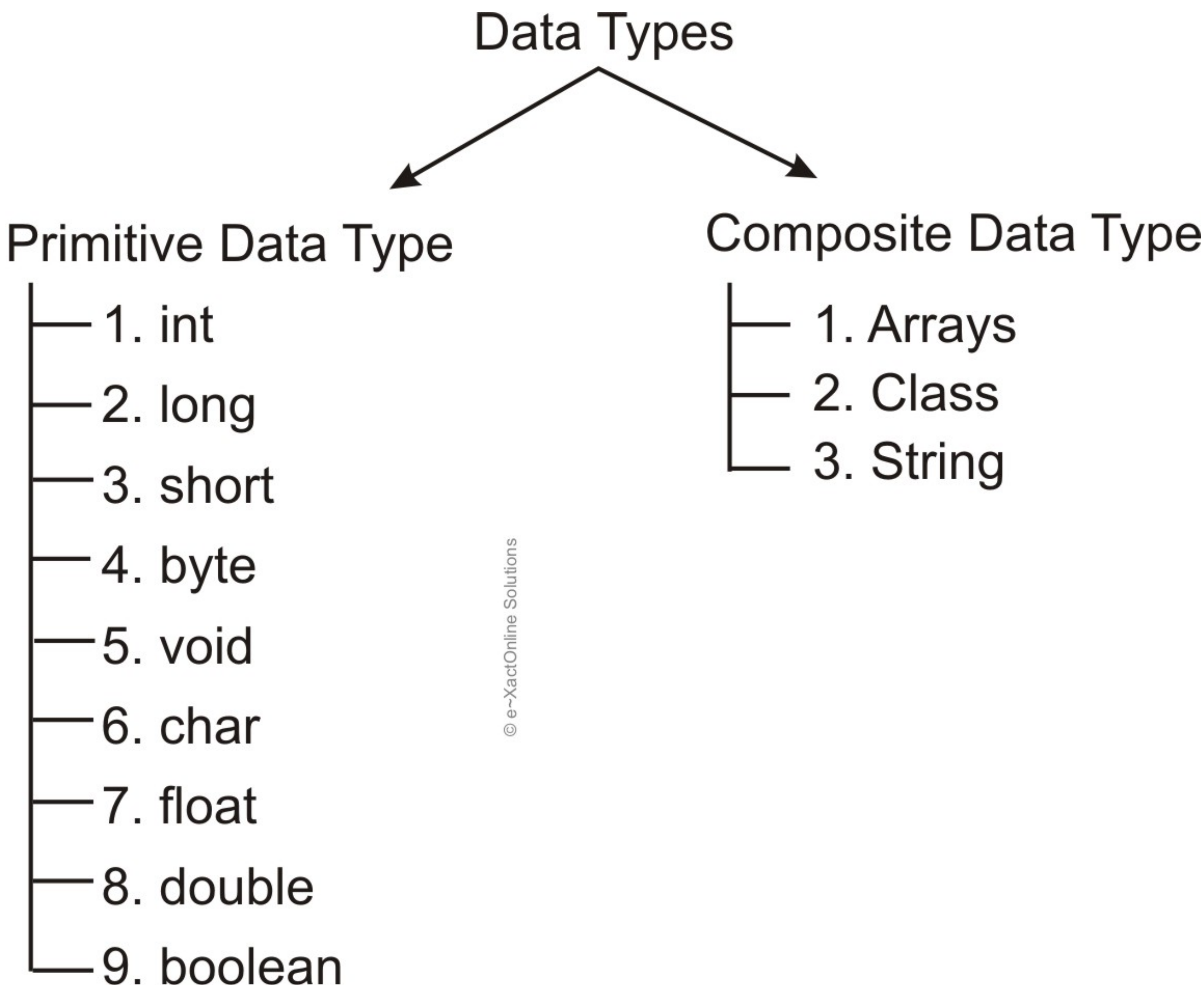
In computer science and computer programming, a **data type** (or simply type) is a set of possible values and a set of allowed operations on it. A data type tells the compiler or interpreter how the programmer intends to use the data.

In a nutshell, data types are the entities that tell the compiler or interpreter that which variable will hold what kind of values. While providing the inputs, there can be a different kind of data entered by a user likewise a number or a character or a sequence of an alphanumeric value. To handle these different kinds of data, the language has Data Types. These data types are of two types:

- **Primitive Data Type**:
  These are the readymade/built-in data type that comes as a part of language compiler.

- **Composite Data Type**:
  These are the data types designed by the user as per requirements. These data types are always based on the primitive ones. Python and Java provide built-in composite data types

(such as lists, sets, arrays, …)



For example,

- Java is a strongly typed (strong typing means that the type of a value doesn't change in unexpected ways) language, every variable must be defined by an explicit data type before usage. Java is considered strongly typed because it demands the declaration of every variable with a data type. Users cannot create a variable without the range of values it can hold.
  - Java example

```java
// bob's data type is int
int bob = 1;

// bob can not change its type: the following line is invalid
// String bob = "bob";

// but, you can use anther variable name
String bob_name = "bob";
```

- Python is strongly, dynamically typed:
    - Strong typing means that the type of a value doesn't change in unexpected ways. A string containing only digits doesn't magically become a number, as may happen in Perl. Every change of type requires an explicit conversion.
    - Dynamic typing means that runtime objects (values) have a type, as opposed to static typing where variables have a type.
        - Python example

```python
# bob's data type is int
bob = 1

# bob's data type changes to str
bob = "bob"
```

This works because the variable does not have a type; it can name any object. After `bob=1`, you'll find that `type(bob)` returns int, but after `bob="bob"`, it returns `str`. (Note that type is a regular function, so it evaluates its argument, then returns the type of the value.)

Primitive Data Type

A data type that allows you to represent a single data value in a single column position. In a nutshell, a primitive data type is either a data type that is built into a programming language, or one that could be characterized as a basic structure for building more sophisticated data types.

- Java examples:

```java
int a = 10;
boolean b = true;
double d = 2.4;
String s = "fox";
String t = null;
```

- Python examples:

```python
a = 10
b = True
d = 2.4
s = "fox"
t = None
```

Composite Data Type

In computer science, a composite data type or compound data type is any data type which can be constructed in a program using the programming language's primitive data types.

- Java examples:

```java
import java.util.Arrays;
import java.util.List;
...
int[] a = {10, 11, 12};
List<String> names = Arrays.asList("n1", "n2", "n3");
```

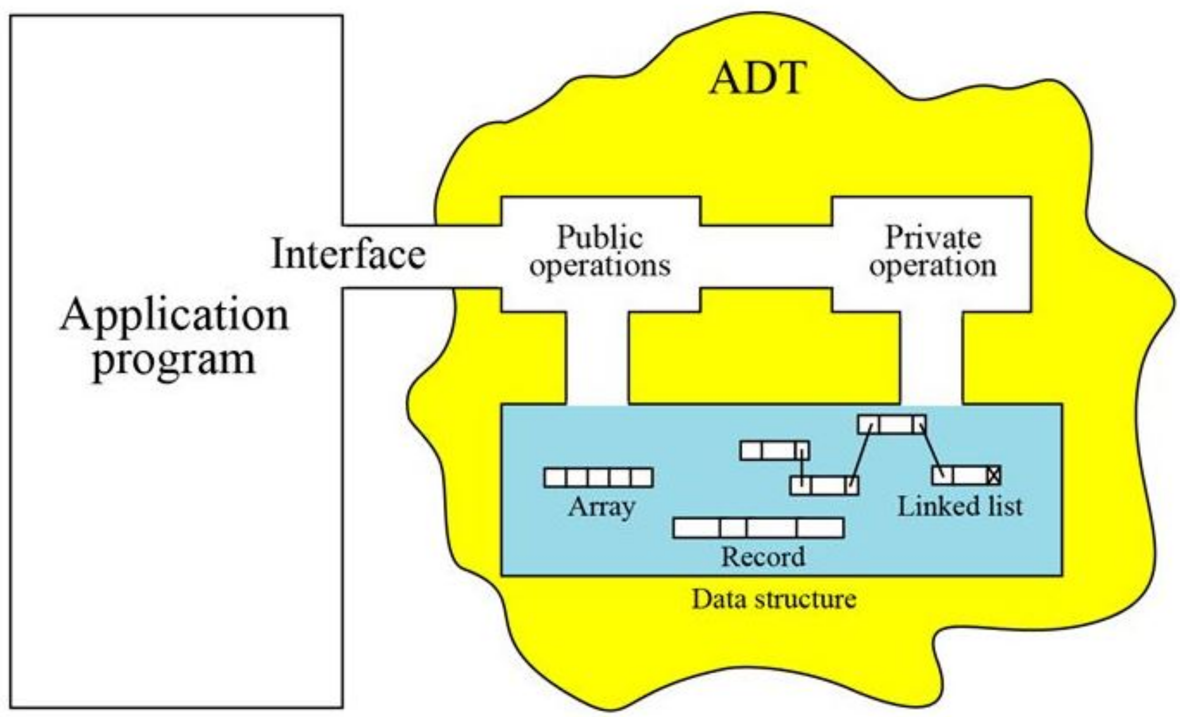
- Python examples:

```python
a = [10, 11, 12];
names = ("n1", "n2", "n3") # immutable
names = ["n1", "n2", "n3"] # mutable
```

In Java and Python, custom composite data types can be created by the concept of "class" and objects are created by instantiation of the class objects.

Abstract Data Type

In computer science, an abstract data type (ADT) is a mathematical model for data types. An abstract data type is defined by its behavior (semantics) from the point of view of a user, of the data, specifically in terms of possible values, possible operations on data of this type, and the behavior of these operations. This mathematical model contrasts with data structures, which are concrete representations of data, and are the point of view of an implementer, not a user.



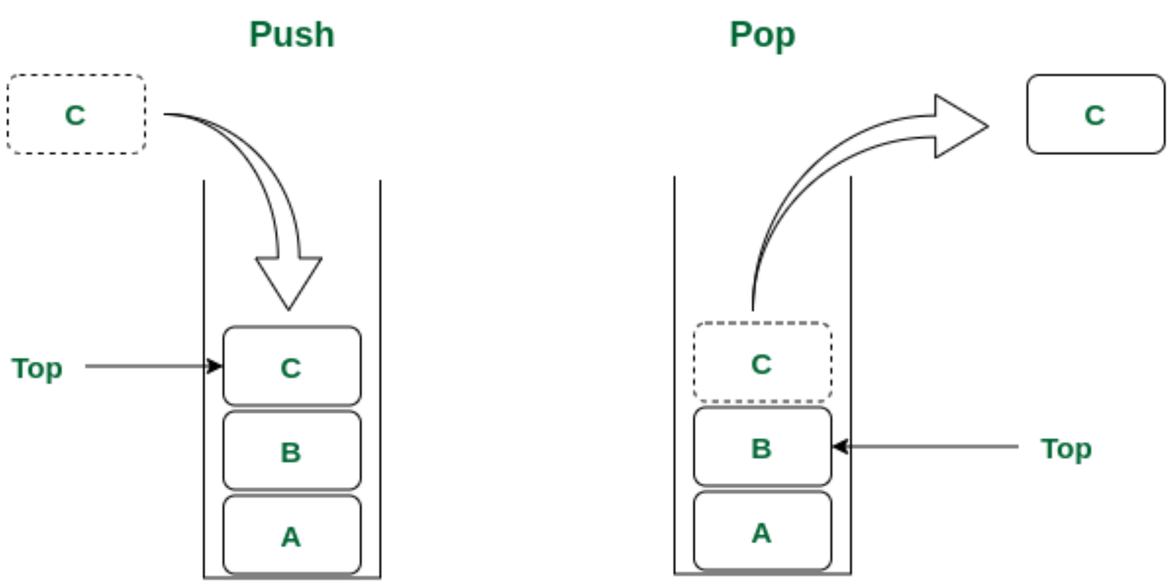
Abstract Data type (ADT) is a type (or class) for objects whose behavior is defined by a set of values and a set of operations. The definition of ADT only mentions what operations are to be performed but not how these operations will be implemented.

Example: Stack as an Abstract Data Type

The stack data structure is a linear data structure that accompanies a principle known as LIFO (Last-In-First-Out) or FILO (First-In-Last-Out). In computer science, a stack is an abstract data type that serves as a collection of elements, with two main operations (adding or removing is only possible at the top):

- `push` , which adds an element to the collection, and
- `pop` , which removes the most recently added element that was not yet removed.

```
##### Stack as an Abstract Data Tyoe #####

# create a new empty Stack
CREATE: -> Stack

# add an Item to a given Stack
PUSH: Stack × Item -> Stack

# Return the top element and remove from the Stack
POP: Stack -> Item

# Gets the element at the top of the Stack without removing it
PEEK: Stack -> Item

# remove the top element and return an updated Stack
REMOVE: Stack -> Stack

# return True if the Stack is empty, otherwise return False
IS_EMPTY: Stack -> Boolean

# return the size of a given Stack
SIZE: Stack -> Integer
```



Stack Data Structure

Example: Queue as an Abstract Data Type

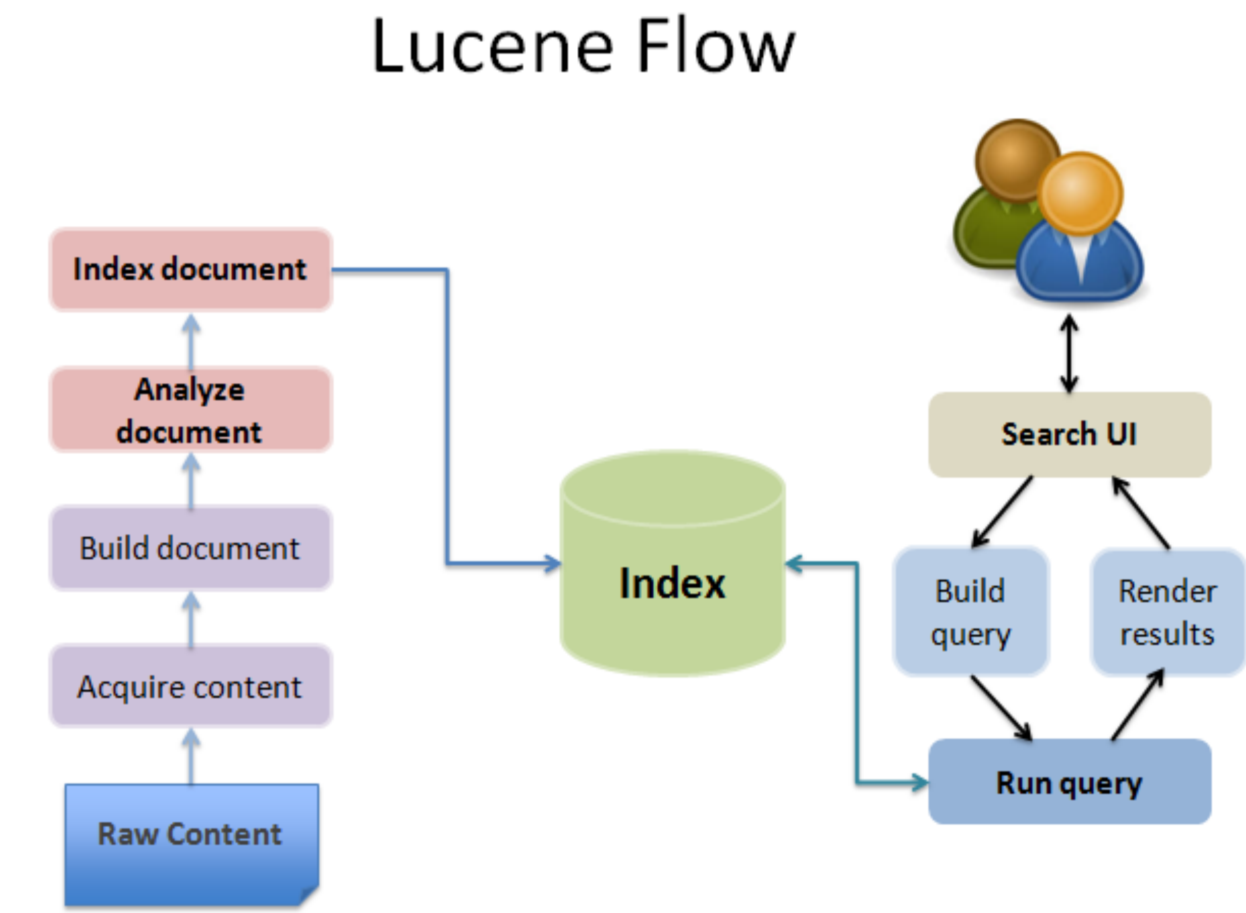
For example, operations for a Queue (First-In-First-Out – FIFO) as an abstract data type can be specified as the following. Note that a Queue can be implemented in many ways (using lists, arrays, linked lists, …). Queue is an abstract data structure, somewhat similar to Stacks. Unlike stacks, a queue is open at both its ends. One end is always used to insert data (enqueue) and the other is used to remove data (dequeue). Queue follows First-In-First-Out methodology, i.e., the data item stored first will be accessed first.

```
##### Queue as an Abstract Data Type #####

# create a new empty Queue
CREATE: -> Queue

# add an Item to a given Queue
ADD: Queue × Item -> Queue

# Return a front element and remove from the Queue
FRONT: Queue -> Item

# Gets the element at the front of the Queue without removing it
PEEK: Queue -> Item

# remove a front element and return an updated Queue
REMOVE: Queue -> Queue

# return True if the Queue is empty, otherwise return False
IS_EMPTY: Queue -> Boolean

# return the size of a given Queue
SIZE: Queue -> Integer
```

Queue Data Structure

Apache Lucene

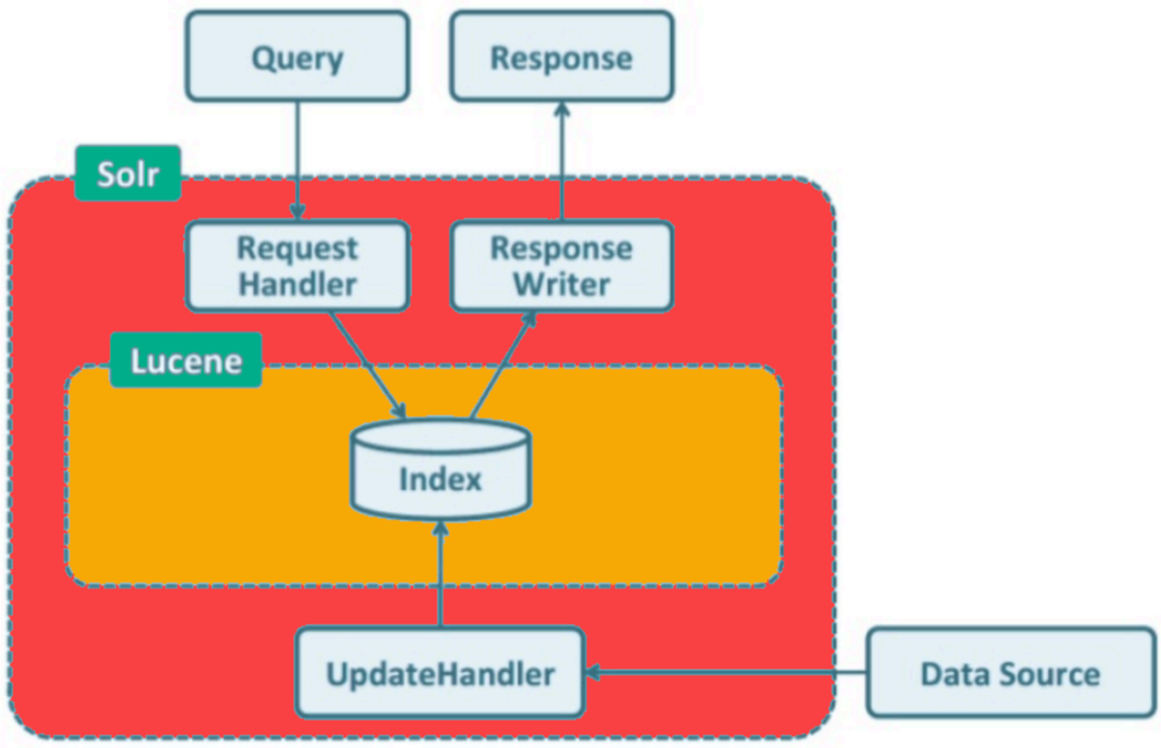
Lucene is an open-source search engine software library written in Java. It provides robust search and indexing features.



Apache Lucene is a high-performance, full-featured search engine library written entirely in Java. It is a technology suitable for nearly any application that requires structured search, full-text search, faceting, nearest-neighbor search across high dimensionality vectors, spell correction or query suggestions.

Apache Solr

Solr is the popular, blazing-fast, open source enterprise search platform built on Apache Lucene. Solr is highly reliable, scalable and fault tolerant, providing distributed indexing, replication and load-balanced querying, automated failover and recovery, centralized configuration and more. Solr powers the search and navigation features of many of the world’s largest internet sites.



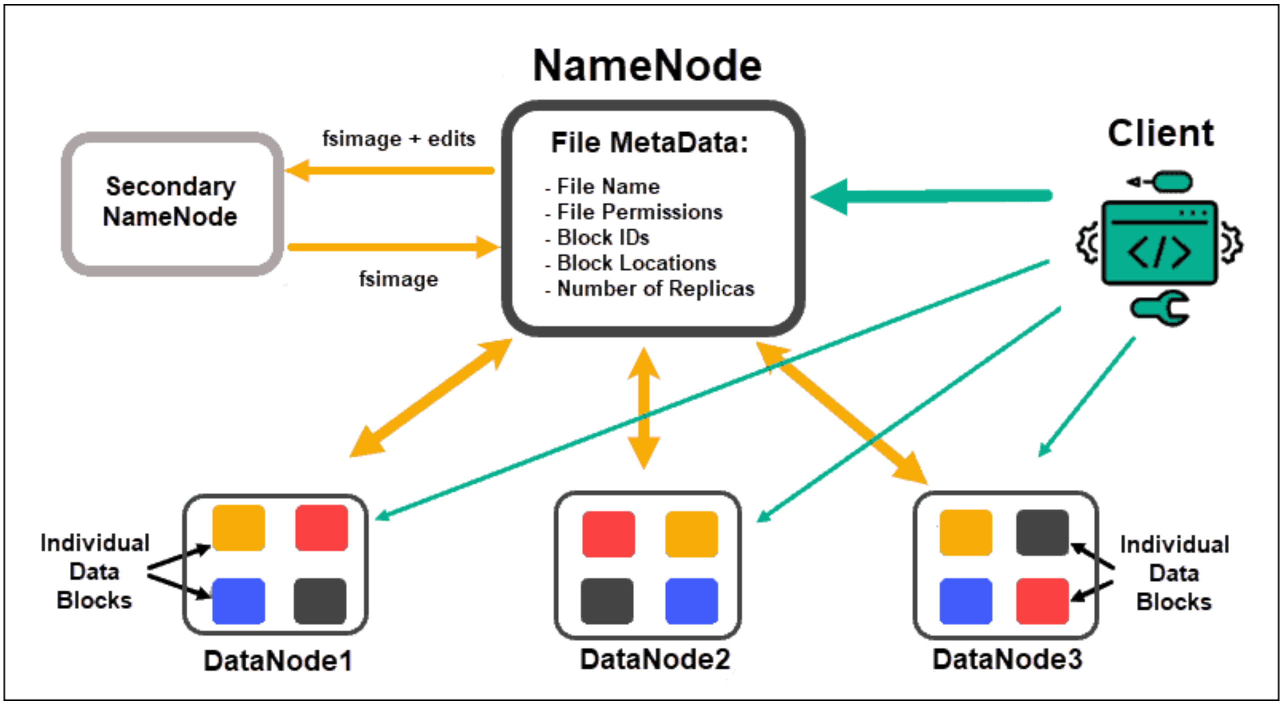
Apache Solr Architecture

Apache Hadoop

Hadoop is an open source framework that is built to enable the process and storage of big data across a distributed file system. Hadoop implements MapReduce paradigm, it is slow and complex and uses disk for read/write operations. Hadoop does not take advantage of in-memory computing. Hadoop runs a computing cluster.

Hadoop takes care of running your MapReduce code (by `map() first, then reduce()` logic) across a cluster of machines. Its responsibilities include chunking up the input data, sending it to each machine, running your code on each chunk, checking that the code ran, passing any results either on to further processing stages or to the final output location, performing the sort that occurs between the **map** and **reduce** stages and sending each chunk of that sorted data to the right machine, and writing debugging information on each job's progress, among other things.

Hadoop architecture:



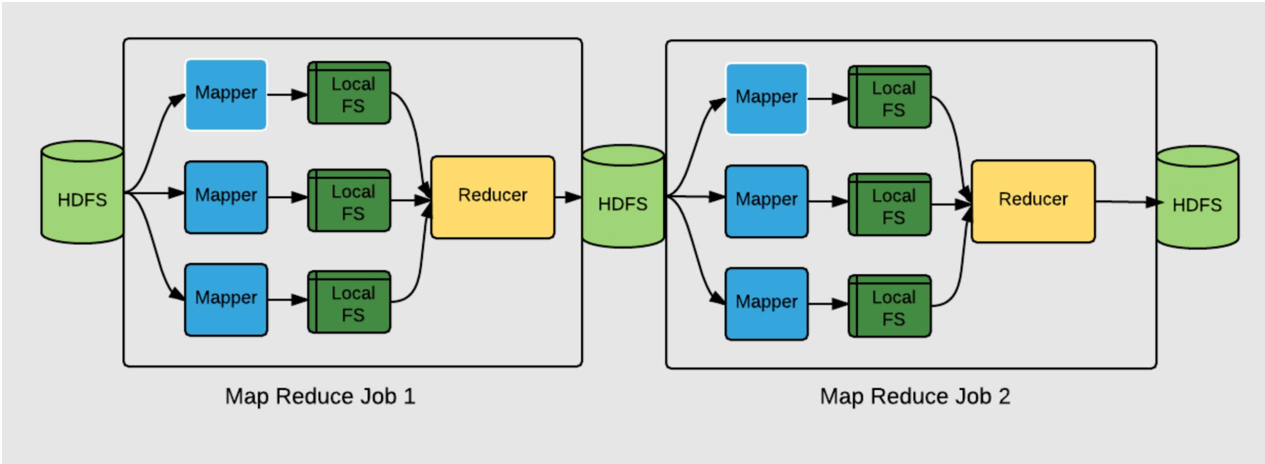
`NameNode` is the master node in the Apache Hadoop HDFS Architecture that maintains and manages the blocks present on the DataNodes (worker nodes). NameNode is a very highly available server that manages the File System Namespace and controls access to files by clients.

Hadoop provides:

- MapReduce: you can run MapReduce jobs by implementing a series of `map() first, then reduce()` functions. With MapReduce, you can analyze data at a scale.
- HDFS: Hadoop Distributed File System

Note that for some big data problems, a single MapReduce job will not be enough to solve the problem, in this case, then you might need to run multiple Mapreduce jobs (as illustrated below):

Big data solution with Hadoop (comprised of 2 MapReduce jobs):



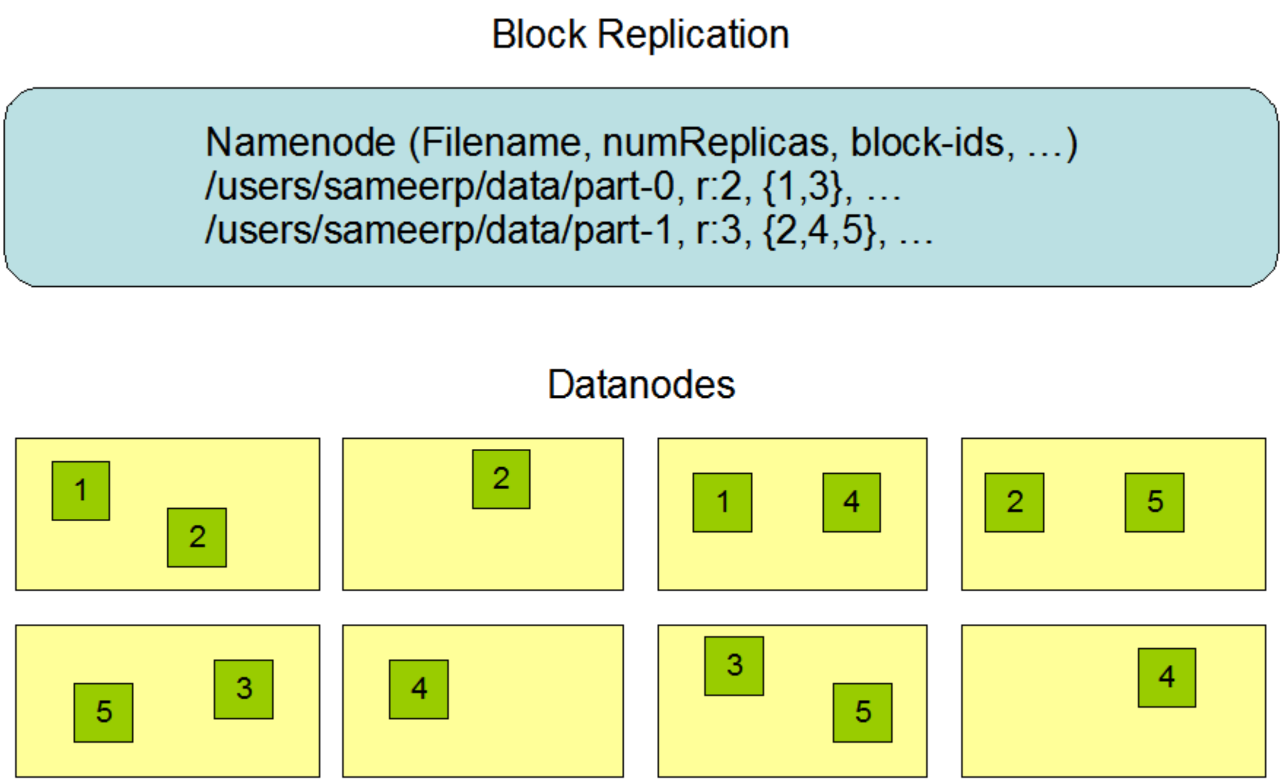
What is the difference between Hadoop and RDBMS?

- Hadoop is an implementation of MapReduce paradigm
- RDBMS denoes a relational database system such as Oracle, MySQL, Maria

Criteria	Hadoop	RDBMS
Data Types	Processes semi-structured and unstructured data	Processes structured data
Schema	Schema on Read	Schema on Write
Best Fit for Applications	Data discovery and Massive Storage/Processing of Unstructured data.	Best suited for OLTP and ACID transactions
Speed	Writes are Fast	Reads are Fast
Data Updates	Write once, Read many times	Read/Write many times
Data Access	Batch	Interactive and Batch
Data Size	Tera bytes to Peta bytes	Giga bytes to Tera bytes
Development	Time consuming and complex	Simple
API	Low level (by `map()` and `reduce()`) functions	SQL and extensive

Replication

In computer science and software engineering, replication refers to the use of redundant resources to improve reliability, fault-tolerance, or performance. One example of a replication is data replication. For example in Hadoop: HDFS (Hadoop Distributed File System) is designed to reliably store very large files across machines in a large cluster. It stores each file as a sequence of blocks; all blocks in a file except the last block are the same size. The blocks of a file are replicated for fault tolerance: it means that if a server holding specific data (say block X) fails, then that specific data (block X) can be retrieved and read from other replicated servers.



In HDFS, the block size and replication factor are configurable per file. An application can specify the number of replicas of a file. The replication factor can be specified at file creation time and can be changed later. Files in HDFS are write-once and have strictly one writer at any time.

Replication Example:

- file name: sample.txt
- file size: 1900 MB
- Data Block Size: 512 MB
- Replication Factor: 3
- Cluster of 6 nodes (one master + 6 worker nodes)::

- One Master node (no actual data is stored in the master node, the master node saves/stores metadata information)
- 5 worker/data nodes (actual data is stored in worker/data nodes) denoted as { W1, W2, W3, W4, W5 }

Since file size is 1900 MB, this means that this file is partitioned into 4 blocks (`1900 <= (4 * 512)`):

- 1900 = 512 + 512 + 512 + 364
- Block-1 (B1): 512 MB
- Block-2 (B2): 512 MB
- Block-3 (B3): 512 MB
- Block-4 (B4): 512 MB (But only 364 MB is utilized)

With replication factor of 3, worker nodes might hold these blocks as (note that there will not be any duplicate blocks per data nodes):

- W1: { B1, B3 }
- W2: { B2, B4 }
- W3: { B3, B4, B2 }
- W4: { B4, B3, B1 }
- W5: { B1, B2 }

Since replication factor is 3, therefore only 2 (3-1) data nodes can safely fail.

Replication Factor (RF)

The total number of replicas across the cluster is referred to as the replication factor (RF). A replication factor of 1 means that there is only one copy of each row in the cluster. If the node containing the row goes down, the row cannot be retrieved. A replication factor of 2 means two copies of each row, where each copy is on a different node. All replicas are equally important; there is no primary or master replica.

Given a cluster of `N+1` nodes (a master and `N` worker nodes), if data replication factotr is `R`, then `(R - 1)` nodes can safely fail without impacting any running job in the cluster.

What makes Hadoop Fault tolerant?

Hadoop is said to be highly fault tolerant. Hadoop achieves this feat through the process of data replication. Data is replicated across multiple nodes in a Hadoop cluster. The data is associated with a replication factor (RF), which indicates the number of copies of the data that are present across the various nodes in a Hadoop cluster. For example, if the replication factor is 4, the data will be present in four different nodes of the Hadoop cluster, where each node will contain one copy each. In this manner, if there is a failure in any one of the nodes, the data will not be lost, but can be recovered from one of the other nodes which contains copies or replicas of the data.

If replication factor is `N`, then `N-1` nodes can safely fail without impacting a running job.

Big Data Formats

Data comes in many varied formats:

- Avro
  - Avro stores the data definition in JSON format making it easy to read and interpret
- Parquet
  - Parquet is an open source, binary, column-oriented data file format designed for efficient data storage and retrieval
- ORC
  - The Optimized Row Columnar (ORC) file format provides a highly efficient way to store Hive data.
- Text files (log data, CSV, …)
- XML
- JSON
- JDBC (read/write from/to relational tables)
- DNA Data Foramts:
  - FASTQ
  - FASTA
  - VCF
  - …
- +more…

Parquet Files

Apache Parquet is a columnar file format that supports block level compression and is optimized for query performance as it allows selection of 10 or less columns from from 50+ columns records.

Apache Spark can read/write from/to Parquet data format.

Parquet is a columnar open source storage format that can efficiently store nested data which is widely used in Hadoop and Spark.

Characteristics of Parquet:

- Free and open source file format.
- Language agnostic.
- Column-based format - files are organized by column, rather than by row, which saves storage space and speeds up analytics queries.
- Used for analytics (OLAP) use cases, typically in conjunction with traditional OLTP databases.
- Highly efficient data compression and decompression.
- Supports complex data types and advanced nested data structures.

Benefits of Parquet:

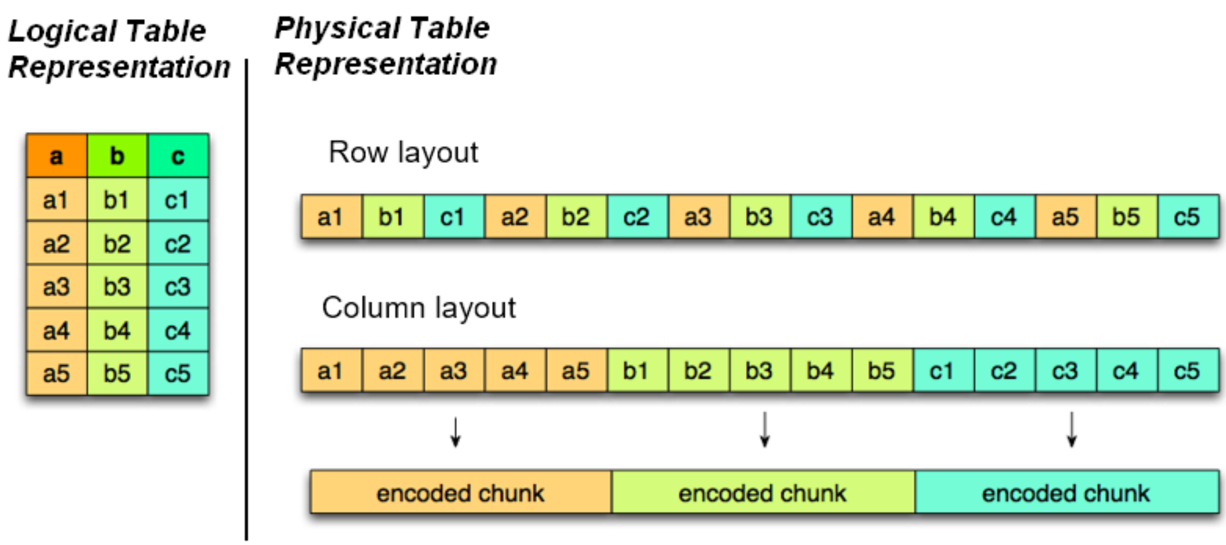
- Good for storing big data of any kind (structured data tables, images, videos, documents).
- Saves on cloud storage space by using highly efficient column-wise compression, and flexible encoding schemes for columns with different data types.
- Increased data throughput and performance using techniques like data skipping, whereby queries that fetch specific column values need not read the entire row of data.

Spark Format Showdown		File Format		
		CSV	JSON	Parquet
Attribute	Columnar	No	No	Yes
	Compressable	Yes	Yes	Yes
	Splittable	Yes*	Yes**	Yes
	Human Readable	Yes	Yes	No
	Nestable	No	Yes	Yes
	Complex Data Structures	No	Yes	Yes
	Default Schema: Named columns	Manual	Automatic (full read)	Automatic (instant)
	Default Schema: Data Types	Manual (full read)	Automatic (full read)	Automatic (instant)

Columnar vs. Row Oriented Databases

Columnar databases have become the popular choice for storing analytical data workloads. In a nutshell, Column oriented databases, store all values from each column together whereas row oriented databases store all the values in a row together.

If you need to read MANY rows but only a FEW columns, then Column-Oriented databases are the way to go. If you need to read a FEW rows but MANY columns then row oriented databases are better suited.



Tez

Apache Tez (which implements MapReduce paradigm) is a framework to create high performance applications for batch and data processing. YARN of Apache Hadoop coordinates with it to provide the developer framework and API for writing applications of batch workloads.

The Tez is aimed at building an application framework which allows for a complex directed-acyclic-graph (DAG) of tasks for processing data. It is currently built atop Apache Hadoop YARN.

Apache HBase

- Apache HBase is an open source, non-relational, distributed database running in conjunction with Hadoop.

- HBase is a column-oriented non-relational database management system that runs on top of Hadoop Distributed File System (HDFS).
- HBase can support billions of data points.

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.

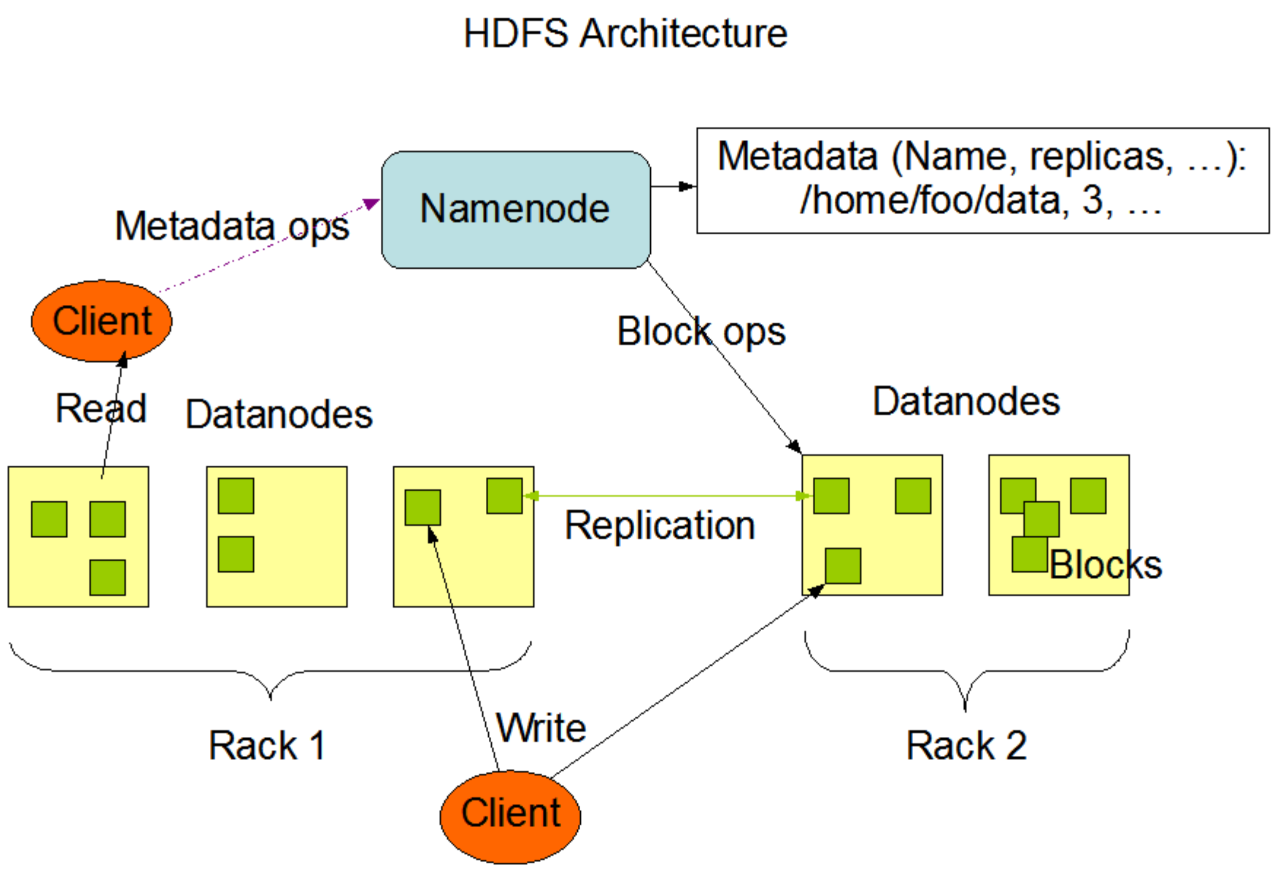
Google Bigtable

According to Google: Google Bigtable is an HBase-compatible, enterprise-grade NoSQL database service with single-digit millisecond latency, limitless scale, and 99.999% availability for large analytical and operational workloads.

Bigtable is a fully managed wide-column and key-value NoSQL database service for large analytical and operational workloads as part of the Google Cloud portfolio.

Hadoop Distributed File System - HDFS

HDFS (Hadoop Distributed File System) is a distributed file system designed to run on commodity hardware. You can place huge amount of data in HDFS. You can create new files or directories. You can delete files, but you can not edit/update files in place.



Features of HDFS:

- Data replication. This is used to ensure that the data is always available and prevents data loss
- Fault tolerance and reliability
- High availability
- Scalability
- High throughput
- Data locality

- HDFS General format:

```
hdfs://<host>:<port>/folder_1/.../folde_n/file
```

- HDFS Example:

```
hdfs://localhost:8020/data/2023-01-07/samples.txt
```

Scalability

Scalability is the ability of a system or process to maintain acceptable performance levels as workload or scope increases.

According to Gartner:

> Scalability is the measure of a system's ability to increase or decrease in performance and cost in response to changes in application and system processing demands. Examples would include how well a hardware system performs when the number of users is increased, how well a database withstands growing numbers of queries, or how well an operating system performs on different classes of hardware. Enterprises that are growing rapidly should pay special attention to scalability when evaluating hardware and software.

For example, an application program would be scalable if it could be moved from a smaller to a larger operating system and take full advantage of the larger operating system in terms of performance (user response time and so forth) and the larger number of users that could be handled.

Amazon S3

Amazon Simple Storage Service (Amazon S3) is an object storage service that offers industry-leading scalability, data availability, security, and performance. Customers of all sizes and industries can use Amazon S3 to store and protect any amount of data for a range of use cases, such as data lakes, websites, mobile applications, backup and restore, archive, enterprise applications, IoT devices, and big data analytics. Amazon S3 provides management features so that you can optimize, organize, and configure access to your data to meet your specific business, organizational, and compliance requirements.

Objects are the fundamental entities stored in Amazon S3. Objects are stored as:

- General format:

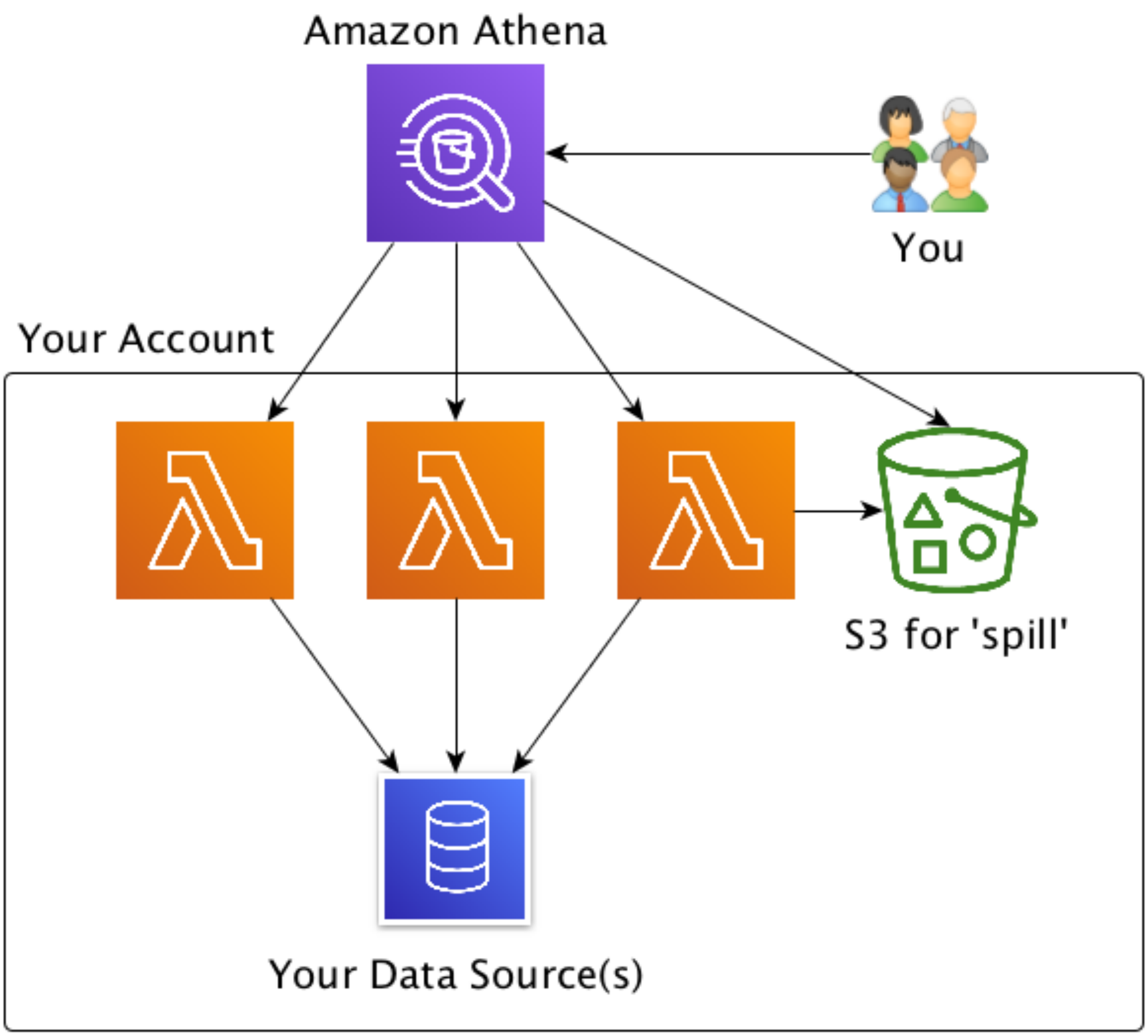
  ```
  s3://<bucket-name>/folder_1/.../folde_n/file
  ```

- Example:

  ```
  s3://my_bucket_name/data/2023-01-07/samples.txt
  ```

Amazon Athena

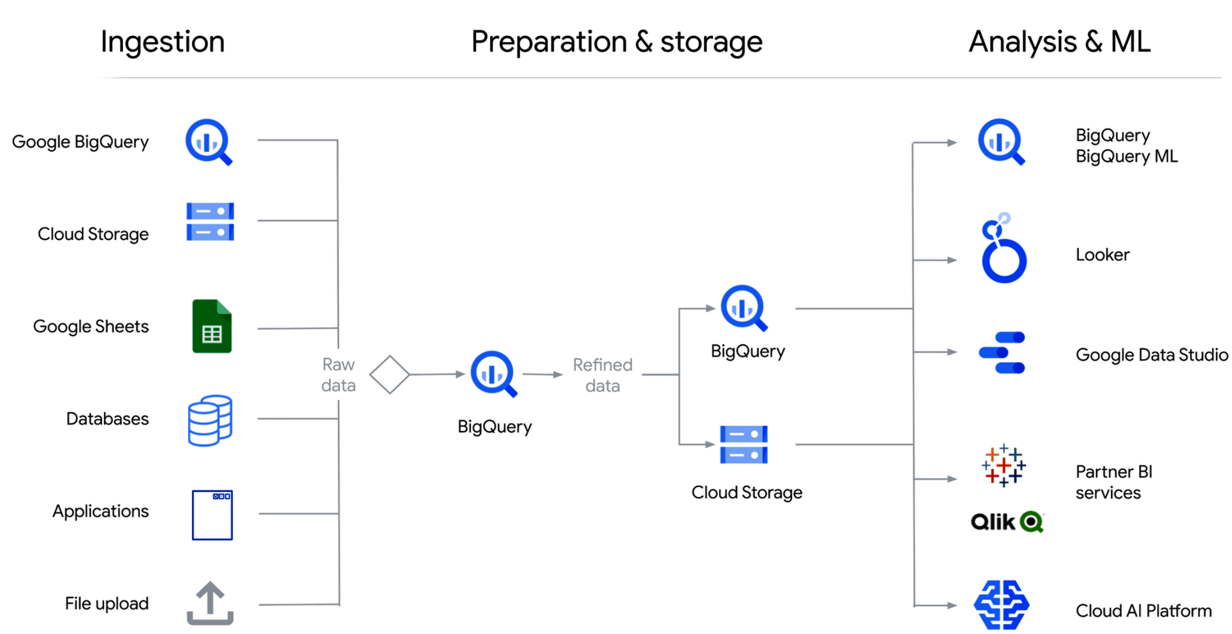
What is Amazon Athena? Amazon Athena is a service that enables data analysts to perform interactive queries using SQL, JDBC, and native API. The Amazon Athena is widely used and is defined as an interactive query service that makes it easy to analyze data in Amazon S3 using the standard SQL.



- Amazon Athena is serverless, so there is no infrastructure to manage, and users pay only for the queries that they run.
    - No cluster set up is required
    - No cluster management is required
    - No database server setup is required

- Amazon Athena is easy to use and simply point to users' data in Amazon S3, define the schema, and start querying using standard SQL.
- Most results are delivered within seconds. With Athena, there's no need for complex ETL jobs to prepare user's data for the analysis and this makes it easy for anyone with SQL skills to quickly analyze large-scale datasets.
- Amazon Athena is out-of-the-box integrated with the AWS Glue Data Catalog allowing users to create the unified metadata repository across various services, crawl data sources to discover schemas and populate their Catalog with new and modified table and partition definitions, and maintain the schema versioning.
- Amazon Athena is the serverless data query tool which means it is scalable and cost-effective at the same time. Usually, customers are charged on a pay per query basis which further translates to the number of queries that are executed at a given time.
- The normal charge for scanning 1TB of data from S3 is 5 USD and although it looks quite a small amount at a first glance when users have multiple queries running on hundreds and thousands of GB of data, the price might get out of control at times.

Google BigQuery



- BigQuery is a serverless and cost-effective enterprise data warehouse.

- BigQuery supports the Google Standard SQL dialect, but a legacy SQL dialect is also available.
- BigQuery has built-in machine learning and BI that works across clouds, and scales with your data.
- BigQuery is a fully managed enterprise data warehouse that helps you manage and analyze your data with built-in features like machine learning, geospatial analysis, and business intelligence.
- BigQuery's query engine can run SQL queries on terabytes of data within seconds, and petabytes within minutes. BigQuery gives you this performance without the need to maintain the infrastructure or rebuild or create indexes. BigQuery's speed and scalability make it suitable for use in processing huge datasets.
- BigQuery storage: BigQuery stores data using a columnar storage format that is optimized for analytical queries. BigQuery presents data in tables, rows, and columns and provides full support for database transaction semantics (ACID). BigQuery storage is automatically replicated across multiple locations to provide high availability.
- With Google Cloud's pay-as-you-go pricing structure, you only pay for the services you use.

Commodity server/hardware

Commodity hardware (computer), sometimes known as off-the-shelf server/hardware, is a computer device or IT component that is relatively inexpensive, widely available and basically interchangeable with other hardware of its type. Since commodity hardware is not expensive, it is used in building/creating clusters for big data
computing (scale-out architecture). Commodity hardware is often deployed for high availability and disaster recovery purposes.

Fault Tolerance and Data Replication.

Fault-tolerance is the ability of a system to continue to run when a component of the system (such as a server node, disk, …) fails.

HDFS is designed to reliably store very large files across machines in a large cluster. It stores each file as a sequence of blocks; all blocks in a file except the last block are the same size. The blocks of a file are replicated for fault tolerance.

Block size can be configured. For example, let block size to be 512 MB. Now, let's place a file (sample.txt) of 1800 MB in HDFS:

```
1800MB = 512MB (Block-1) + 512MB (Block-2) + 512MB (Block-3) + 264MB (Block-4
Lets denote
           Block-1 by B1
           Block-2 by B2
           Block-3 by B3
           Block-4 by B4
```

Note that the last block, Block-4, has only 264 MB of useful data.

Let's say, we have a cluster of 6 nodes (one master and 5 worker nodes {W1, W2, W3, W4, W5} and master does not store any actual data), also assume that the replication factor is 2, therefore, blocks will be placed as:

```
    W1: B1, B4
    W2: B2, B3
    W3: B3, B1
    W4: B4
    W5: B2
```

Fault Tolerance: if replication factor is `N`, then `(N-1)` nodes can safely fail without a job fails.

High-Performance-Computing (HPC)

Using supercomputers to solve highly complex and advanced computing problems. This is a scale-up architecture and not a scale-out architecture. High-performance computing (HPC) uses supercomputers and computer clusters to solve advanced computation problems. HPC has a high cost due to the high cost of supercomputers.

Scaling up is adding further resources, like hard drives and memory, to increase the computing capacity of physical servers. Whereas **scaling out** is adding more servers to your architecture to spread the workload across more server/machines.

Hadoop and Spark use **scale-out** architectures.

History of MapReduce

MapReduce was developed by Google back in 2004 by Jeffery Dean and Sanjay Ghemawat of Google (Dean & Ghemawat, 2004). In their paper, [MAPREDUCE: SIMPLIFIED DATA PROCESSING ON LARGE CLUSTERS]() and was inspired by the `map()` and `reduce()` functions commonly used in functional programming. At that time, Google's proprietary MapReduce system ran on the Google File System (GFS). Apache Hadoop is an open-source implementation of Google's MapReduce.

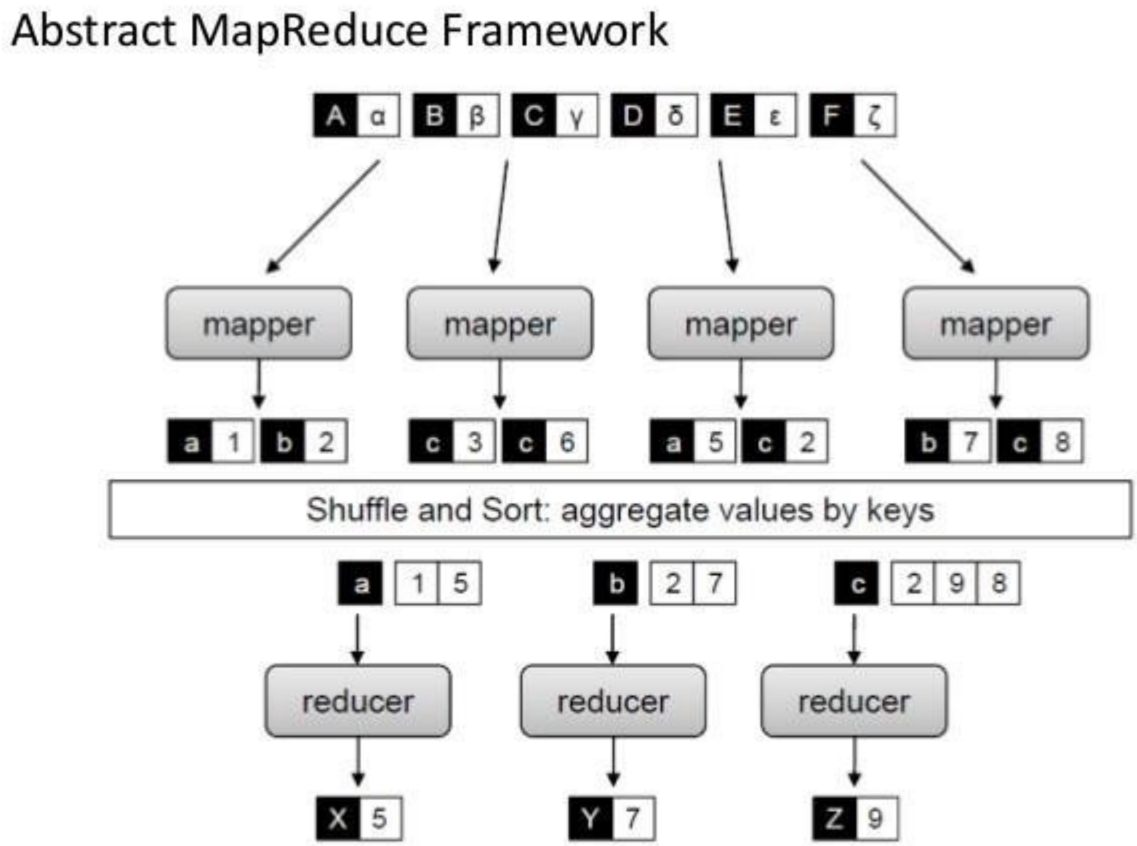
MapReduce

- Motivation: Large Scale Data Processing
- Scale-out Architecture: use many commodity servers in cluster computing environment
- Many tasks: Process lots of data in parallel (using cluster computing) to produce other needed data
- Want to use hundreds or thousands of servers to minimize analytics time
- … but this needs to be easy

Mapreduce is a software framework for processing vast amounts of data. MapReduce is a parallel programming model for processing data on a distributed system. MapReduce is a programming model and an associated implementation for processing and generating big data sets with a parallel, distributed algorithm on a cluster.

MapReduce provides:

- Automatic parallelization and distribution
- Fault-tolerance
- I/O scheduling
- Status and monitoring



MapReduce's Programming model

- Input & Output: each a set of `(key, value)` pairs
- Programmer specifies two functions:
- ***map()*** function:

```
map (in_key, in_value) -> list(out_key, intermediate_value)
# Processes input (in_key, in_value) pair
# Produces set of intermediate pairs
```

- ***reduce()*** function:

```
reduce (out_key, list(intermediate_value)) -> list(out_value)
# Combines all intermediate values for a particular key
# Produces a set of merged output values
# Inspired by similar primitives in LISP and other languages
```

In a nutshell, MapReduce provides 3 functions (provided by a programmer) to analyze huge amounts of data:

- `map()` provided by programmer: process the records of the data set:

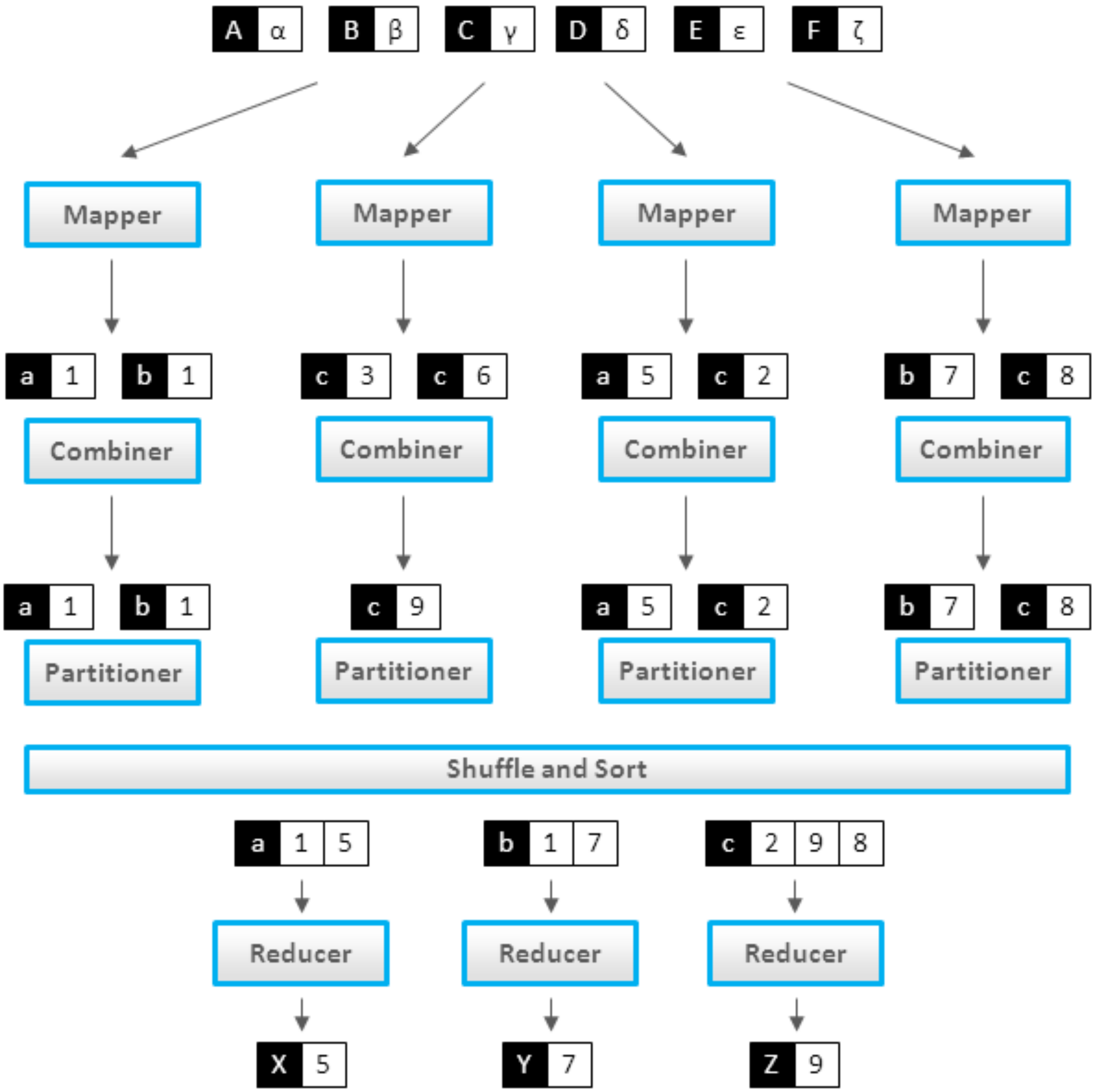
```
# key: partition number of record number, which might be ignored
# or the “key” might refer to the offset address for each record
# value : an actual input record
map(key, value) -> {(K2, V2), ...}

NOTE: If a mapper does not emit any (K2, V2), then it
means that the input record is filtered out.
```

- `reduce()` provided by programmer: merges the output from mappers:

```
# key: unique key as K2
# values : [v1, v2, ...], values associated by K2
# the order of values {v1, v2, ...} are undefined.
reduce(key, values) -> {(K3, V3), ...}

NOTE: If a reducer does not emit any (K3, V3), then it
means that the key (as K2) is filtered out.
```

- `combine()` provided by programmer [optional]
    - Mini-Reducer
    - Optimizes the result sets from the mappers before sending them to the reducers

The following image illustrates the basic concepts of mappers, combiners, and reducers in MapReduce paradigm.



The genie/magic/power of MapReduce is a Sort & Shuffle phase (provided by MapReduce implementation), which groups keys generated by all mappers. For example, if all mappers (from all servers) have created the following `(key, value)` pairs:

```
(C, 4), (C, 5),
(A, 2), (A, 3),
(B, 1), (B, 2), (B, 3), (B, 1), (B, 0), (B, 5)
(D, 7), (D, 8), (D, 8)
(E, 9)
```

then Sort & Shuffle phase creates the following `(key, value)` pairs (not in any particular order) to be consumed by reducers: Note that the keys `{ A, B, C, D, E }` are unique:

```
(A, [2, 3])
(B, [1, 2, 3, 1, 0, 5])
(C, [4, 5])
(D, [7, 8, 8])
(E, [9])
```

Options for MapReduce implementation:

- Hadoop (slow and complex) is an implementation of MapReduce.

- Spark (fast and simple) is a superset implementation of MapReduce.

MapReduce Terminology

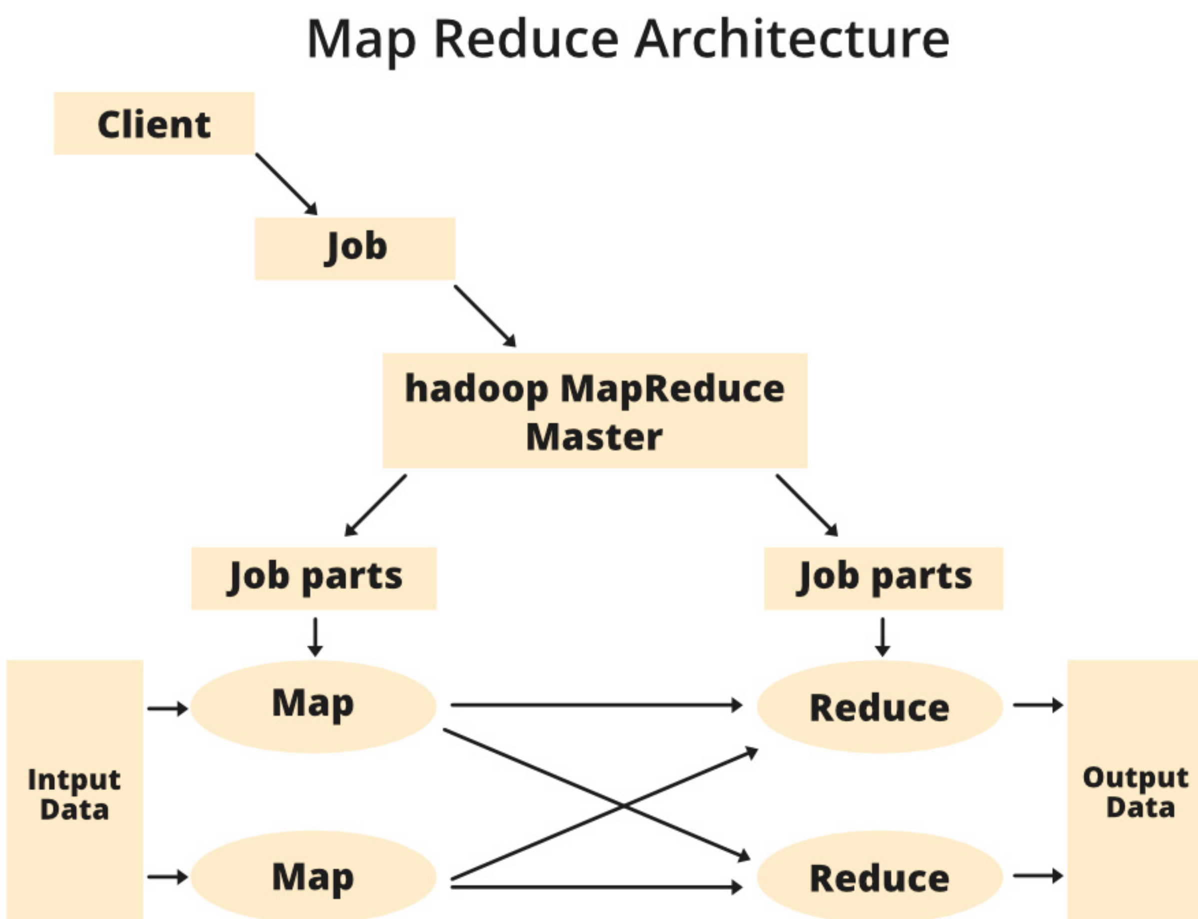
- **Job** - A “full MapReduce program” - an execution of a Mapper (as `map()`) and Reducer (as `reduce()`) across an input data set; for example, running “Word Count” across 60 input files is one job. A MapReduce job must identify the following:

  - Input Path (identifies input files)
  - Output Path (identifies output directory)
  - Mapper function definition
  - Reducer function definition

- **Task** – An execution of a Mapper or a Reducer on a slice of data a.k.a. Task-In-Progress (TIP)

- **Task Attempt** – A particular instance of an attempt to execute a task on a machine

Mapreduce Architecture



Components of MapReduce Architecture:

- **Client**: The MapReduce client is the one who brings the Job to the MapReduce for processing. There can be multiple clients available that continuously send jobs for processing to the Hadoop MapReduce Manager.
- **Job**: The MapReduce Job is the actual work that the client wanted to do which is comprised of so many smaller tasks that the client wants to process or execute.
- **Hadoop/MapReduce Master**: It divides the particular job into subsequent job-parts.
- **Job-Parts**: The task or sub-jobs that are obtained after dividing the main job. The result of all the job-parts combined to produce the final output.
- **Input Data**: The data set that is fed to the MapReduce for processing.
- **Output Data**: The final result is obtained after the processing.

MapReduce Task:

The **MapReduce Task** is mainly divided into 3 phases i.e. 1) Map phase, 2) Sort & Shuffle phase, and 3) Reduce phase.

- **Map**: As the name suggests its main use is to map the input data in (key, value) pairs. The input to the map may be a (key, value) pair where the key can be the id of some kind of address (mostly ignored by the mapper) and value is the actual value (a single record of input) that it keeps. The `map()` function will be executed in its memory repository on each of these input (key, value) pairs and generates the intermediate `(key2, value2)` pairs. The `map()` is provided by a programmer.

- **Sort & Shuffle**: The input to this pahse is the output of all mappers as `(key2, value2)` pairs. The main function of Sort & Shuffle phase is to group the keys (`key2` as output of mappers) by their associated values: therefore, Sort & Shuffle will create a set of:

  ```
  (key2, [v1, v2, v3, ...])
  ```

which will be fed as input to the reducers. In MapReduce paradigm, **Sort & Shuffle** is handled by the MapReduce implementation and it is so called the genie of the MapReduce paradigm. A programmer does not write any code for the **Sort & Shuffle** phase.

For example, for a MapReduce job, if all mappers have created the following `(key, value)` pairs (with 3 distinct keys as `{A, B, C}` :

```
    (A, 2), (A, 3)
    (B, 4), (B, 5), (B, 6), (B, 7)
    (C, 8)
```

Then **Sort & Shuffle** phase will produce the following output (which will be sent as input to the reducers – note the values are not sorted in any order at all):

```
    (A, [2, 3])
    (C, [8])
    (B, [7, 4, 5, 6])
```

- **Reduce**: The intermediate (key, value) pairs that work as input for Reducer are shuffled and sort and send to the `reduce()` function. Reducer aggregate or group the data based on its `(key, value)` pair as per the reducer algorithm written by the developer.

For the example, listed above, 3 reducers will be executed (in parallel):

```
    reduce(A, [2, 3])
    reduce(C, [8])
    reduce(B, [7, 4, 5, 6])
```

where each reducer can generate any number of new `(key3, value3)` pairs.

What is an Example of a Mapper in MapReduce

Imagine that you have records, which describe values for genes and each record is identified as:

```
<gene_id><,><gene_value_1><,><gene_value_2>
```

Sample records might be:

```
INS,1.1,1.4
INSR,1.7,1.2
```

Suppose the goal is to find the median value for the smaller of the two gene values. Therefore we need to produce `(key, value)` pairs such that `key` is a `gene_id` and value is minimum of `<gene_value_1>` and `<gene_value_2>`.

The following pseudo-code will accomplish the mapper task:

```
# key: record number or offset of a record number
# key will be ignored since we do not need it
# value: an actual record with the format of:
# <gene_id><,><value_1><,><value_2>
map(key, value) {
   # tokenize input record
   tokens = value.split(",")
   gene_id = tokens[0]
   gene_value_1 = double(tokens[1])
   gene_value_2 = double(tokens[2])
   minimum = min(gene_value_1, gene_value_2)
   # now emit output of the mapper:
   emit(gene_id, minimum)
}
```

For example, if we had the following input:

```
INS,1.3,1.5
INS,1.1,1.4
INSR,1.7,1.2
INS,1.6,1.0
INSR,0.7,1.2
```

Then output of mappers will be:

```
(INS, 1.3)
(INS, 1.1)
(INSR, 1.2)
(INS, 1.0)
(INSR, 0.7)
```

Note that, for the preceding mappers output, the Sort & Shuffle phase will produce the follwong `(key, values)` pairs to be consumed by the reducers.

```
(INS, [1.3, 1.1, 1.0])
(INSR, [1.2, 0.7])
```

What is an Example of a Reducer in MapReduce

Imagine that mappers have produced the following output: (key, value) where key is a gene_id and value is an associated gene value:

```
(INS, 1.3)
(INS, 1.1)
(INSR, 1.2)
(INS, 1.0)
(INSR, 0.7)
```

Note that, for the preceding mappers output, the Sort & Shuffle phase will produce the follwong `(key, values)` pairs to be consumed by the reducers.

```
(INS, [1.3, 1.1, 1.0])
(INSR, [1.2, 0.7])
```

Now, assume that the goal of reducers is to find the median of values per key (as a gene_id). For simplicity, we assume that there exists a `median()` function, which accepts a list of values and computes the median of given values.

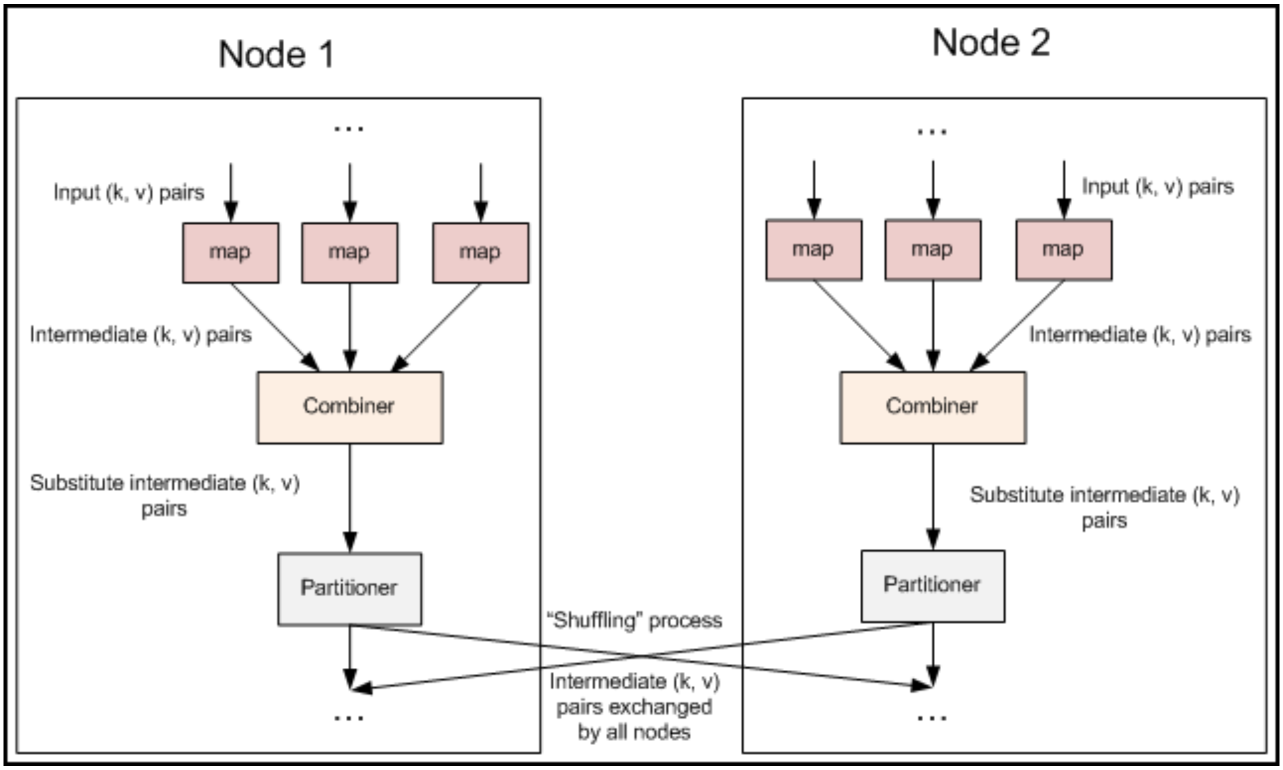
```
# key: a unique gene_id
# values: Iteable<Double> (i.e., as a list of values)
reduce(key, values) {
   median_value = median(values)
   # now output final (key, value)
   emit(key, median_value)
}
```

Therefore, with this reducer, reducers will create the following (key, value) pairs:

```
(INS, 1.1)
(INSR, 0.95)
```

What is an Example of a Combiner in MapReduce

In MapReduce, a Combiner, also known as a semi-reducer, is an optional class that operates by accepting the inputs from the Map class and thereafter passing the output key-value pairs to the Reducer class. The main function of a Combiner is to summarize the map output records with the same key. Combiner always works in between Mapper and Reducer.



Consider a classic word count program in MapReduce. Let's Consider 3 partitions with mappers output (assume that each partition goes to a separate node):

```
Partition-1   Partition-2    Partition-3
===========   ===========    ===========
(A, 1)        (A, 1)         (C, 1)
(A, 1)        (B, 1)         (C, 1)
(B, 1)        (B, 1)         (C, 1)
(B, 1)        (C, 1)         (C, 1)
(B, 1)                       (B, 1)
```

Without a combiner, Sort & Shuffle will output the following (for all partitions):

```
(A, [1, 1, 1])
(B, [1, 1, 1, 1, 1, 1])
(C, [1, 1, 1, 1, 1])
```

With a combiner, Sort & Shuffle will output the following (for all partitions):

```
(A, [2, 1])
(B, [3, 2, 1])
(C, [1, 4])
```

As you can see, with a combiner, values are combined for the same key on a partition-by-partition basis. In MapReduce, combiners are mini-reducer optimizations and they reduce network traffic by combining many values into a single value.

Partition

Data can be partitioned into smaller logical units. These units are called partitions. In big data, partitions are used as a unit of parallelisim.

For example, in a nutshell, Apache spark partitions your data and then each partition is executed by an executor.

For example, given a data size of `80,000,000,000` records, this data can be partitioned into `80,000` chunks, where each chunk/partition will have about `1000,000` records. Then in a transformation (such as mapper, filter, ...) these partitions can be processed in paralle. The maximum parallelism for this example is `80,000`. If the cluster does not have `80,000` points of parallelism, then some of the partitions will be queued for parallelism.

In MapReduce, input is partitioned and then passed to mappers (so that the mappers can be run in parallel).

In Apache Spark, a programmer can control the partitioning data (by using `coalesce()`, ...) and hence controlling paralleism.

Spark examples:

- `RDD.coalesce(numPartitions: int, shuffle: bool = False)` : return a new RDD that is reduced into `numPartitions` partitions.
- `DataFrame.coalesce(numPartitions: int)` : returns a new DataFrame that has exactly `numPartitions` partitions.

Parallel Computing

[Parallel computing](#) (also called concurrent computing) is a type of computation in which many calculations or processes are carried out simultaneously (at the same time). Large problems can often be divided into smaller ones, which can then be solved at the same time. There are several different forms of parallel computing: bit-level, instruction-level, data, and task parallelism. Parallelism has long been employed in high-performance computing, … parallel computing has become the dominant paradigm in computer architecture, mainly in the form of multi-core processors.

Parallel Programming Primer:

> A common misconception is that simply running your code on a cluster will result in your code running faster. Clusters do not run code faster by magic; for improved performance the code must be modified to run in parallel, and that modification must be explicitly done by the programmer. In other words, the burden of modifying code to take advantage of multiple cores or nodes is on the programmer.

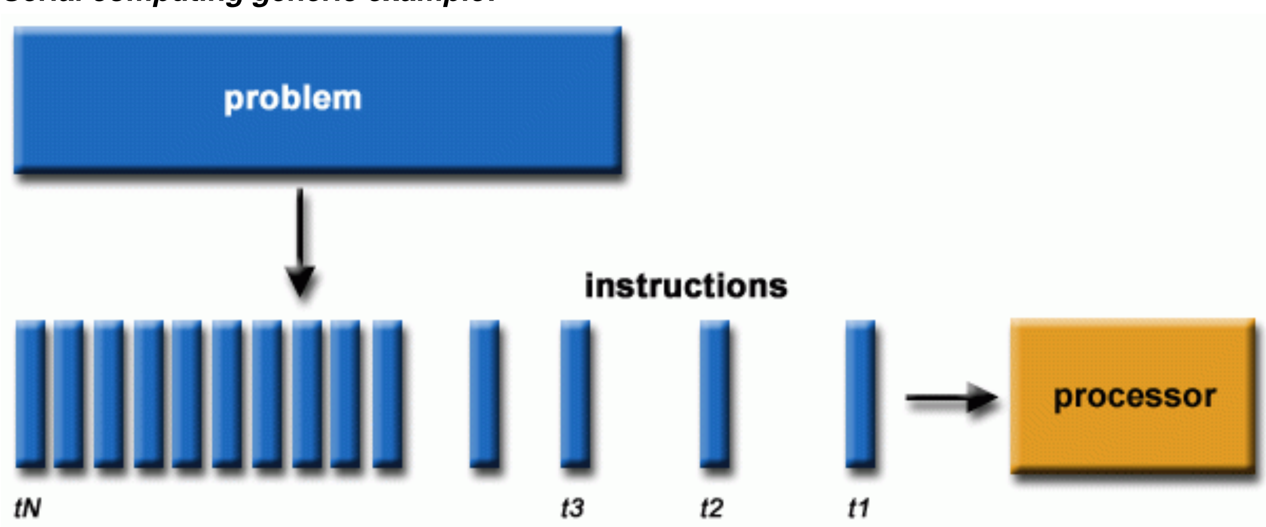
MapReduce and Spark employs parallelism by data partitioning. Based on available resources, partitions are executed independently and in parallel.

Serial Computing:

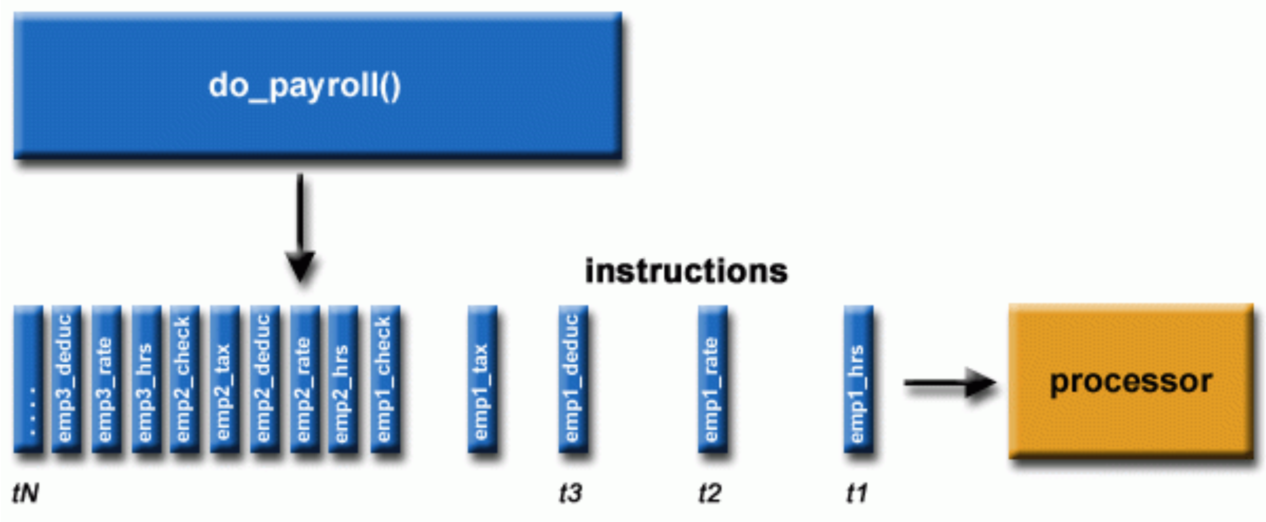
Traditionally, software has been written for serial computation:

- A problem is broken into a discrete series of instructions
- Instructions are executed sequentially one after another
- Executed on a single processor
- Only one instruction may execute at any moment in time

Serial computing generic example:



Serial computing example of processing payroll:

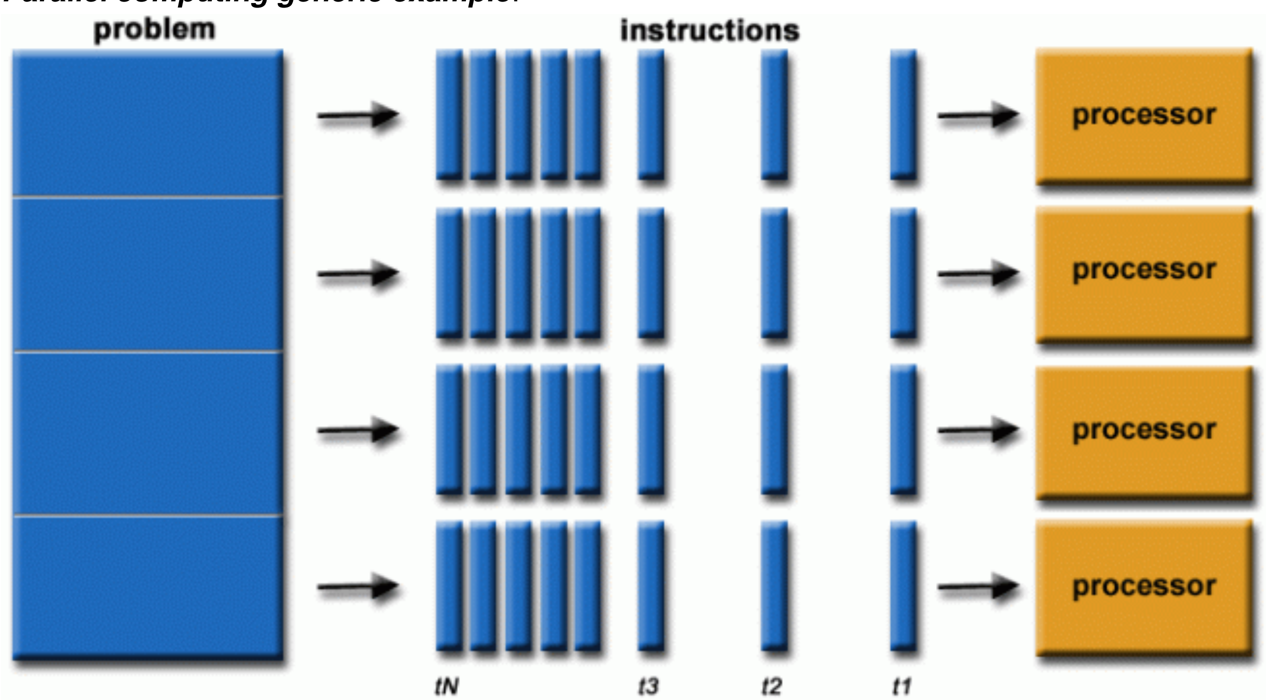


[Parallel Computing](#):

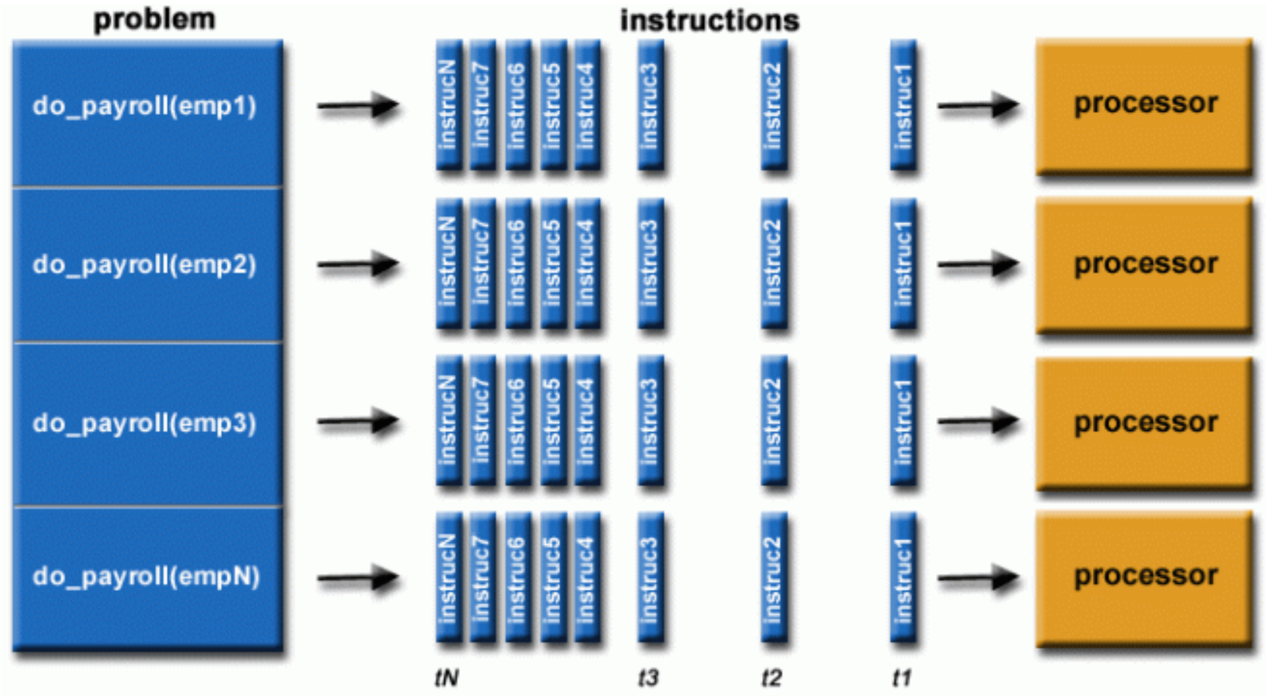
In the simplest sense, parallel computing is the simultaneous use of multiple compute resources to solve a computational problem:

- A problem is broken into discrete parts that can be solved concurrently
- Each part is further broken down to a series of instructions
- Instructions from each part execute simultaneously on different processors
- An overall control/coordination mechanism is employed

Parallel computing generic example:

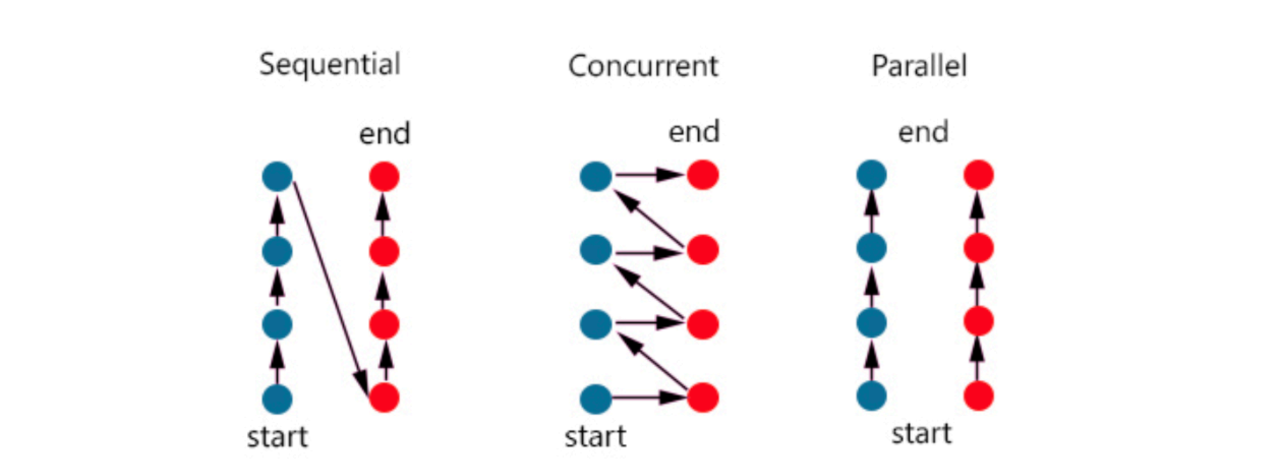


Parallel computing example of processing payroll:



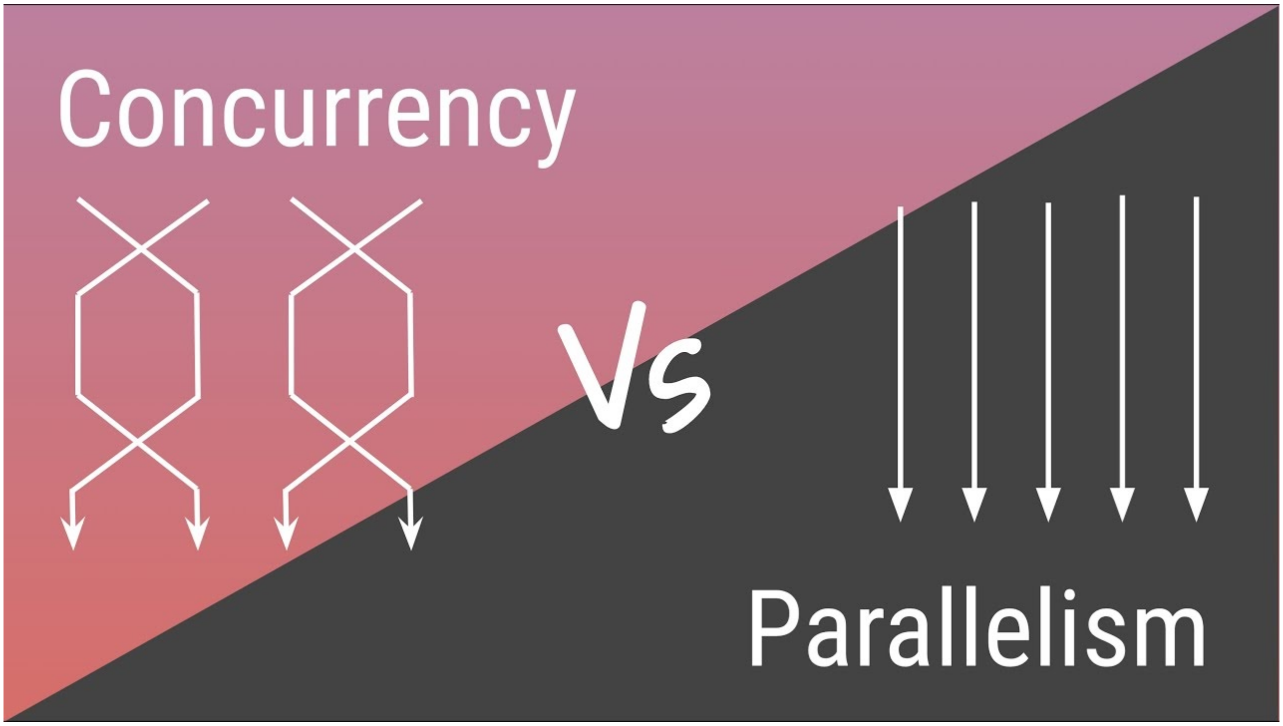
Difference between Concurrency and Parallelism?

[What is the difference between concurrency and parallelism?]()



Concurrency is when two or more tasks can start, run, and complete in overlapping time periods. It doesn't necessarily mean they'll ever both be running at the same instant. For example, multitasking on a single-core machine.

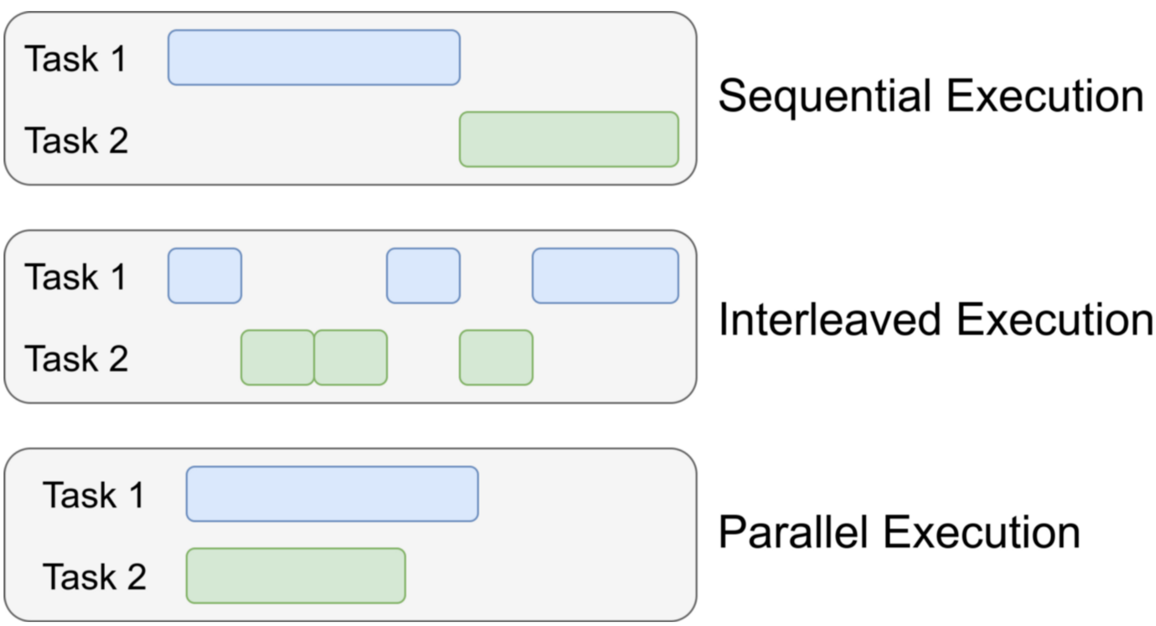
Parallelism is when tasks literally run at the same time, e.g., on a multicore processor.

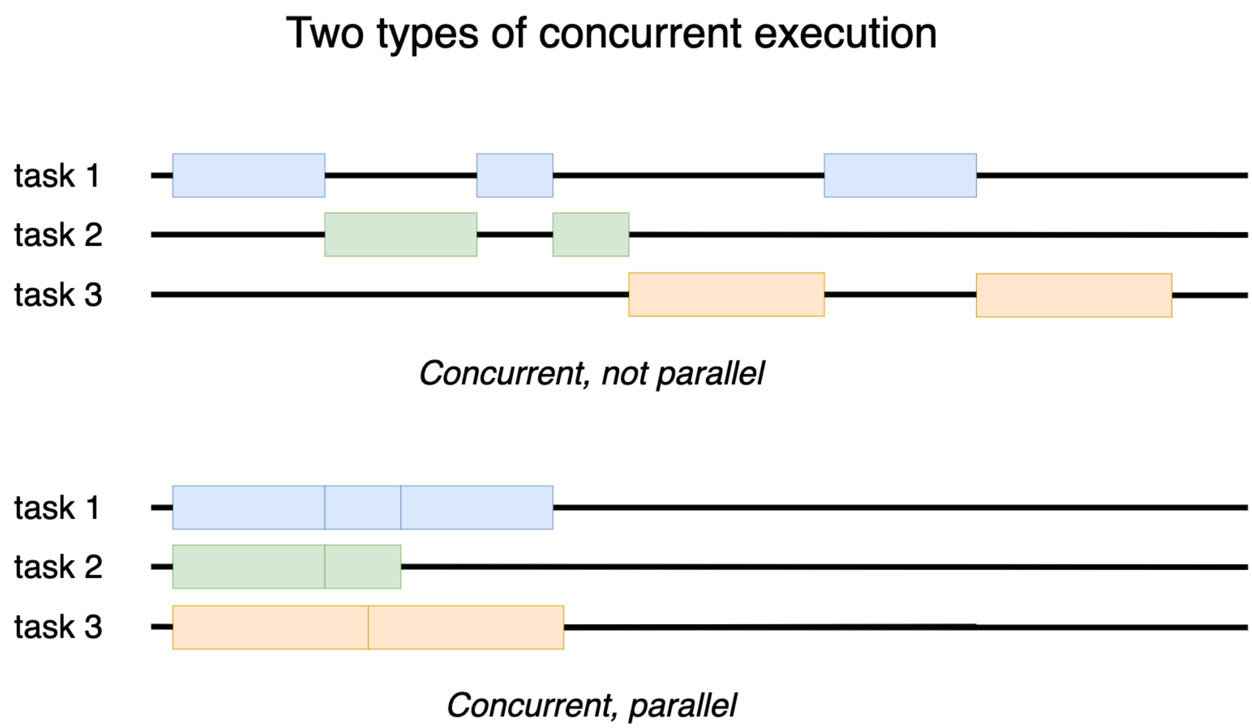


Quoting Sun's Multithreaded Programming Guide:

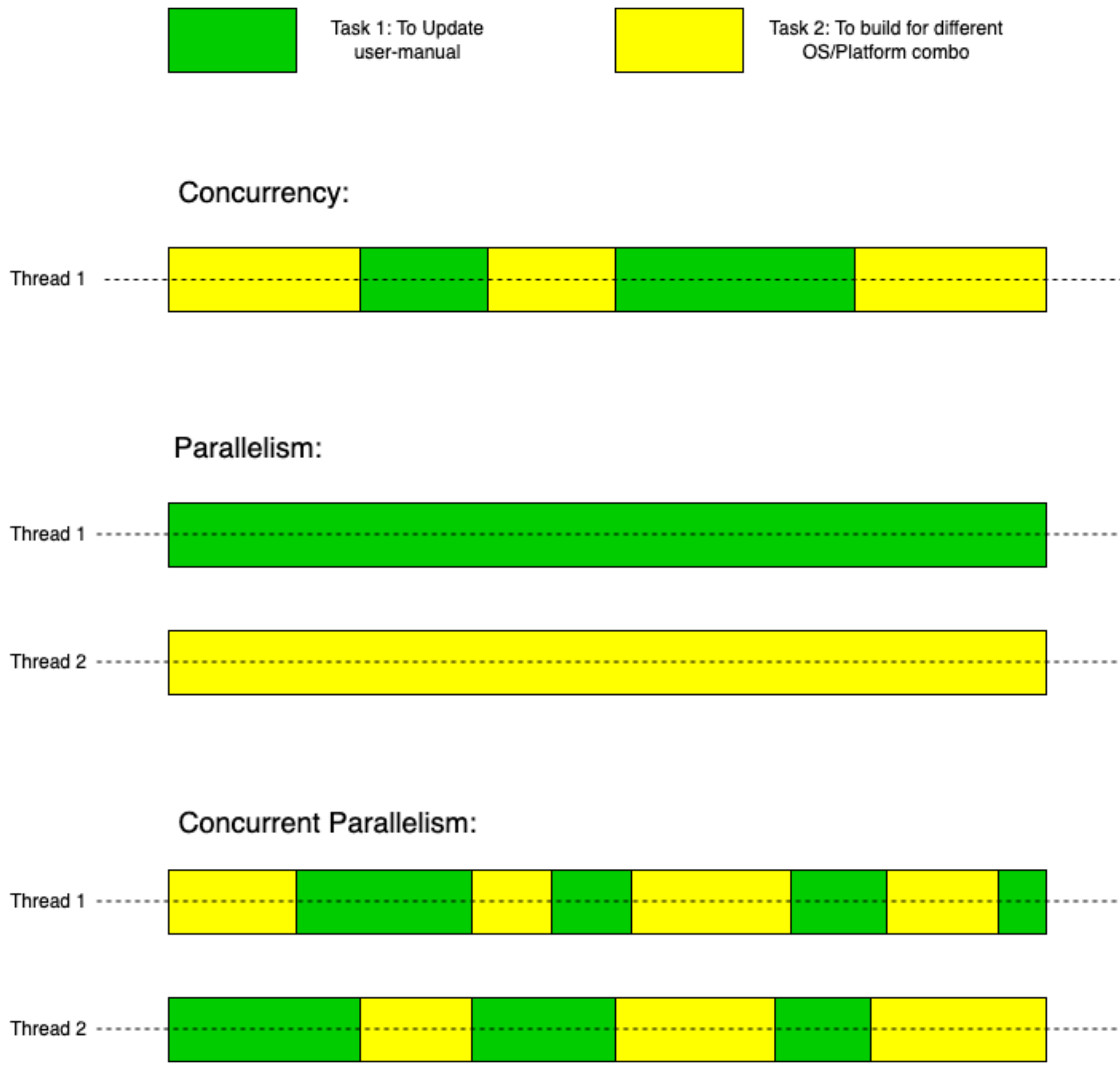
Concurrency: A condition that exists when at least two threads are making progress. A more generalized form of parallelism that can include time-slicing as a form of virtual parallelism.

Parallelism: A condition that arises when at least two threads are executing simultaneously.





Concurrent Parallelism



How does MapReduce work?

A MapReduce system (an implementation of MapReduce mpdel) is usually composed of three steps (even though it's generalized as the combination of Map and Reduce operations/functions). The MapReduce operations are:

- **Map**: The input data is first split (partitioned) into smaller blocks. For example, the Hadoop framework then decides how many mappers to use, based on the size of the data to be processed and the memory block available on each mapper server. Each block is then assigned to a mapper for processing. Each 'worker' node applies the map function to the local data, and writes the output to temporary storage. The primary (master) node ensures that only a single copy of the redundant input data is processed.

```
map(key, value) -> { (K2, V2), ...}
```

- **Shuffle, combine and partition**: worker nodes redistribute data based on the output keys (produced by the map function), such that all data belonging to one key is located on the same worker node. As an optional process the combiner (a reducer) can run individually on each mapper server to reduce the data on each mapper even further making reducing the data footprint and shuffling and sorting easier. Partition (not optional) is the process that decides how the data has to be presented to the reducer and also assigns it to a particular reducer. Sort & Shuffle output (note that mappers have created `N` unique keys – such as K2):

```
(key_1, [V_1_1, V_1_2, ...])
(key_2, [V_2_1, V_2_2, ...])
...
(key_N, [V_N_1, V_N_2, ...])
```

- **Reduce**: A reducer cannot start while a mapper is still in progress. Worker nodes process each group of (key, value) pairs output data, in parallel to produce (key,value) pairs as output. All the map output values that have the same key are assigned to a single reducer, which then aggregates the values for that key. Unlike the map function which is mandatory to filter and sort the initial data, the reduce function is optional.

Word Count in MapReduce

Given a set of text documents (as input), Word Count algorithm finds frequencies of unique words in input. The `map()` and `reduce()` functions are provided as a **pseudo-code**.

- ***Mapper function***:

```
# key: partition number, record number, offset in input file,
# the key is ignored in this example.
# value: an actual input record
map(key, value) {
  words = value.split(" ")
  for w in words {
     emit(w, 1)
  }
}
```

Of course, you can customize your mapper to exclude words (called filtering) with less than 3 characters:

- ***Mapper function with Filter***:

```
# key: partition number, record number, offset in input file,
# the key is ignored in this example.
# value: an actual input record
map(key, value) {
  words = value.split(" ")
  for w in words {
     # apply a filter
     if (len(w) > 2) {
        emit(w, 1)
     }
  }
}
```

- ***Reducer function (long version)***:

```
# key: a unique word
# values: Iterable<Integer>
reduce(key, values) {
  total = 0
  for n in values {
     total += n
  }
  emit(key, total)
}
```

- ***Reducer function (short version)***:

```
# key: a unique word
# values: Iterable<Integer>
reduce(key, values) {
  total = sum(values)
  emit(key, total)
}
```

Of course, you can customize your reducer to exclude words (called filtering) where its final frequency is less than `10`.

- ***Reducer function (short version), with Filter***:

```
# key: a unique word
# values: Iterable<Integer>
reduce(key, values) {
  total = sum(values)
  # apply a filter
  if (total >= 10) {
      emit(key, total)
  }
}
```

- ***Combiner function (short version)***:

```
# key: a unique word
# values: Iterable<Integer>
combine(key, values) {
  total = sum(values)
  emit(key, total)
}
```

Finding Average in MapReduce

Given a set of gene*id(s) and gene*value(s) (as input), the average algorithm finds average of gene values per gene_id for canceric genes. Assume that the input is formatted as:

```
    <gene_id_as_string><,><gene_value_as_double><,><cancer-or-benign>

    where <cancer-or-benign> has value as {"cancer", "benign"}
```

The `map()` and `reduce()` functions are provided as a **pseudo-code**.

- ***Mapper function***:

```
# key: partition number, record number, offset in input file, ignored.
# value: an actual input record as:
# <gene_id_as_string><,><gene_value_as_double><,><cancer-or-benign>
map(key, value) {
  tokens = value.split(",")
  gene_id = tokens[0]
  gene_value = tokens[1]
  status = tokens[2]
  if (status == "cancer" ) {
     emit(gene_id, gene_value)
  }
}
```

- ***Reducer function (long version)***:

```
# key: a unique gene_id
# values: Iterable<double>
reduce(key, values) {
  total = 0
  count = 0
  for v in values {
     total += v
     count += 1
  }
  avg = total / count
  emit(key, avg)
}
```

- ***Reducer function (short version)***:

```
# key: a unique gene_id
# values: Iterable<double>
reduce(key, values) {
  total = sum(values)
  count = len(values)
  avg = total / count
  emit(key, avg)
}
```

To have a combiner function, we have to change the output of mappers (since average of average is not an average). This means that average (`avg`) function is a commutative, but not assocaitive. Changing output of mappers will make it commutative and associative.

Commutative means that:

```
avg(a, b) = avg(b, a)
```

Associative means that:

```
avg( avg(a, b), c) = avg( a, avg(b, c))
```

For details on commutative and associative properties refer to [Data Aldorithms with Spark].

- ***Revised Mapper function***:

```
# key: partition number, record number, offset in input file, ignored.
# value: an actual input record as:
# <gene_id_as_string><,><gene_value_as_double><,><cancer-or-benign>
map(key, value) {
  tokens = value.split(",")
  gene_id = tokens[0]
  gene_value = tokens[1]
  status = tokens[2]
  if (status == "cancer" ) {
     # revised mapper output
     emit(gene_id, (gene_value, 1))
  }
}
```

- ***Combiner function***:

```
# key: a unique gene_id
# values: Iterable<(double, Integer)>
combine(key, values) {
  total = 0
  count = 0
  for v in values {
     # v = (double, integer)
     # v = (sum, count)
     total += v[0]
     count += v[1]
  }
  # note the combiner does not calculate avg
  emit(key, (total, count))
}
```

- ***Reducer function***:

```
# key: a unique gene_id
# values: Iterable<(double, Integer)>
combine(key, values) {
  total = 0
  count = 0
  for v in values {
     # v = (double, integer)
     # v = (sum, count)
     total += v[0]
     count += v[1]
  }
  # calculate avg
  avg = total / count
  emit(key, avg)
}
```

What is an Associative Law

An associative operation:

```
    f: X x X -> X
```

is a binary operation such that for all `a, b, c` in `X` :

```
    f(a, f(b, c)) = f(f(a, b), c)
```

For example, + (addition) is an associative function because

```
    (a + (b + c)) = ((a + b) + c)
```

For example, * (multiplication) is an associative function because

```
    (a * (b * c)) = ((a * b) * c)
```

While, - (subtraction) is not an associative function because

```
    (4 - (6 - 3) != ((4 - 6) - 3)
         (4 - 3) != (-2 - 3)
               1 != -5
```

While average operation is not an associative function.

```
FACT: avg(1, 2, 3) = 2

avg(1, avg(2, 3)) != avg(avg(1, 2), 3)
    avg(1, 2.5) != avg(1.5, 3)
           1.75 != 2.25
```

What is a Commutative Law

A commutative function `f` is a function that takes multiple inputs from a set X and produces an output that does not depend on the ordering of the inputs.

For example, the binary operation `+` (addition) is commutative, because `2 + 5 = 5 + 2 = 7`.

For example, the binary operation `*` (multiplication) is commutative, because `2 * 5 = 5 * 2 = 10`.

Function `f` is commutative if the following property holds:

```
f(a, b) = f(b, a)
```

While, `-` (subtraction) is not an commutative function because

```
2 - 4 != 4 - 2
   -2 != 2
```

While, `/` (division) is not an commutative function because

```
2 / 4 != 4 / 2
  0.5 != 2
```

Monoid

Monoids are algebraic structures. A monoid M is a triplet `(X, f, i)`, where

- `X` is a set
- `f` is an associative binary operator
- `i` is an identity element in `X`

The monoid axioms (which govern the behavior of `f`) are as follows.

1. (Closure) For all `a`, `b` in `X`, `f(a, b)` and `f(b, a)` is also in `X`.

2. (Associativity) For all `a, b, c` in `X`:

   ```
   f(a, f(b, c)) = f(f(a, b), c)
   ```

3. (Identity) There is an `i` in `X` such that, for all `a` in `X`:

   ```
   f(a, i) = f(i, a) = a
   ```

Monoid Examples

Example-1

Let X denotes non-negative integer numbers.

* Let `+` be an addition function, then `M(X, +, 0)` is a monoid.
* Let `*` be an multiplication function, then `M(X, *, 1)` is a monoid.

Example-2

Let `S` denote a set of strings including an empty string (`""`) of length zero, and `||` denote a concatenation operator,

Then `M(S, ||, "")` is a monoid.

Non Monoid Examples

Then `M(X, -, 0)` is not a monoid, since binary subtraction function is not an associative function.

Then `M(X, /, 1)` is not a monoid, since binary division function is not an associative function.

Then `M(X, AVG, 0)` is not a monoid, since `AVG` (an averge function) is not an associative function.

Monoids as a Design Principle for Efficient MapReduce Algorithms

According to Jimmy Lin: “it is well known that since the sort/shuffle stage in MapReduce is costly, local aggregation is one important principle to designing efficient algorithms. This short paper represents an attempt to more clearly articulate this design principle in terms of monoids, which generalizes the use of combiners and the in-mapper combining pattern.

For example, in Spark (using PySpark), in a distributed computing environment, we can not write the following transformation to find average of integer numbers per key:

```
# each rdd element is of the form (String, Integer)
# rdd: RDD[(String, Integer)] : RDD[(key, value)]
# WARNING: The Following Transformation is WRONG
# since reduceByKey() uses combiners in partitions
# and average of an average is not an average.
avg_per_key = rdd.reduceByKey(lambda x, y: (x+y) / 2)
```

This will not work, because averge of average is not an average. In Spark, `RDD.reduceByKey()` merges the values for each key using an **associative** and **commutative** reduce function. Average function is not an associative function.

How to fix this problem? Make it a Monoid:

```
    # rdd: RDD[(String, Integer)] : RDD[(key, value)]
    # convert (key, value) into (key, (value, 1))
    # rdd2 elements will be monoidic structures for addition (+)
    rdd2 = rdd.mapValues(lambda v: (v, 1))
    # rdd2: RDD[(String, (Integer, Integer))]
    # rdd2: RDD[(key, (sum, count))]

    # find (sum, count) per key: a Monoid
    sum_count_per_key = rdd2.reduceByKey(
      lambda x, y: (x[0]+y[0], x[1]+y[1])
    )

    # find average per key
    # v : (sum, count)
    avg_per_key = sum_count_per_key.mapValues(
       lambda v: float(v[0]) / v[1]
    )
```

Note that by mapping `(key, value)` to `(key, (value, 1))` we make addition of values such as (sum, count) to be a monoid. Consider the follwing two partitions:

```
Partition-1        Partition-2
(A, 1)             (A, 3)
(A, 2)
```

By mapping `(key, value)` to `(key, (value, 1))`, we will have (as `rdd2`):

```
Partition-1        Partition-2
(A, (1, 1))         (A, (3, 1))
(A, (2, 1))
```

Then `sum_count_per_key` RDD will hold:

```
Partition-1       Partition-2
(A, (3, 2))        (A, (3, 1))
```

Finally, `avg_per_key` RDD will produce the final value per key: `(A, 2)`.

What Does it Mean that "Average of Average is Not an Average”

In distributed computing environments (such as MapReduce, Hadoop, Spark, …) correctness of algorithms are very very important. Let’s say, we have only 2 partitions:

```
Partition-1       Partition-2
(A, 1)            (A, 3)
(A, 2)
```

and we want to calculate the average per key. Looking at these partitions, the average of `(1, 2, 3)` will be exactly `2.0`. But since we are ina distributed environment (operations/functions are done on data partitions), then the average will be calculated per partition:

```
Partition-1: avg(1, 2) = 1.5
Partition-2: avg(3) = 3.0

avg(Partition-1, Partition-2) = (1.5 + 3.0) / 2 = 2.25

===> which is NOT the correct average we were expecting.
```

To fix this problem, we can change the output of mappers: new revised output is as: `(key, (sum, count))`:

```
Partition-1       Partition-2
(A, (1, 1))       (A, (3, 1))
(A, (2, 1))
```

Now, let’s calculate average:

```
Partition-1: avg((1, 1), (2, 1)) = (1+2, 1+1) = (3, 2)
Partition-2: avg((3, 1)) = (3, 1)
avg(Partition-1, Partition-2) = avg((3,2), (3, 1))
                              = avg(3+3, 2+1)
                              = avg(6, 3)
                              = 6 / 3
                              = 2.0
                              ===> CORRECT AVERAGE
```

Advantages of MapReduce

Is there any benefit in using MapReduce paradigm? With MapReduce, developers do not need to write code for parallelism, distributing data, or other complex coding tasks because those are already built into the model. This alone shortens analytical programming time.

The following are advantages of MapReduce:

- Scalability
- Flexibility
- Security and authentication
- Faster processing of data
- Very simple programming model
- Availability and resilient nature
- Fault tolerance

What is a MapReduce Job

Job – A program is an execution of a Mapper and Reducer across a dataset. Minimally, a MapReduce job will have the following components:

- Input path: identifies input directories and files
- Output path: identifies a directory where the outputs will be written
- Mapper: a `map()` function
- Reducer: a `reduce()` function
- Combiner: a `combine()` function [optional]

Disadvantages of MapReduce

- Rigid `Map-and-then-Reduce` programming paradigm

    - Low level API
    - Must use `map()`, `reduce()` one or more times to solve a problem
    - Join operation is not supported
    - Complex: have to write lots of code
    - One type of reduction is supported: GROUP BY KEY

- Disk I/O (makes it slow)
- Read/Write Intensive (does not utilize in-memory computing)
- Java Focused
    - Have to write lots of lines of code to do some simple map and then reduce functions
    - API is a low level

- Interactive mode (for testing/debugging) is not supported

What the MapReduce's Job Flow

1-InputFormat: Splits input into `(key_1, value_1)` pairs and passes them to mappers. When Hadoop submits a job, it splits the input data logically (Input splits) and these are processed by each Mapper. The number of Mappers is equal to the number of input splits created. Hadoop's `InputFormat.getSplits()` function is responsible for generating the input splits which uses each split as input for each mapper job.

2-Mapper: `map(key_1, value_1)` emits a set of `(key_2, value_2)` pairs. If a mapper does not emit any `(key, value)` pairs, then it means that `(key_1, value_1)` is filtered out (for example, tossing out the invalid/bad records).

3-Combiner: [optional] `combine(key_2, [value-2, ...])` emits `(key_2, value_22)`. The combiner might emit no (key, value) pair if there is a filtering algorithm (based on the key (i.e., `key_2` and its associated values)).

Note that `value_22` is an aggregated value for `[value-2, ...]`

4-Sort & Shuffle: Group by keys of mappers with their associated values. If output of all mappers/combiners are:

```
    (K_1, v_1), (K_1, v_2), (K_1, v_3), ...,
    (K_2, t_1), (K_2, t_2), (K_2, t_3), ...,
    ...
    (K_n, a_1), (K_n, a_2), (K_n, a_3), ...
```

Then output of Sort & Shuffle will be (which will be fed as an inut to reducers as `(key, values)`:

```
    (K_1, [v_1, v_2, v_3, ...])
    (K_2, [t_1, t_2, t_3, ...])
    ...
    (K_n, [a_1, a_2, a_3, ...])
```

5-Reducer: We will have `n` reducers, sicnce we have `n` unique keys. All these reducers can run in parallel (if we have enough resources).

`reduce(key, values)` will emit a set of `(key_3, value_3)` pairs and eventually thay are written to output. Note that reducer key will be one of `{K_1, K_2, ..., K_n}`.

6-OutputForamt: Reponsible for writing `(key_3, value_3)` pairs to output medium. Note that some of the reducers might not emit any `(key_3, value_3)` pairs: this means that the reducer is filtering out some keys based of the associated values (for example, if the median of the values is less than 10, then filter out).

Hadoop vs. Spark

Feature	Haoop	Spark
Data Processing	Provides batch processing	Provides both batch processing and stream processing
Memory usage	Disk-bound	Uses large amounts of RAM
Security	Better security features	Basic security is provided
Fault Tolerance	Replication is used for fault tolerance	RDD and various data storage models are used for fault tolerance.
Graph Processing	Must develop custom algorithms	Comes with a graph computation library called GraphX and external library as GraphFrames
Ease of Use	Difficult to use	Easier to use
Powerful		

API	Low level API	High level API
Real-time	Batch only	Batch and Interactive and Stream
Interactive data processing	Not supported	Supported by PySpark, …
Speed	SLOW: Hadoop's MapReduce model reads and writes from a disk, thus it slows down the processing speed.	FAST: Spark reduces the number of read/write cycles to disk and store intermediate data in memory, hence faster-processing speed.
Latency	It is high latency computing framework.	It is a low latency computing and can process data interactively
Machine Learing API	Not supported	Supported by ML Library
Data Source Support	Limited	Extensive
Storage	Has HDFS (Hadoop Distributed File System)	Does not have a storage system, but may use S3 and HDFS and many other data sources and storages
MapReduce	Implements MapReduce	Implements superset of MapReduce and beyond
Join Operation	Does not support Join directly	Has extensive API for Join

Apache Spark

In a nutshell, we can say that Apache Spark is the most active open big data tool reshaping the big data market.Apache Spark is an engine for large-scale data analytics. Spark is a multi-language (Python , Java, Scala, R, SQL) engine for executing data engineering, data science, and machine learning on single-node machines or
clusters. Spark implements superset of MapReduce paradigm and uses memory/RAM as much as possible and can run up to 100 times faster than Hadoop. Spark is considered the successor

of Hadoop/Mapreduce and has addressed many problems of Hadoop.

With using Spark, developers do not need to write code for parallelism, distributing data, or other complex coding tasks because those are already built into the spark engine. This alone shortens analytical programming time.

Apache Spark is one of the best alternatives to Hadoop and currently is the defacto standard for big data analytics. Spark offers simple API and provides high-level mappers, filters, and reducers.

Spark is a fast, in-memory open source data processing engine to efficiently execute streaming, machine learning or SQL workloads that require fast iterative access to datasets. Spark is generally a lot faster than MapReduce. Spark is a superset of MapReduce and eliminates the need for MapReduce's "map-then-reduce" paradigm.

Spark's architecture consists of two main components:

- Drivers - convert the user's code into tasks to be distributed across worker nodes
- Executors - run on those nodes and carry out the tasks assigned to them

PySpark is an interface for Spark in Python. PySpark has two main data abstractions:

- RDD (Resilient Distributed Dataset)
    - Low-level
    - Immutable (to avoid synchronization)
    - Partitioned for parallelism
    - Can represent billions of data points, called elements
    - For unstructured and semi-structured data
- DataFrame
    - High-level
    - Immutable (to avoid synchronization)
    - Partitioned for parallelism
    - Can represent billions of rows with named columns
    - For structured and semi-structured data

Spark addresses many problems of hadoop:

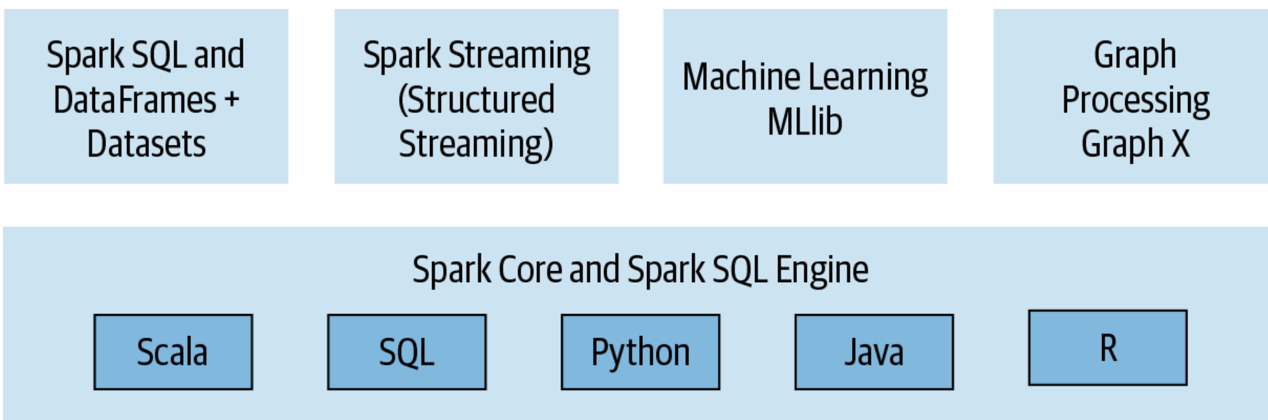
- It is a superset of Hadoop/MapReduce
- Provides in-memory computing
- Provides simple, powerful, and high-level transformations

- Provides join operations for RDDs and DataFrames
- You do not need to write too many lines of a code to solve a big data problem
- For structured data, transformations can be expressed in SQL

Apache Spark Components

Apache Spark provides:

- Core components: RDDs, DataFrames, SQL
- Data Streaming
- Machine Learning
- Graph Processing (GraphX and GrahFrames)
- Multi-language support (Python, Java, Scala, R, SQL)



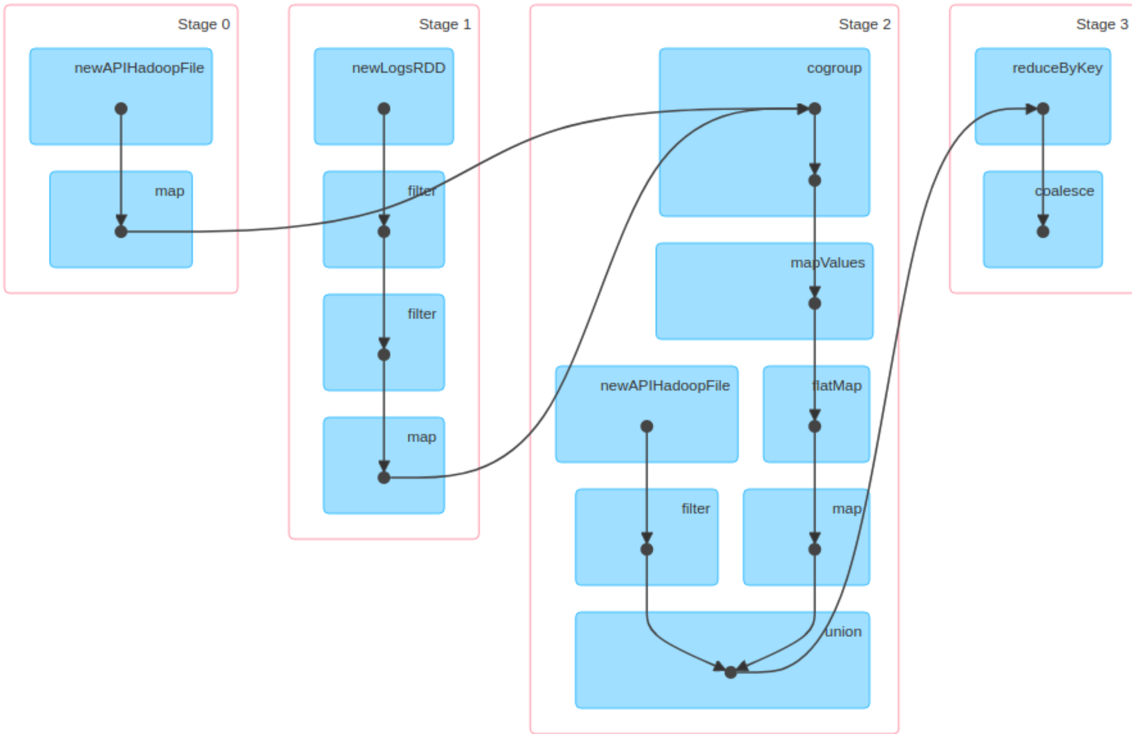
Apache Spark in Large-Scale Sorting

[Spark Officially Sets a New Record in Large-Scale Sorting](). Databricks team sorted 100 TB of data on disk in 23 minutes. In comparison, the previous world record set by Hadoop MapReduce used 2100 machines and took 72 minutes. This means that Apache Spark sorted the same data 3X faster using 10X fewer machines. All the sorting took place on disk (HDFS), without using Spark's in-memory cache.

	Hadoop MR Record	**Spark Record**	**Spark 1 PB**
Data Size	102.5 TB	100 TB	1000 TB
Elapsed Time	72 mins	23 mins	234 mins
# Nodes	2100	206	190
# Cores	50400 physical	6592 virtualized	6080 virtualized
Cluster disk throughput	3150 GB/s (est.)	618 GB/s	570 GB/s
Sort Benchmark Daytona Rules	Yes	Yes	No
Network	dedicated data center, 10Gbps	virtualized (EC2) 10Gbps network	virtualized (EC2) 10Gbps network
Sort rate	**1.42 TB/min**	**4.27 TB/min**	**4.27 TB/min**
Sort rate/node	**0.67 GB/min**	**20.7 GB/min**	**22.5 GB/min**

DAG in Spark

Spark DAG (directed acyclic graph) is the strict generalization of the MapReduce model. The DAG operations can do better global optimization than the other systems like MapReduce. The Apache Spark DAG allows a user to dive into the stage and further expand on detail on any stage.

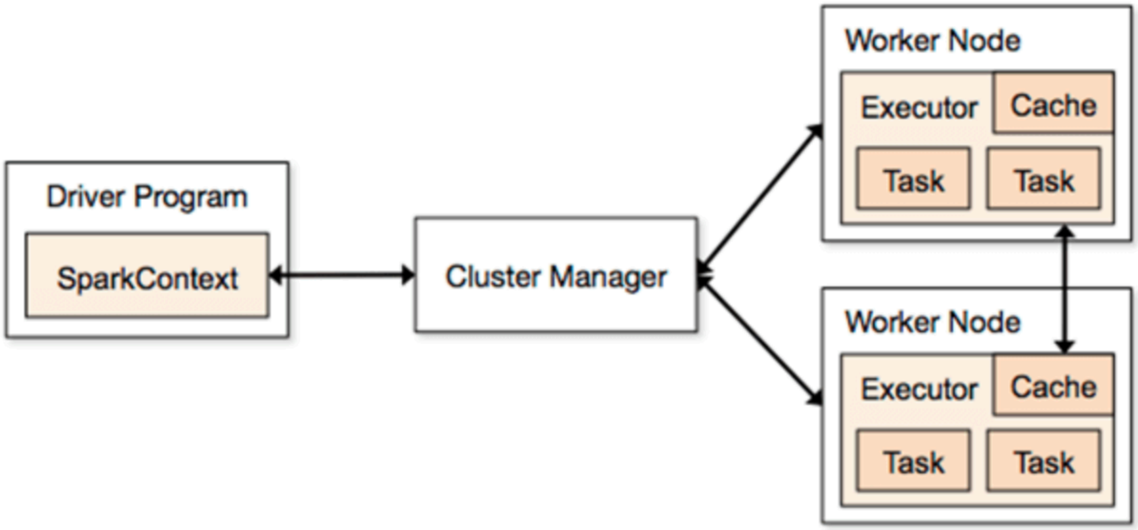


DAG in Spark is a set of vertices and edges, where vertices represent the RDDs and the edges represent the Operation to be applied on RDD. In Spark DAG, every edge directs from earlier to later in the sequence. On the calling of Action, the created DAG submits to DAG Scheduler which further splits the graph into the stages of the task.

By using [Spark Web UI](), you can view Spark jobs and their associated DAGs.

Spark Concepts and Key Terms

- [Spark Architecture]()



- Spark Cluster: a collection of machines or nodes in the public cloud or on-premise in a private data center on which Spark is installed. Among those machines are Spark workers, a Spark Master (also a cluster manager in a Standalone mode), and at least one Spark Driver.

- Spark Master: As the name suggests, a Spark Master JVM acts as a cluster manager in a Standalone deployment mode to which Spark workers register themselves as part of a quorum. Depending on the deployment mode, it acts as a resource manager and decides where and how many Executors to launch, and on what Spark workers in the cluster.

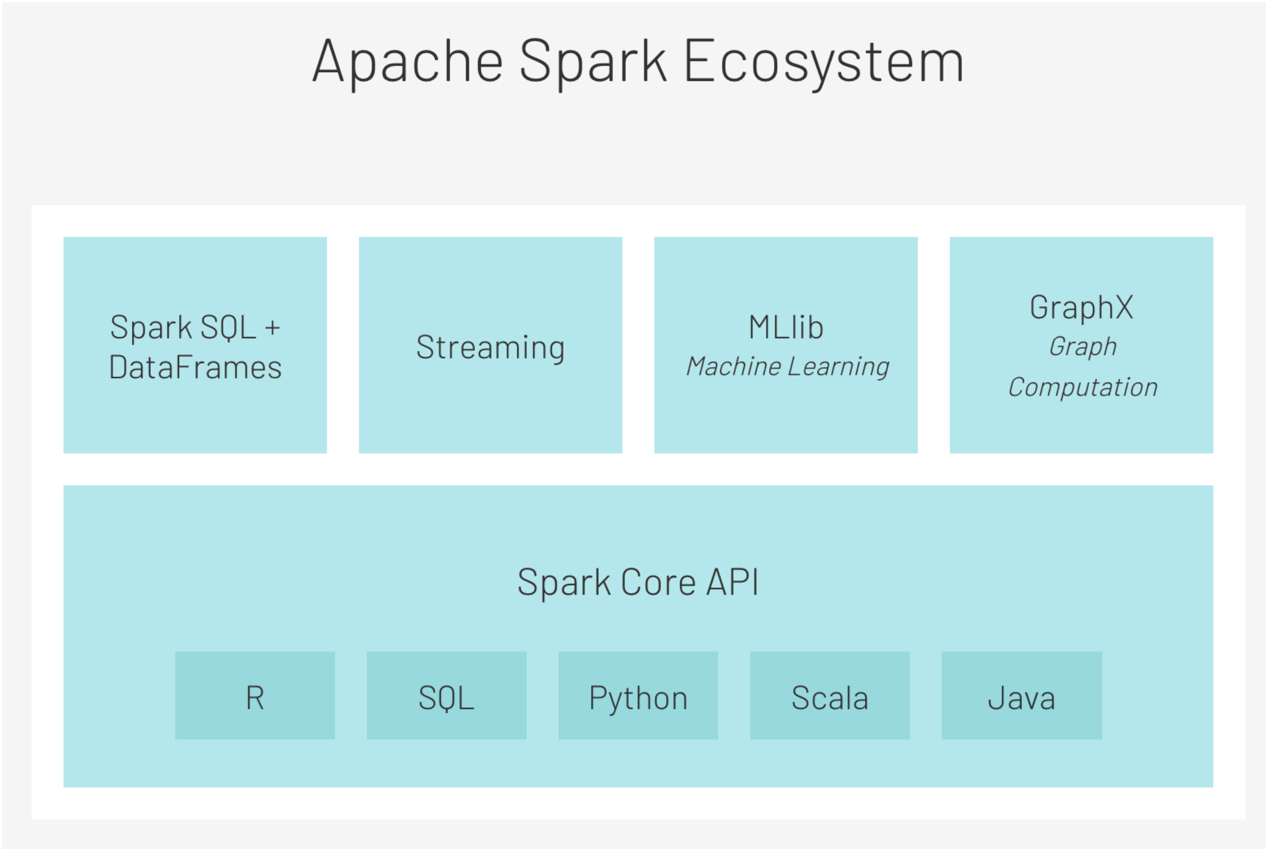
- Spark Worker: Upon receiving instructions from Spark Master, the Spark worker JVM launches Executors on the worker on behalf of the Spark Driver. Spark applications, decomposed into units of tasks, are executed on each worker's Executor. In short, the worker's job is to only launch an Executor on behalf of the master.

- Spark Executor: A Spark Executor is a JVM container with an allocated amount of cores and memory on which Spark runs its tasks. Each worker node launches its own Spark Executor, with a configurable number of cores (or threads). Besides executing Spark tasks, an Executor also stores and caches all data partitions in its memory.

- Spark Driver: Once it gets information from the Spark Master of all the workers in the cluster and where they are, the driver program distributes Spark tasks to each worker's Executor. The driver also receives computed results from each Executor's tasks.

- Task: A unit of work that will be sent to one executor.

Apache Spark Ecosystem



What are the main components of Spark ecosystem?

Components of Apache Spark (EcoSystem):

- **Spark Core**: Spark Core is the underlying general execution engine for the Spark platform that all other functionality is built on top of. It provides in-memory computing capabilities to deliver speed, a generalized execution model to support a wide variety of applications, and Java, Scala, and Python APIs for ease of development.

- **Spark SQL + DataFrames**: Many data scientists, analysts, and general business intelligence users rely on interactive SQL queries for exploring data. Spark SQL is a Spark module for structured data processing. It provides a programming abstraction called DataFrames and can also act as distributed SQL query engine. It enables unmodified Hadoop Hive queries to run up to 100x faster on existing deployments and data. It also provides powerful integration with the rest of the Spark ecosystem (e.g., integrating SQL query processing with machine learning).

- **Spark Streaming**: Many applications need the ability to process and analyze not only batch data, but also streams of new data in real-time. Running on top of Spark, Spark Streaming enables powerful interactive and analytical applications across both streaming and historical data, while inheriting Spark's ease of use and fault tolerance characteristics.

It readily integrates with a wide variety of popular data sources, including HDFS, Flume, Kafka, and Twitter.

- **MLlib (Machine learning library)**: Machine learning has quickly emerged as a critical piece in mining Big Data for actionable insights. Built on top of Spark, MLlib is a scalable machine learning library that delivers both high-quality algorithms (e.g., multiple iterations to increase accuracy) and blazing speed (up to 100x faster than MapReduce). The library is usable in Java, Scala, and Python as part of Spark applications, so that you can include it in complete workflows.

- **GraphX**: GraphX is a graph computation engine built on top of Spark that enables users to interactively build, transform and reason about graph structured data at scale. It comes complete with a library of common algorithms. Note that GraphX is not available for PySpark, but you may use an external graph library called GraphFrames (which is a DataFrames based solution).

Spark as a superset of MapReduce

Spark is a true successor of MapReduce and maintains MapReduce's linear scalability and fault tolerance, but extends it in 7 important ways:

1. Spark does not rely on a low-level and rigid `map-then-reduce` workflow. Spark's engine can execute a more general Directed Acyclic Graph (DAG) of operators. This means that in situations where MapReduce must write out intermediate results to the distributed file system (such as HDFS and S3), Spark can pass them directly to the next step in the pipeline. Rather than writing many `map-then-reduce` jobs, in Spark, you can use transformations in any order to have an optimized solution.

2. Spark complements its computational capability with a simple and rich set of transformations and actions that enable users to express computation more naturally. Powerful and simple API (as a set of functions) are provided for various tasks including numerical computation, datetime processing and string manipulation.

3. Spark extends its predecessors (such as Hadoop) with in-memory processing. MapReduce uses disk I/O (which is slow), but Spark uses in-memory computing as much as possible and it can be up to 100 times faster than MapReduce implementations. This means that future steps that want to deal with the same data set need not recompute it or reload it from disk. Spark is well suited for highly iterative algorithms as well as adhoc queries.

4. Spark offers interactive environment (for example using PySpark interactively) for testing

and debugging data transformations.

5. Spark offers extensive Machine Learning libraries (Hadoop/MapReduce does not have this capability)

6. Spark offers extensive graph API by GraphX (built-in) and GraphFrames (as an external library).

7. Spark Streaming is an extension of the core Spark API that allows data engineers and data scientists to process real-time data from various sources including (but not limited to) Kafka, Flume, and Amazon Kinesis. This processed data can be pushed out to file systems, databases, and live dashboards.

What is an Spark RDD

Spark's RDD (full name in PySpark as: `pyspark.RDD`) is a Resilient Distributed Dataset (`RDD`), the basic abstraction in Spark. RDD represents an immutable, partitioned collection of elements that can be operated on in parallel. Basically, an RDD represents your data (as a collection, text files, databases, Parquet files, JSON, CSV files, …). Once your data is represented as an RDD, then you call apply transformations (such as filters, mappers, and reducers) to your RDD and create new RDDs.

An RDD can be created from many data sources such as Python collections, text files, CSV files, log files, JSON, …

An RDD is more suitable to unstructured and semi-structured data (while a DataFrame is more suitable to structured and semi-structured data).

Spark RDD has the following properties:

- Can be denoted (informal notation) by `RDD[T]` : means each element is of data type `T`

- Low-level API

- Immutable (RDDs are read-only to avoid synchronization)

- Partitioned for parallelism

- Can represent billions of data points, called elements

- Ideal for for unstructured and semi-structured data (but you can represent any type of data in RDD)

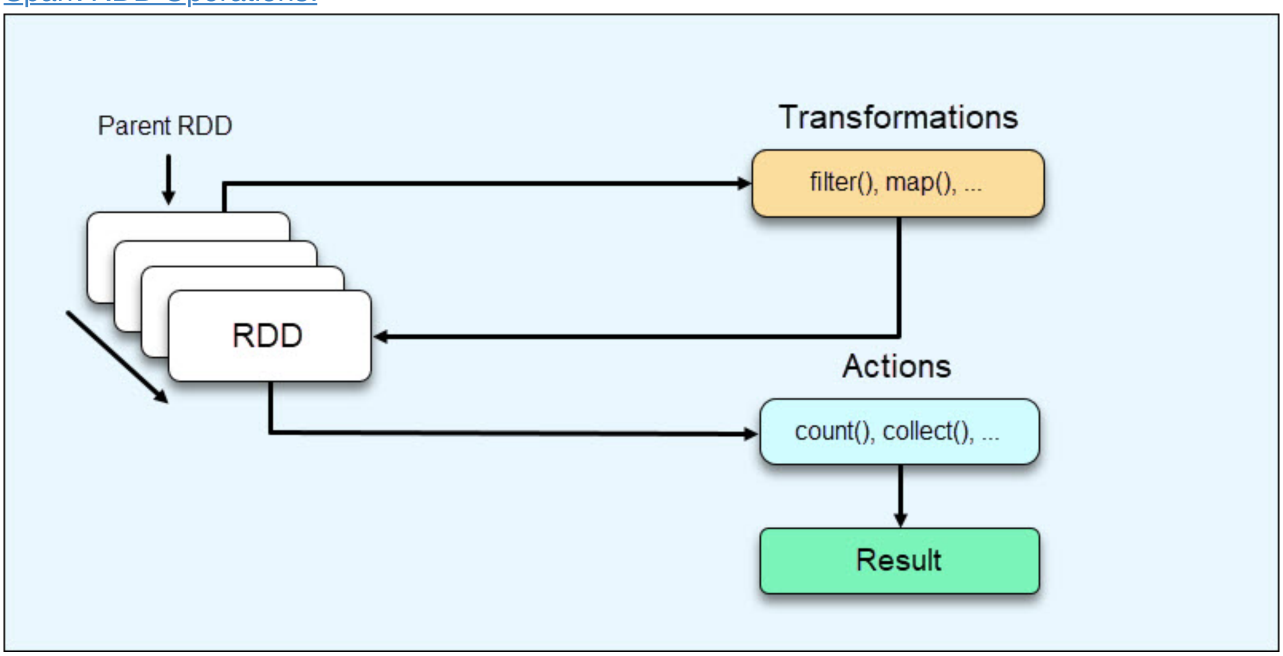
- Action/Transformations: all computations in RDDs are actions or transformations (can apply transformations such as mappers, filters, reducers, and can apply actions such as counting, saving, listing).

  RDDs offer two operation types:

  1. Transformations are operations on RDDs that result in RDD creation.
  2. Actions are operations that do not result in RDD creation and provide some other value.

- In-memory computation. Data calculation resides in memory for faster access and fewer I/O operations
- Fault tolerance. The tracking of data creation helps recover or recreate lost data after a node failure
- Lazy evaluation
- Cacheable: It holds data in persistent storage (memory/disk) so that they can be retrieved more quickly on the next request for them.
- Persistence: Option of choosing which storage will be used either in-memory or on-disk.

Spark RDD Operations:



What are Spark Mappers?

Spark offers comprehensive mapper functions for RDDs and DataFrames. Spark `map()` is a transformation operation that is used to apply the transformation on every element of RDD, DataFrame, and Dataset and finally returns a new RDD/Dataset respectively.

Mappers for RDDs:

- `RDD.map()`
  - 1-to-1 mapping
  - maps an RDD (source) element to a single RDD (target) element
- `RDD.flatMap()`
  - 1-to-many mapping
  - maps an RDD (source) element to multiple RDD (target) elements
- `RDD.mapPartitions()`
  - many-to-1 mapping
  - maps a single partition (comprised of many elements) into a single RDD (target) element

Mappers for DataFrames:

Mappers for Spark Dataframes can be handled by two means:

- Using direct DataFrame's API
- Using SQL on a table (a DataFrame can be registred as a table or rows with named columns)

What are Spark Reducers?

The reducer function receives an intermediate key and a set of associated values (not sorted in any order). It processes these values and generates output as `(key, value)` pairs by grouping values for each key. Example of reduction will be:

Let `key` denotes a key and `values` denotes a set of values for a given `key`, then the following are example of reducers:

- Given a `(key, values)`, find average of values for a given key
- Given a `(key, values)`, find median of values for a given key
- Given a `(key, values)`, find `(minimum, maximum)` of values for a given key

Spark offers comprehensive reducer functions for RDDs and DataFrames.

Reducers for RDDs:

- `RDD.groupByKey()`
- `RDD.reduceByKey()`
- `RDD.combineByKey()`
- `RDD.aggregateByKey()`

Reducers for DataFrames:

Reductions for Spark Dataframes can be handled by two means:

- Using `DataFrame.groupBy()`
- Using SQL's **GROUP BY** on a table (a DataFrame can be registred as a table or rows with named columns)

Data Structure

In computer science, a data structure is a data organization, management, and storage format that is usually chosen for efficient access to data.

There are numerous types of data structures, generally built upon simpler primitive data types. Well known examples are:

- Array
- Set
- Stack
- Linked List
- Double Linked List
- Record
- Tuples
- Hash tables
- Graphs
- Tables
- Tree
- Binary tree

Difference between Spark’s Action and Transformation

A Spark transformation (such as `map()`, `filter()`, `reduceByKey()`, …) applies to a source RDD and creates a new target RDD. While, an action (such as `collect()`, `save()`, …) applies to a source RDD and creates a non-RDD element (such as a number or another data structure).

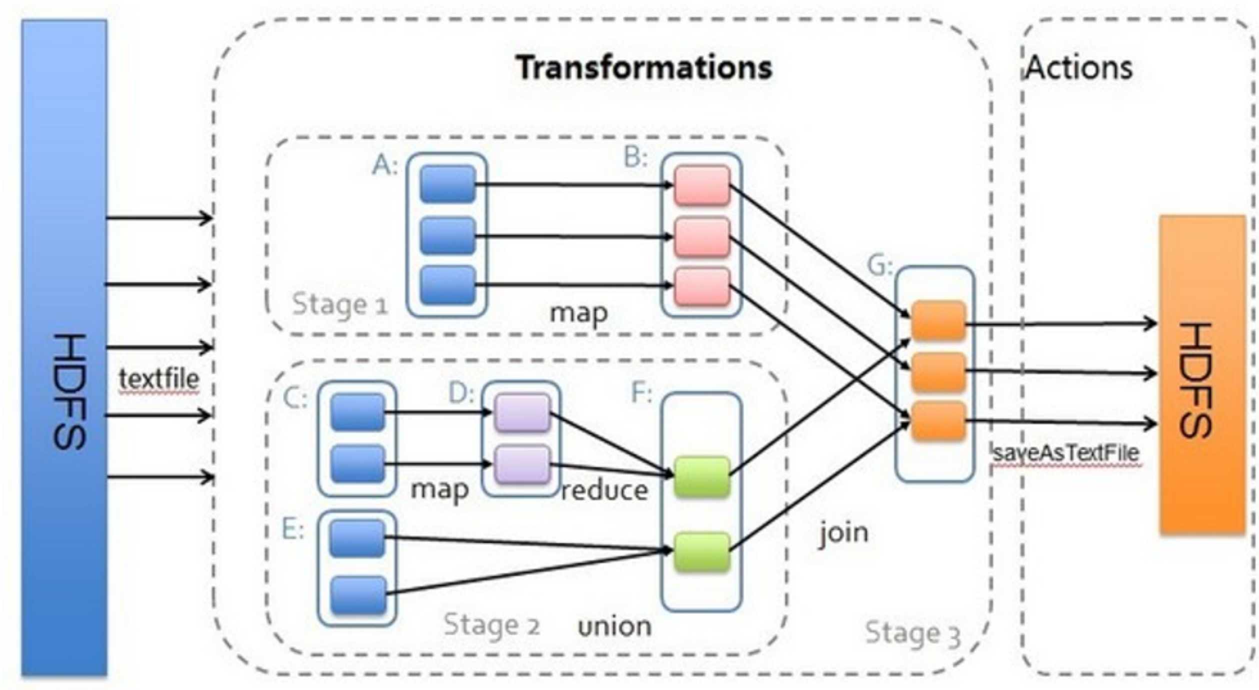
In Spark, if a function returns a DataFrame, Dataset, or RDD, it is a transformation. If it returns anything else or does not return a value at all (or returns Unit in the case of Scala API), it is an action.

What is Lineage In Spark?

Spark RDDs are immutable (READ-ONLY) distributed collection of elements of your data that can be stored in memory or disk across a cluster of machines. The data is partitioned across machines in your cluster that can be operated in parallel with a low-level API that offers transformations and actions. RDDs are fault tolerant as they track data lineage information to rebuild lost data automatically on failure.

What are Spark operations/functions?

Two types of Spark RDD operations are: Transformations and Actions.



- **Transformation**: a transformation is a function that produces new/target RDDs from the source/existing RDDs
  - `Transformation: source_rdd --> target_rdd`
  - `map()` , `filter()` , `flatMap()` , `mapPartitions()`
  - `groupByKey()` , `reduceByKey()` , `combineByKey()`
  - …
- **Action**: when we want to work with the actual dataset, at that point Action is performed. For RDD, anction is defined as the Spark operations that return raw values. In other words, any of the RDD functions that return other than the `RDD[T]` is considered an action in the spark programming.
  - `Action: source_rdd --> NONE_rdd`
  - `collect()`
  - `count()`
  - …

The Spark Programming Model

Spark programming starts with a data set (which can be represented as an RDD or a DataFame), usually residing in some form of distributed, persistent storage like Amazon S3 or Hadoop HDFS. Writing a Spark program typically consists of a few related steps:

1. Define a set of transformations on the input data set.
2. Invoke actions that output the transformed data sets to persistent storage or return results to the driver's local memory.
3. Run local computations that operate on the results computed in a distributed fashion. These can help you decide what transformations and actions to undertake next.

What is Lazy Binding In Spark?

Lazy binding/evaluation in Spark means that the execution of **transformations** will not start until an **action** is triggered.

In programming language theory, lazy evaluation, or call-by-need, is an evaluation strategy which delays the evaluation of an expression until its value is needed (non-strict evaluation) and which also avoids repeated evaluations (sharing).

Spark consists of TRANSFORMATIONS and ACTIONS. Lazy Evaluation in Sparks means Spark will not start the execution of the process until an ACTION is called. Until we are doing only transformations on the dataframe/RDD, Spark is the least concerned. Once Spark sees an ACTION being called, it starts looking at all the transformations and creates a DAG. DAG is simply sequence of operations that need to be performed in a process to get the resultant output.

For example, consider the following 4 Spark transformations, followed by an ACTION:

```python
# sc : SparkContext

# transformation t1
rdd = sc.parallelize(range(0, 100000000), 40)

# transformations t2
rdd2 = rdd.map(lambda x : x+20)

# transformations t3
rdd3 = rdd.map(lambda x : x-5)

# transformations t4
rdd4 = rdd3.filter(lambda x: (x % 5) == 0)

# ACTION
num_of_elements = rdd4.count()
```

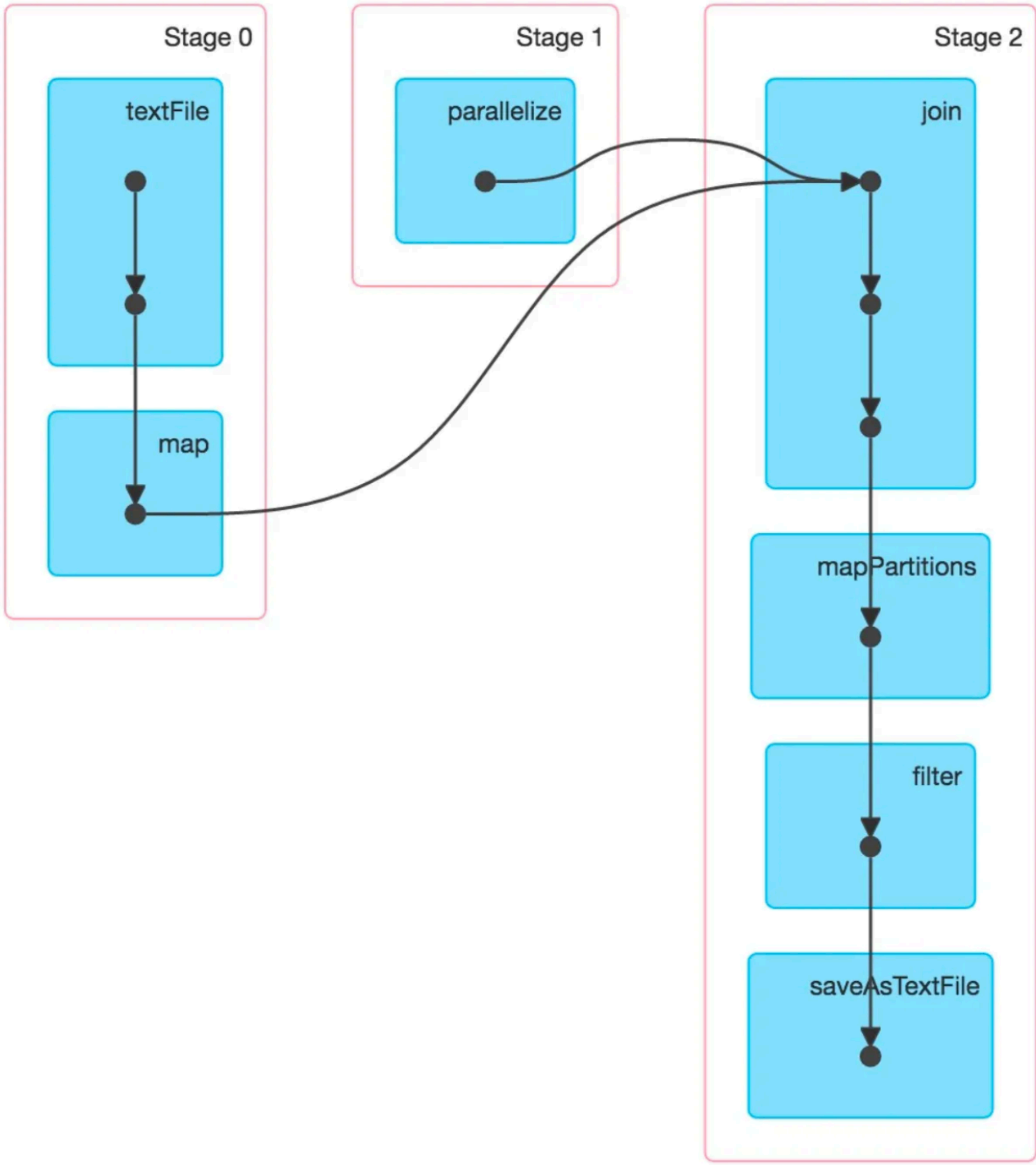
When ACTION is triggered, Spark will optimize all of the transformations `{ t1, t2, t3, t4 }` before finding the `num_of_elmenets`. This is called Lazy binding.

For details see Explain Spark Lazy Evaluation in Detail.

Spark Transformations, Actions, and DAG

```python
def create_key_value(x):
  y = int(x)
  return (y, y * y)
#end-def

def partition_handler(partition):
  result = []
  # e as (k,(v1,v2))
  for e in partition:
    result.append((e[0], e[1][0]+e[1][1]))
  #end-for
  return result
#end-def

# sc : SparkContext
rdd  = sc.textFile("/data/input7")
         .map(create_key_value)
rdd2 = sc.parallelize(range(0, 100000))
         .map(lambda x : (x, x * x +1))
joined = rdd.join(rdd2)
mapped = joined.mapPartitions(partition_handler)
final_rdd = mapped.filter(lambda x:  (x[1] % 10) == 0)
final_rdd.saveAsTextFile("/data/output7")
```

DAG visualization:



Stage 0 and Stage 1 executes in parallel to each other as they are not inter-dependent.

Stage 2 (join operation) depends on stage 0 and stage 1 so it will be executed after executing both the stages.

Difference between `reduceByKey()` and `combineByKey()`

`reduceByKey()`

`RDD.reduceByKey()` merges the values for each key using an **associative** and **commutative** reduce function. This will also perform the merging locally on each mapper before sending results to a reducer, similarly to a “combiner” in MapReduce.

This can be expressed as:

```
reduceByKey: RDD[(K, V)] --> RDD[(K, V)]
```

`combineByKey()`

```
combineByKey: RDD[(K, V)] --> RDD[(K, C)]
# where V and C can be different types
```

`RDD.combineByKey()` is a generic function to combine the elements for each key using a custom set of aggregation functions. `RDD.combineByKey()` turns an `RDD[(K, V)]` into a result of type `RDD[(K, C)]`, for a “combined type” `C`.

```
# rdd : RDD[(K, V)]
# rdd2: RDD[(K, C)]
# where V and C can be different types
rdd2 = rdd.combineByKey(create_combiner, merge_value, merge_combiners)
```

For `combineByKey()`, users provide three functions:

- `create_combiner`, which turns a `V` into a `C` (e.g., creates a one-element list as type `C`)

  ```
  create_combiner: V --> C
  ```

- `merge_value`, to merge a `V` into a `C` (e.g., adds it to the end of a list)

  ```
  merge_value: C x V --> C
  ```

- `merge_combiners`, to combine two `C’s` into a single one (e.g., merges the lists)

  ```
  merge_combiners: C x C --> C
  ```

This can be expressed as:

```
combineByKey: RDD[(K, V)] --> RDD[(K, C)]

where V and C can be the same or different
```

What is an example of `RDD.combineByKey()`?

Combine all of values per key.

```

# combineByKey: RDD[(String, Integer)] --> RDD[(String, [Integer])]

# sc : SparkContext
# rdd : RDD[(String, Integer)]
rdd = sc.parallelize([("a", 1), ("b", 7), ("a", 2), ("a", 3), ("b", 8), ("z",

# V --> C
def to_list(a):
    return [a]

# C x V --> C
def append(a, b):
    a.append(b)
    return a

# C x C --> C
def extend(a, b):
    a.extend(b)
    return a

# rdd: RDD[(String, Integer)]
# rdd2: RDD[(String, [Integer])]
rdd2 = rdd.combineByKey(to_list, append, extend)
rdd2.collect()

[
 ('z', [5]),
 ('a', [1, 2, 3]),
 ('b', [7, 8])
]

# Note that values of keys does not need to be sorted
```

What is an example of `RDD.reduceByKey()` ?

Find maximum of values per key.

```
# reduceByKey: RDD[(String, Integer)] --> RDD[(String, Integer)]

# sc : SparkContext
rdd = sc.parallelize([("a", 1), ("b", 7), ("a", 2), ("a", 3), ("b", 8), ("z",

# rdd: RDD[(String, Integer)]
# rdd2: RDD[(String, Integer)]
rdd2 = rdd.reduceByKey(lambda x, y: max(x, y))
rdd2.collect()

[
 ('z', 5),
 ('a', 3),
 ('b', 8)
]
```

What is an example of `RDD.groupByKey()` ?

Combine/Group values per key.

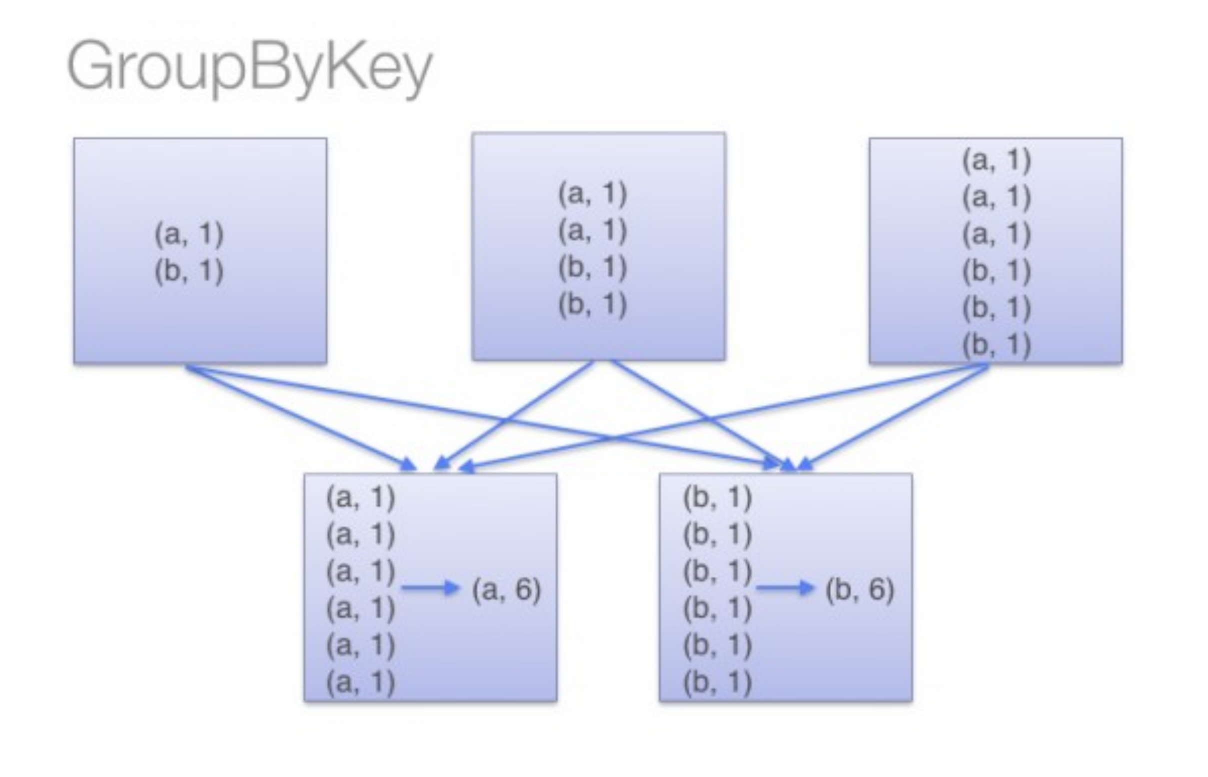
```
# reduceByKey: RDD[(String, Integer)] --> RDD[(String, [Integer])]

# sc : SparkContext
rdd = sc.parallelize([("a", 1), ("b", 7), ("a", 2), ("a", 3), ("b", 8), ("z",

# rdd: RDD[(String, Integer)]
# rdd2: RDD[(String, [Integer])]
rdd2 = rdd.groupByKey()
rdd2.collect()

[
 ('z', [5]),
 ('a', [1, 2, 3]),
 ('b', [7, 8])
]
```

Difference of `RDD.groupByKey()` and

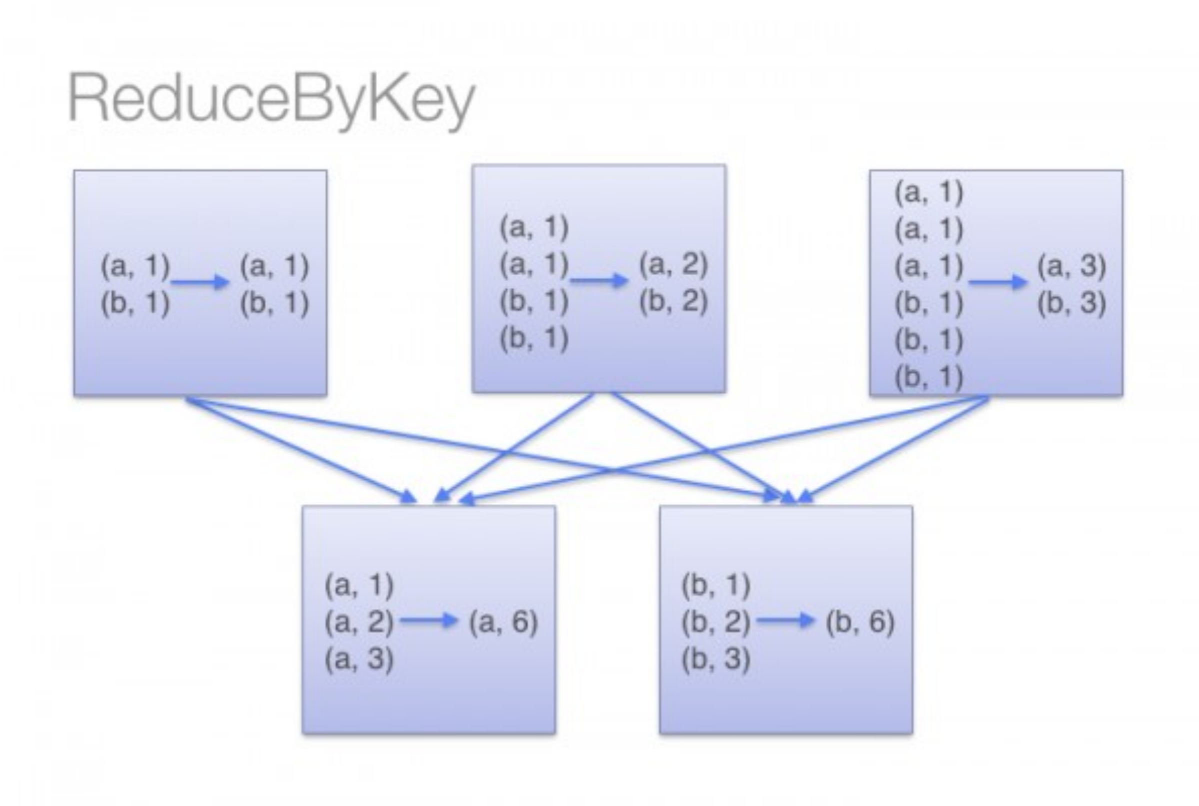
`RDD.reduceByKey()`

Both `reduceByKey()` and `groupByKey()` result in wide transformations which means both triggers a shuffle operation. The key difference between `reduceByKey()` and `groupByKey()` is that `reduceByKey()` does a map side combine and `groupByKey()` does not do a map side combine. Overall, `reduceByKey()` is optimized with a map side combine. Note that the reducer function for the `reduceByKey()` must be associative and commutative.

- `groupByKey: RDD[(K, V)] --> RDD[(K, [V])]`



- `reduceByKey: RDD[(K, V)] --> RDD[(K, V)]`



What is a DataFrame?

A DataFrame is a data structure that organizes data into a 2-dimensional table of rows and columns, much like a spreadsheet or a relational table. DataFrames are one of the most common data structures used in modern data analytics because they are a flexible and intuitive way of storing and working with data.

Python DataFrame Example

DataFrame is a 2-dimensional mutable labeled data structure with columns of potentially different types. You can think of it like a spreadsheet or SQL table, or a dict of Series objects. It is generally the most commonly used `Pandas` object. A `Pandas` DataFrame is a 2-dimensional data structure, like a 2-dimensional array, or a table with rows and columns. The number of rows for `Pandas` DataFrame is mutable and limited to the computer and memory where it resides.

```python
import pandas as pd

data = {
  "calories": [100, 200, 300],
  "duration": [50, 60, 70]
}

#load data into a DataFrame object:
df = pd.DataFrame(data)

print(df)

# Result:

      calories  duration
  0       100        50
  1       200        60
  2       300        70
```

Spark DataFrame Example

Like an RDD, a DataFrame is an immutable distributed collection of data. Unlike an RDD, data is organized into named columns, like a table in a relational database.
In Spark, a DataFrame is a distributed collection of data grouped into named columns. Spark's DataFrame is immutable and can have billions of rows. A DataFrame is equivalent to a relational table in Spark SQL, and can be created using various functions in `SparkSession`:

```python
# PySpark code:

input_path = "..."
# spark: as a SparkSession object
people = spark.read.parquet(input_path)
```

Once created, it can be manipulated using the various domain-specific-language (DSL) functions or you may use `SQL` to execute queries against DataFrame (registered as a table).

A more concrete example:

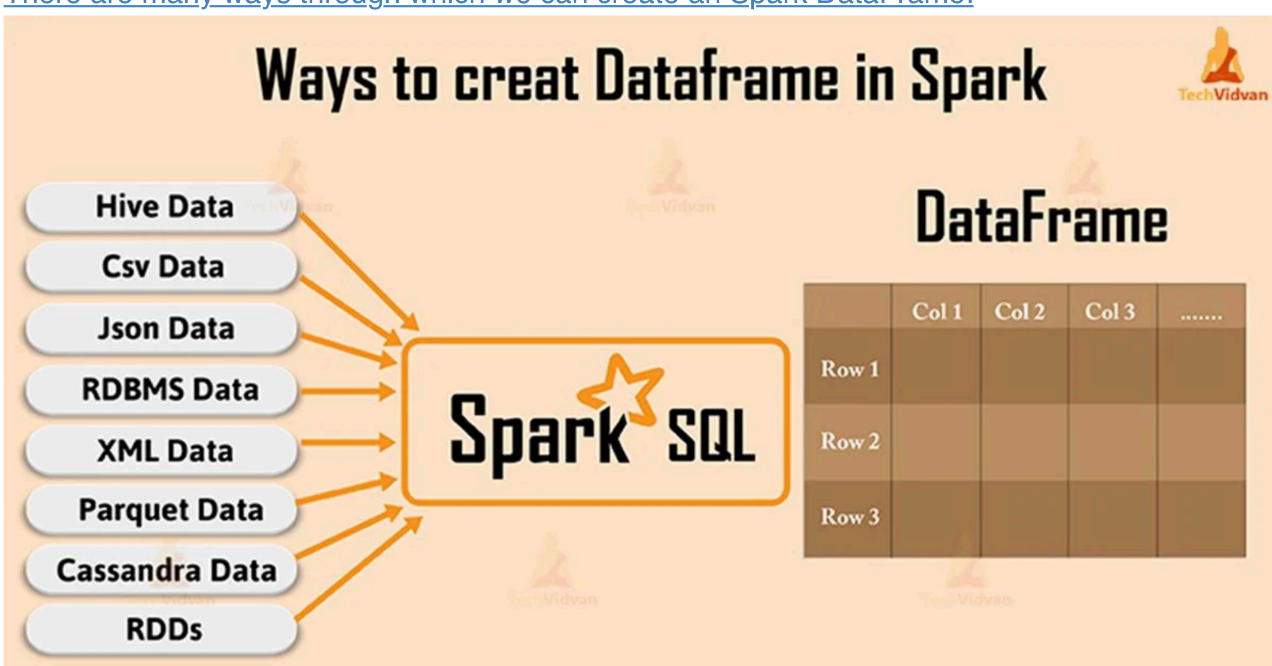
```
# PySpark code:

# To create DataFrame using SparkSession
input_path_people = "..."
people = spark.read.parquet(input_path_people)
input_path_dept = "..."
department = spark.read.parquet(input_path_dept)

result = people.filter(people.age > 30)\
               .join(department, people.deptId == department.id)\
               .groupBy(department.name, "gender")\
               .agg({"salary": "avg", "age": "max"})
```

What is an Spark DataFrame?

Spark's DataFrame (full name as: `pyspark.sql.DataFrame`) is an immutable and distributed collection of data grouped into named columns. Once your DataFrame is created, then your DataFrame can be manipulated and transformed into another DataFrame by DataFrame's native API and SQL.

A DataFrame can be created from Python collections, relational databases, Parquet files, JSON, CSV files, …). DataFrame is more suitable to structured and semi-structured data (while an RDD is more suitable to unstructured and semi-structured data).

[There are many ways through which we can create an Spark DataFrame:]



Features of Spark DataFrames:

- Immutable (to avoid synchronization)
- Partitioned (to support parallelism)
- Data Formats: Support for various data formats, such as Hive, CSV, XML, JSON, RDDs, Cassandra, Parquet, etc.
- Support for integration with various Big Data tools.
- The ability to process mega/giga bytes of data on smaller machines and petabytes on clusters.
- Catalyst optimizer for efficient data processing across multiple languages.
- Structured data handling through a schematic view of data.
- Custom memory management to reduce overload and improve performance compared to RDDs.
- APIs for Java, R, Python, and Spark.

Spark RDD Example

An Spark RDD can represent billions of elements.

```
>>> sc
<SparkContext master=local[*] appName=PySparkShell>
>>> sc.version
'3.3.1'
>>> numbers = sc.parallelize(range(0,1000))
>>> numbers
PythonRDD[1] at RDD at PythonRDD.scala:53
>>> numbers.count()
1000
>>> numbers.take(5)
[0, 1, 2, 3, 4]
>>> numbers.getNumPartitions()
16
>>> total = numbers.reduce(lambda x, y: x+y)
>>> total
499500
```

Spark DataFrame Example

A Spark DataFrame can represent billions of rows of named columns.

```
>>> records = [("alex", 23), ("jane", 24), ("mia", 33)]
>>> spark
<pyspark.sql.session.SparkSession object at 0x12469e6e0>
>>> spark.version
'3.3.1'
>>> df = spark.createDataFrame(records, ["name", "age"])
>>> df.show()
+----+---+
|name|age|
+----+---+
|alex| 23|
|jane| 24|
| mia| 33|
+----+---+

>>> df.printSchema()
root
 |-- name: string (nullable = true)
 |-- age: long (nullable = true)
```

Join Operation in MapReduce

The MapReduce paradigm does not have a direct join API. But the join can be implemented as a set of custom mappers and reducers.

Below, an inner join is presented for MapReduce:

Let `R` be a relation as `(K, a1, a2, ...)`, where `K` is a key and `a1, a2, ...` are additional attributes of `R`, which we denote it as `(K, A)`, where `A` denotes attributes `(a1, a2, ...)`.

Let `S` be a relation as `(K, b1, b2, ...)`, where `K` is a key and `b1, b2, ...` are additional attributes of `S`, which we denote it as `(K, B)`, where `B` denotes attributes `(b1, b2, ...)`.

We want to implement `R.join(S)`, which will return `(K, (a, b))`, where `(K, a)` is in `R` and `(K, b)` is in `S`.

Step-1: Map relation R: inject the name of relation into an output value as:

```
input (K, a)
output: (K, ("R", a))
```

Step-2: Map relation S: inject the name of relation into an output value as:

```
input (K, b)
output: (K, ("S", b))
```

Step-3: Merge outputs of Step-1 and Step-2 into `/tmp/merged_input/`, which will be used as an input path for Step-4 (as an identity mapper):

Step-4: is an identity mapper:

```
# key: as K
# value as: ("R", a) OR ("S", b)
map(key, value) {
    emit(key, value)
}
```

Step-4.5: Sort & Shuffle (provided by MapReduce implementation): will create (key, value) pairs as:

```
(K, Iterable<(relation, attribute)>
```

where `K` is the common key of `R` and `S`, relation is either “R” or “S”, and attribe is either `a` in `A` or `b` in `B`.

Step-5: Reducer

```
# key as K is the common key of R and S
# values : Iterable<(relation, attribute)>
reduce(key, values) {
   # create two lists: one for R and another one for S
   R_list = []
   S_list = []

   # iterate values and build/update R_list and S_list
   for pair in values {
      relation = pair[0]
      attribute = pair[1]
      if (relation == "R") {
         R_list.append(attribute)
      }
      else {
         # relation == "S"
         S_list.append(attribute)
      }
   } #end-for

   # drop keys, which are not common
   if (len(R_list) == 0) or (len(S_list) == 0) {
       # no join, no common attributes
       return
   }

   # Process common keys
   # Both lists are non-empty:
   # len(R_list) > 0) AND len(S_list) > 0
   # perform a cartesian product of R and S
   for a in R_list {
       for b in S_list {
             emit (key, (a, b))
        }
   }
} # end-reduce
```

Note that the left-join and right-join operations can be implemented by revising the reducer function.

Example: Demo Inner Join

Relation R:

```
(x, 1)
(x, 2)
(y, 3)
(y, 4)
(z, 5)
```

Relation S:

```
(x, 22)
(x, 33)
(y, 44)
(p, 55)
(p, 66)
(p, 77)
```

Step-1: output:

```
(x, ("R", 1))
(x, ("R", 2))
(y, ("R", 3))
(y, ("R", 4))
(z, ("R", 5))
```

Step-2: output:

```
(x, ("S", 22))
(x, ("S", 33))
(y, ("S", 44))
(p, ("S", 55))
(p, ("S", 66))
(p, ("S", 77))
```

Step-3: combine outputs of Step-1 and Step-2:

```
    (x, ("R", 1))
    (x, ("R", 2))
    (y, ("R", 3))
    (y, ("R", 4))
    (z, ("R", 5))
    (x, ("S", 22))
    (x, ("S", 33))
    (y, ("S", 44))
    (p, ("S", 55))
    (p, ("S", 66))
    (p, ("S", 77))
```

Step-4: Identity Mapper output:

```
    (x, ("R", 1))
    (x, ("R", 2))
    (y, ("R", 3))
    (y, ("R", 4))
    (z, ("R", 5))
    (x, ("S", 22))
    (x, ("S", 33))
    (y, ("S", 44))
    (p, ("S", 55))
    (p, ("S", 66))
    (p, ("S", 77))
```

Step-4.5: Sort & Shuffle output:

```
(x, [("R", 1), ("R", 2), ("S", 22), ("S", 33)])
(y, [("R", 3), ("R", 4), ("S", 44)])
(z, [("R", 5)])
(p, [("S", 55), ("S", 66), ("S", 77)])
```

Step-5: Reducer output:

```
(x, (1, 22))
(x, (1, 33))
(x, (2, 22))
(x, (2, 33))
(y, (3, 44))
(y, (4, 44))
```

Join Operation in Spark

Spark has an extensive support for join operation.

Join in RDD

Let A be an `RDD[(K, V)]` and B be an `RDD[(K, U)]`, then `A.join(B)` will return a new RDD (call it as C) as `RDD[(K, (V, U)]`. Each pair of C elements will be returned as a `(k, (v, u))` tuple, where `(k, v)` is in A and `(k, u)` is in B. Spark performs a hash join across the cluster.

Example:

```
# sc : SparkContext
x = sc.parallelize([("a", 1), ("b", 4), ("c", 6), ("c", 7)])
y = sc.parallelize([("a", 2), ("a", 3), ("c", 8), ("d", 9)])
x.join(y).collect())
[
 ('a', (1, 2)),
 ('a', (1, 3)),
 ('c', (6, 8)),
 ('c', (7, 8))
]
```

Join in DataFrame

```
# PySpark API:

DataFrame.join(other: pyspark.sql.dataframe.DataFrame,
               on: Union[str, List[str],
               pyspark.sql.column.Column,
               List[pyspark.sql.column.Column], None] = None,
               how: Optional[str] = None)
                → pyspark.sql.dataframe.DataFrame

Joins with another DataFrame, using the given join expression.
```

Example: inner join

```
# SparkSession available as 'spark'.
>>> emp = [(1, "alex", "100", 33000), \
...        (2, "rose", "200", 44000), \
...        (3, "bob", "100", 61000), \
...        (4, "james", "100", 42000), \
...        (5, "betty", "400", 35000), \
...        (6, "ali", "300", 66000) \
...   ]
>>> emp_columns = ["emp_id", "name", "dept_id", "salary"]
>>> emp_df = spark.createDataFrame(data=emp, schema = emp_columns)
>>>
>>> emp_df.show()
+------+-----+-------+------+
|emp_id| name|dept_id|salary|
+------+-----+-------+------+
|     1| alex|    100| 33000|
|     2| rose|    200| 44000|
|     3|  bob|    100| 61000|
|     4|james|    100| 42000|
|     5|betty|    400| 35000|
|     6|  ali|    300| 66000|
+------+-----+-------+------+

>>> dept = [("Finance", 100), \
...         ("Marketing", 200), \
...         ("Sales", 300), \
...         ("IT", 400) \
...   ]
>>> dept_columns = ["dept_name", "dept_id"]
>>> dept_df = spark.createDataFrame(data=dept, schema = dept_columns)
```

```
>>> dept_df.show()
+---------+-------+
|dept_name|dept_id|
+---------+-------+
|  Finance|    100|
|Marketing|    200|
|    Sales|    300|
|       IT|    400|
+---------+-------+

>>> joined = emp_df.join(dept_df, emp_df.dept_id ==  dept_df.dept_id, "inner'
>>> joined.show()
+------+-----+-------+------+---------+-------+
|emp_id| name|dept_id|salary|dept_name|dept_id|
+------+-----+-------+------+---------+-------+
|     1| alex|    100| 33000|  Finance|    100|
|     3|  bob|    100| 61000|  Finance|    100|
|     4|james|    100| 42000|  Finance|    100|
|     2| rose|    200| 44000|Marketing|    200|
|     6|  ali|    300| 66000|    Sales|    300|
|     5|betty|    400| 35000|       IT|    400|
+------+-----+-------+------+---------+-------+

>>> joined = emp_df.join(dept_df, emp_df.dept_id ==  dept_df.dept_id, "inner'
                   .drop(dept_df.dept_id)
>>> joined.show()
+------+-----+-------+------+---------+
|emp_id| name|dept_id|salary|dept_name|
+------+-----+-------+------+---------+
|     1| alex|    100| 33000|  Finance|
|     3|  bob|    100| 61000|  Finance|
|     4|james|    100| 42000|  Finance|
|     2| rose|    200| 44000|Marketing|
|     6|  ali|    300| 66000|    Sales|
|     5|betty|    400| 35000|       IT|
+------+-----+-------+------+---------+
```

Spark Partitioning

A partition in spark is an atomic chunk of data (logical division of data) stored on a node in the cluster. Partitions are basic units of parallelism in Apache Spark. RDDs and DataFrames in Apache Spark are collection of partitions. So, how partitioning of an RDD (or a DataFrame) is

related to parallelism?
Spark is an engine for parallel processing of data on a cluster. One important way to increase parallelism of spark processing is to increase the number of executors (executors are worker nodes' processes in charge of running individual tasks in a given Spark job) on the cluster. However, knowing how the data should be distributed, so that the cluster can process data efficiently is extremely important. The secret to achieve this is partitioning in Spark.

Data (represented as an RDD or DataFrame) partitioning in Spark helps achieve more parallelism. For example, if your RDD/DataFrame is partitioned into 100 chunks (or partitions), then for `RDD.map()`, there is a chance of running 100 mappers in parallel/concurrently (at the same time). Therefore, Spark RDDs and DataFrames are stored in partitions and operated in parallel.

For example, in PySpark you can get the current number of partitions by running `RDD.getNumPartitions()`.
For Spark partitioning, refer to Spark Partitioning & Partition Understanding.

Physical Data Partitioning

Physical Data Partitioning is a technique used in data warehouses and big data query engines.

Physical Data Partitioning is a way to organize a very large data into several smaller data based on one or multiple columns (partition key, for example, continent, country, date, state e.t.c).

The main point of Physical Data Partitioning is to analyze slice of a data rather than the whole data. For example, if we have a temprature data for 7 continents, and we are going to query data based on the continent name, then to reduce the query time, we can partition data by the continent name: this enables us to query slice of a data (such as: `continent_name = asia`) rather than the whole data. When we phisically partition data, we create separate folder (or directory) per partitioned column.

In Spark, for Physical Data Partitioning, you may use `pyspark.sql.DataFrameWriter.partitionBy()`.

PySpark Example:

```
output_path = "...target-output-path..."
df.write.partitionBy('continent')\
  .parquet(output_path)
```

For example, given a DataFrame as:

```
DataFrame(continent, country, city, temprature)
```

Then partitioning by `continent`, the following physical folders/directories will be created (for example, if we had data for 7 continents, then 7 folders will be created):

```
<output_path>
      |
      +------- continent=Asia   --- <data-for-asia>
      |
      +------- continent=Europe --- <data-for-europe>
      |
      + ...
```

For details, refer to [Physical Data Partitioning tutorial](#).

GraphFrames

[GraphFrames](#) is an external package for Apache Spark which provides DataFrame-based Graphs. It provides high-level APIs in Scala, Java, and Python. It aims to provide both the functionality of GraphX (included in Spark API) and extended functionality taking advantage of Spark DataFrames. This extended functionality includes motif finding, DataFrame-based serialization, and highly expressive graph queries.

> GraphFrames are to DataFrames as GraphX is to RDDs.

To build a graph, you build 2 DataFrames (one for vertices and another one for the edges) and then glue them together to create a graph:

```
# each node is identified by "id" and an optional attributes
# vertices: DataFrame(id, ...)

# each edge is identified by (src, dst) and an optional attributes
# where src and dst are node ids
# edges: DataFrame(src, dst, ...)

# import required GraphFrame library
from graphframes import GraphFrame

# create a new directed graph
graph = GraphFrame(vertices, edges)
```

Example of a GraphFrame

This example shows how to build a directed graph using graphframes API.

To invoke PySpark with GraphFrames:

```
% # define the home directory for Spark
% export SPARK_HOME=/home/spark-3.2.0
% # import graphframes library into PySpark and invoke interactive PySpark:
% $SPARK_HOME/bin/pyspark --packages graphframes:graphframes:0.8.2-spark3.2-s
Python 3.8.9 (default, Mar 30 2022, 13:51:17)
...
Welcome to
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /__ / .__/\_,_/_/ /_/\_\   version 3.2.0
      /_/

Using Python version 3.8.9 (default, Mar 30 2022 13:51:17)
Spark context Web UI available at http://10.0.0.234:4040
Spark context available as 'sc' (master = local[*], app id = local-165067039
SparkSession available as 'spark'.
>>>
```

Then PySpark is ready to use GraphFrames API:

```
>>># create list of nodes
>>> vert_list = [("a", "Alice", 34),
...               ("b", "Bob", 36),
...               ("c", "Charlie", 30)]
>>>
>>># define column names for a node
>>> column_names_nodes = ["id", "name", "age"]
>>>
>>># create vertices_df as a Spark DataFrame
>>> vertices_df = spark.createDataFrame(
...      vert_list,
...      column_names_nodes
... )

>>>
>>># create list of edges
>>> edge_list = [("a", "b", "friend"),
...               ("b", "c", "follow"),
...               ("c", "b", "follow")]
>>>
>>># define column names for an edge
>>> column_names_edges = ["src", "dst", "relationship"]
>>>
>>># create edges_df as a Spark DataFrame
>>> edges_df = spark.createDataFrame(
...           edge_list,
...           column_names_edges
... )
>>>
>>># import required libriaries
>>> from graphframes import GraphFrame
>>>
>>># build a graph using GraphFrame library
>>> graph = GraphFrame(vertices_df, edges_df)
>>>
>>># examine built graph
>>> graph
GraphFrame(
  v:[id: string, name: string ... 1 more field],
  e:[src: string, dst: string ... 1 more field]
)
>>>
>>># access vertices of a graph
>>> graph.vertices.show()
```

```
+---+-------+---+
| id|   name|age|
+---+-------+---+
|  a|  Alice| 34|
|  b|    Bob| 36|
|  c|Charlie| 30|
+---+-------+---+

>>># access edges of a graph
>>> graph.edges.show()
+---+---+------------+
|src|dst|relationship|
+---+---+------------+
|  a|  b|      friend|
|  b|  c|      follow|
|  c|  b|      follow|
+---+---+------------+
```

Advantages of using Spark

- **Superset of MapReduce**
- **Speed**: for large scale data analysis and processing, Spark is 100 times faster than Hadoop. This is achieved by:
    - Modern architecture, better ECO system
    - Provides parallelism with simple and powerful API
    - Utilizing In-Memory (RAM) processing architecture
- **Ease of Use**: Spark provides simple and powerful APIs for working with big data sets. Spark offers over 100 high-level operators and transformations that makes creating parallel programs a breeze
- **Advanced Analytics**: Spark implements superset of MapReduce paradigm. Spark does much more than `map-then-reduce` of MapReduce paradigm.
- Sparks offers **Machine Learning**, **Graph processing**, **streaming data**, and **SQL queries**.
- **Dynamic**: Spark allows simple creation of parallel applications. Spark offers over 100 high-level operators, transformations, and actions.
- **Multilingual**: Python, Java, Scala, R, and SQL are supported by Spark

- **Simple and Powerful**: Because of its low-latency in-memory data processing capacity, Spark can handle a wide range of analytics problems. Spark has an extensive libraries for Machine Learning and Graph analytics at a scale
- **Open-Source**: Spark is an open-source and hosted by Apache Sofware Foundation.

GraphX

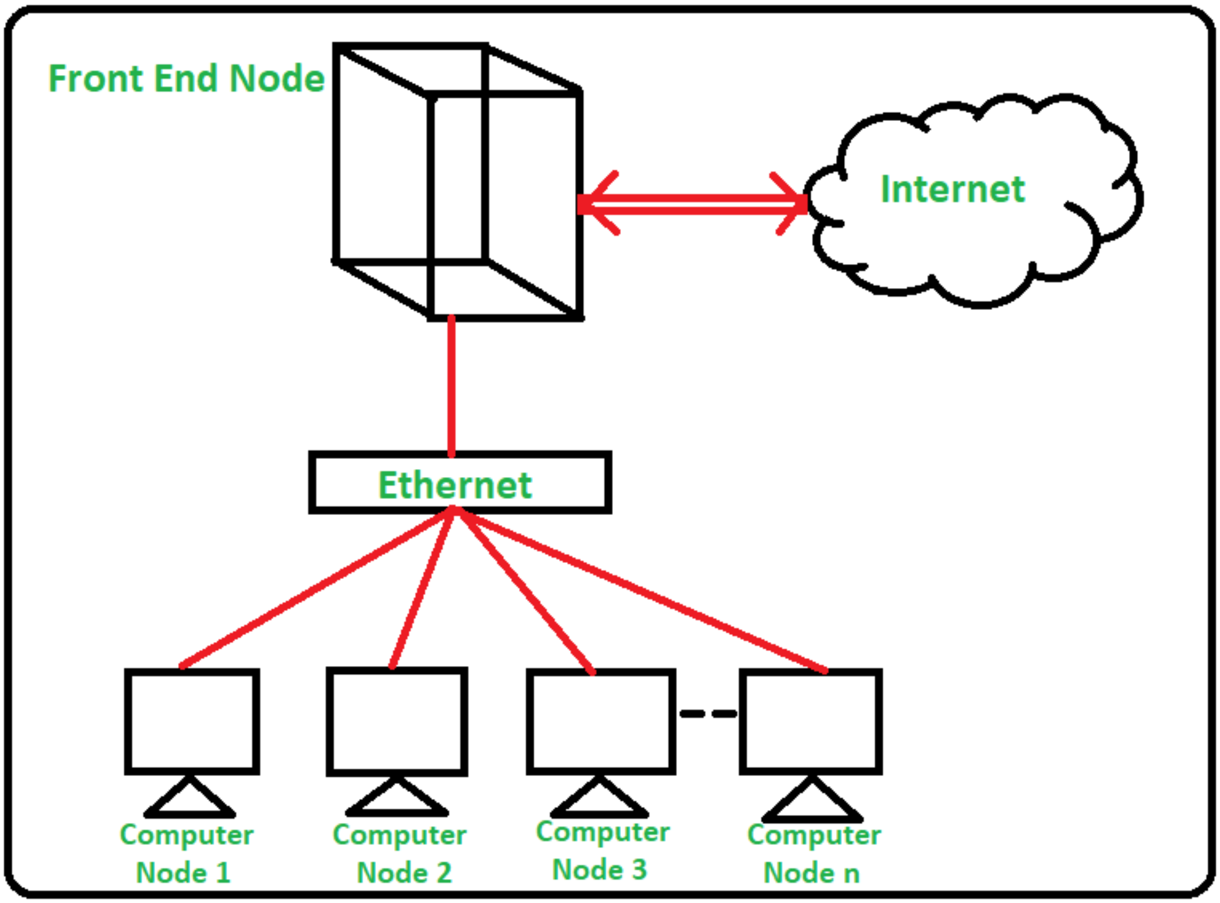
GraphX is Apache Spark's API (RDD-based) for graphs and graph-parallel computation, with a built-in library of common algorithms. GraphX has API for Java and Scala, but does not have an API for Python (therefore, PySpark does not support GraphX).

To use graphs in PySpark, you may use GraphFrames (DataFrame-based).

Cluster

Cluster is a group of servers on a network that are configured to work together. A server is either a master node or a worker node. A cluster may have a master node and many worker nodes. In a nutshell, a master node acts as a cluster manager.

A cluster may have one (or two) master nodes and many worker nodes. For example, a cluster of 15 nodes: one master and 14 worker nodes. Another example: a cluster of 101 nodes: one master and 100 worker nodes.

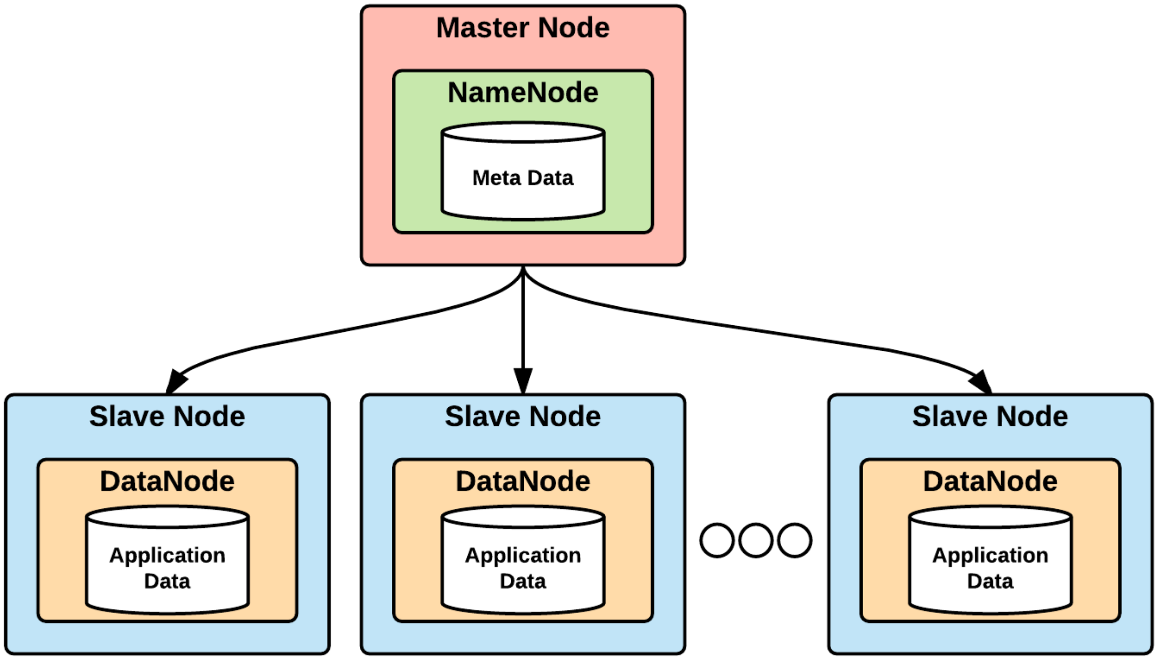


A cluster may be used for running many jobs (Spark and MapReduce jobs) at the same time.

Master node

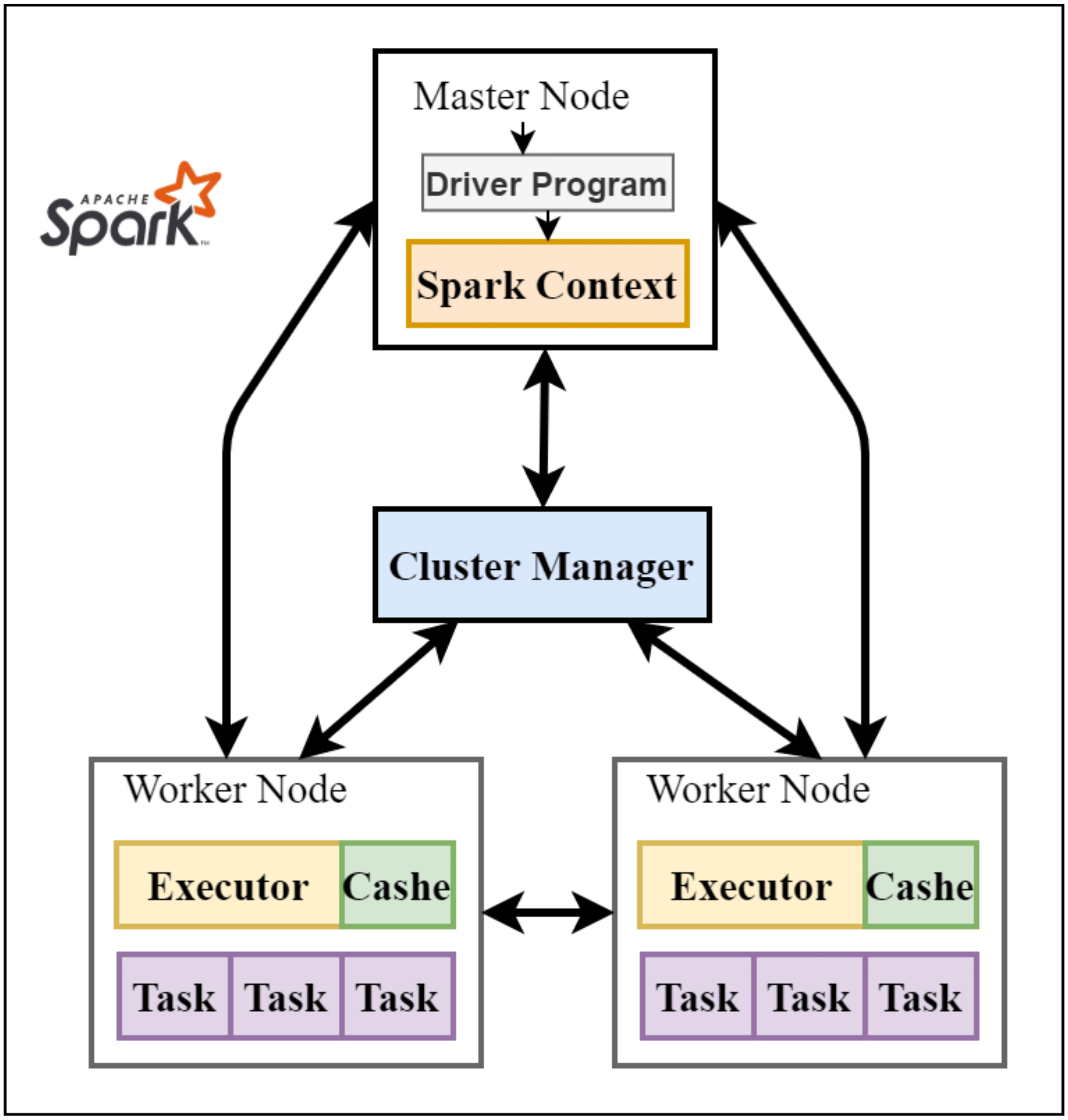
In Hadoop, Master nodes (set of one or more nodes) are responsible for storing data in HDFS and overseeing key operations, such as running parallel computations on the data using MapReduce. The worker nodes comprise most of the virtual machines in a Hadoop cluster, and perform the job of storing the data and running computations.

Hadoop-Master-Worker: the following images shows Hadoop's master node and worker nodes.



In Spark, the master node contains driver program, which drives the application by creating Spark context object. Spark context object works with cluster manager to manage different jobs. Worker nodes job is to execute the tasks and return the results to Master node.

Spark-Master-Worker: the following images shows master node and 2 worker nodes.



Worker node

In Hadoop, the worker nodes comprise most of the virtual machines in a Hadoop cluster, and perform the job of storing the data and running computations. Each worker node runs the DataNode and TaskTracker services, which are used to receive the instructions from the master nodes.

In Spark, worker node is ny node that can run application code in the cluster. Executor is a process launched for an application on a worker node, that runs tasks and keeps data in memory or disk storage across them. Each application has its own executors.

Cluster computing

Cluster computing is a collection of tightly or loosely connected computers that work together so that they act as a single entity. The connected computers execute operations all together thus creating the idea of a single system. The clusters are generally connected through fast local area networks (LANs). A cluster computing is comprised of a one or more masters (manager for the whole cluster) and many worker nodes. For example, a cluster computer may have a single master node (which might not participate in tasks such as mappers and reducers) and 100 worker nodes (which actively participate in carrying tasks such as mappers and reducers). A small cluster might have one master node and 5 worker nodes. Large clusters might have hundreds or thousands of worker nodes.

Concurrency

Performing and executing multiple tasks and processes at the same time. Let's define 5 tasks {T1, T2, T3, T4, T5} where each will take 10 seconds. If we execute these 5 tasks in sequence, then it will take about 50 seconds, while if we execute all of them in parallel, then the whole thing will take about 10 seconds. Cluster computing enables concurrency and parallelism.

Histogram

A graphical representation of the distribution of a set of numeric data, usually a vertical bar graph

Structured data

Structured data — typically categorized as quantitative data — is highly organized and easily decipherable by machine learning algorithms. Developed by IBM in 1974, structured query language (SQL) is the programming language used to manage structured data. By using a relational (SQL) database, business users can quickly input, search and manipulate structured data. In structured data, each record has a precise record format. Structured data is identifiable as it is organized in structure like rows and columns.

Structured data is data that has a predefined data model or is organized in a predefined way.

Unstructured data

n the modern world of big data, unstructured data is the most abundant. It's so prolific because unstructured data could be anything: media, imaging, audio, sensor data, log data, text data, and much more. Unstructured simply means that it is datasets (typical large collections of files) that aren't stored in a structured database format. Unstructured data has an internal structure, but it's not predefined through data models. It might be human generated, or machine generated in a textual or a non-textual format. Unstructured data is regarded as data that is in general text heavy, but may also contain dates, numbers and facts.

Unstructured data is data that does not have a predefined data model or is not organized in a predefined way.

Correlation analysis

The analysis of data to determine a relationship between variables and whether that relationship is negative `(- 1.00)` or positive `(+1.00)`.

Data aggregation tools

The process of transforming scattered data from numerous sources into a single new one.

Data analyst

Someone analysing, modelling, cleaning or processing data

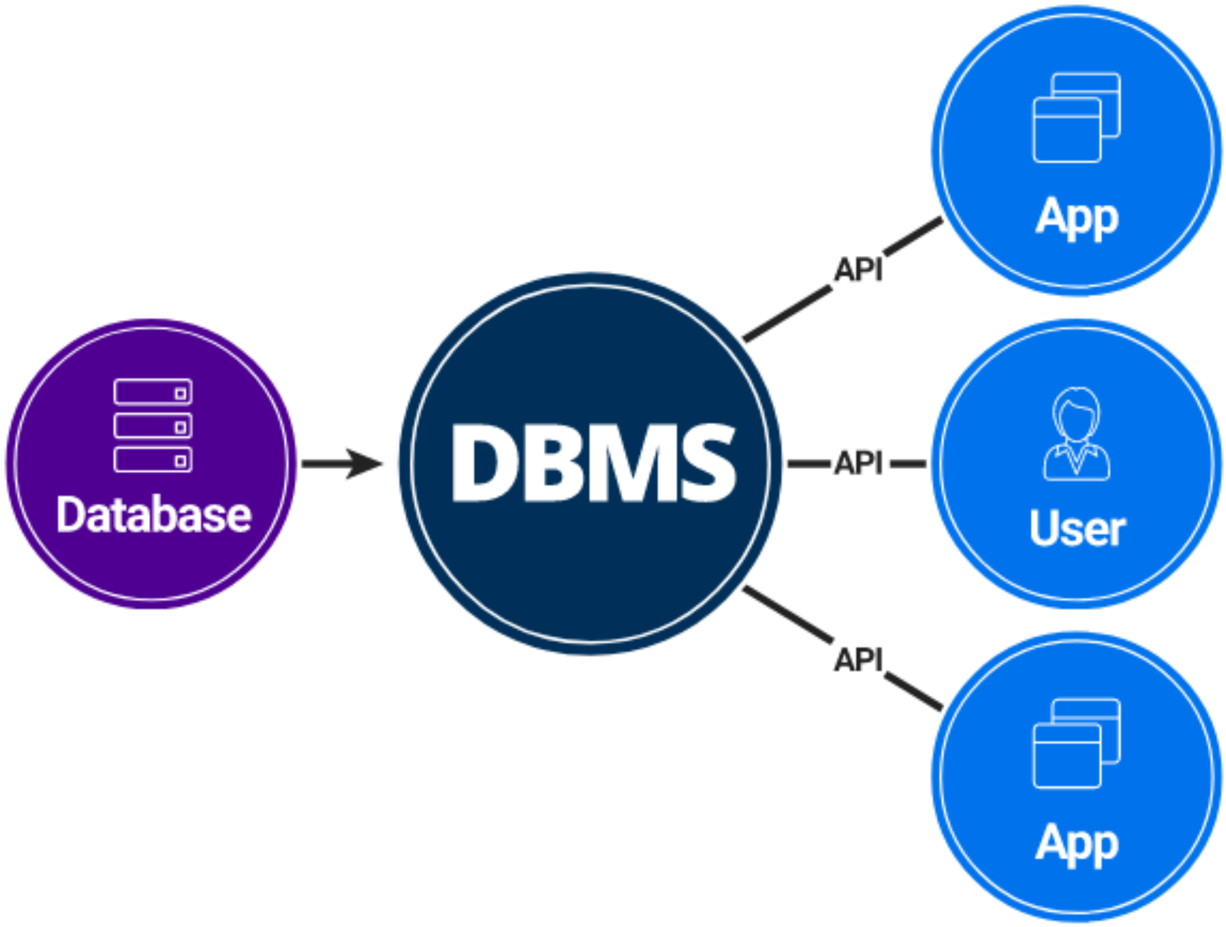
Database

A digital collection of data stored via a certain technique. In computing, a database is an organized collection of data (rows or objects) stored and accessed electronically.

Database Management System

Database Management System is a system for collecting, storing and providing access of data.

A database management system (or DBMS) is essentially nothing more than a computerized data-keeping system. Users of the system are given facilities to perform several kinds of operations on such a system for either manipulation of the data in the database or the management of the database structure itself.



What are the different types of DBMS?

- Relational database.
- Object oriented database.
- Hierarchical database.
- Network database.

Data cleansing

The process of reviewing and revising data in order to delete duplicates, correct errors and provide consistency

Data mining

The process of finding certain patterns or information from data sets. Data Mining is done for purposes like Market Analysis, determining customer purchase pattern, financial planning, fraud detection, etc.

Data mining is a study of extracting useful information from structured/unstructured data taken from various sources. This is done usually for

1. Mining for frequent patterns
2. Mining for associations
3. Mining for correlations
4. Mining for clusters
5. Mining for predictive analysis

Data virtualization

A data integration process in order to gain more insights. Usually it involves databases, applications, file systems, websites, big data techniques, etc.)

De-identification

Same as anonymization; ensuring a person cannot be identified through the data

ETL (Extract, Transform and Load)

ETL (Extract, Transform and Load) is thhe process of extracting raw data, transforming by cleaning and enriching the data to make it fit operational needs and loading into the appropriate repository for the system's use. Even though it originated with data warehouses, ETL processes are used while taking/absorbing data from external sources in big data systems.

ETL is a process in a database and data warehousing meaning extracting the data from various sources, transforming it to fit operational needs and loading it into the database or some storage. For example, processing DNA data, creating output records in specific Parquet format and loading it to Amazon S3 is an ETL process.

- Extract: the process of reading data from a database or data sources
- Transform: the process of conversion of extracted data in the desired form so that it can be put into another database.
- Load: the process of writing data into the target database to data source

Failover

Switching automatically to a different server or node should one fail Fault-tolerant design – a system designed to continue working even if certain parts fail Feature - a piece of measurable information about something, for example features you might store about a set of people, are age, gender and income.

Graph Databases

Graph databases are purpose-built to store and navigate relationships. Relationships are first-class citizens in graph databases, and most of the value of graph databases is derived from these relationships. Graph databases use nodes to store data entities, and edges to store relationships between entities. An edge always has a start node, end node, type, and direction, and an edge can describe parent-child relationships, actions, ownership, and the like. There is no limit to the number and kind of relationships a node can have.

Grid computing

Connecting different computer systems from various location, often via the cloud, to reach a common goal

Key-Value Databases

Key-Value Databases store data with a primary key, a uniquely identifiable record, which makes easy and fast to look up. The data stored in a Key-Value is normally some kind of primitive of the programming language. As a dictionary, for example, Redis allows you to set and retrieve pairs of keys and values. Think of a "key" as a unique identifier (string, integer, etc.) and a "value" as whatever data you want to associate with that key. Values can be strings, integers, floats, booleans, binary, lists, arrays, dates, and more.

(key, value)

The `(key, value)` notation is used in many places (such as Spark) and in MapReduce Paradigm. In MapReduce paradigm everything works as a `(key, value)`. Note that the `key` and `value` can be

- simple data type: such as String, Integer, Double, …
- combined data types: tuples, structures, arrays, lists, …

In MapReduce, `map()`, `reduce()`, and `combine()` functions use `(key, value)` pairs:

The Map output types should match the input types of the Reduce as shown below:

```
# K1: as a key to map() function
# V1: as a value to map() function
# mapper can emit 0, 1, 2, ... of (K2, V2) pairs
map(K1, V1) -> { (K2, V2) }

# reducer can emit 0, 1, 2, ... of (K3, V3) pairs
# K2 is a unique key from mapper's keys outputs
# [V2, ...] are all values associated with the key K2
reduce(K2, [V2, ...]) -> { (K3, V3) }
```

In Spark, using RDDs, a source RDD must be in `(key, value)` form before we can apply reduction transformations such as `groupByKey()`, `reduceByKey()`, `aggregateByKey()` and `combineByKey()`.

Examples of `(key, value)` pairs:

`key`	`value`
String	String
String	Integer
String	Double
String	(Integer, Integer)
String	(Integer, integer, Integer)
(String, Integer)	Integer
(String, Integer)	(Integer, Integer, Double)
Integer	String
Integer	Integer
Integer	Double
Integer	(Integer, Integer, Integer, Integer)
Integer	(Integer, integer, Integer, Double)
(Integer, Integer)	Integer
(Integer, Integer)	(String, Integer, Integer, Double)

Note that programmers create `(key, value)` pairs based on big data problem requirements.

Java

Java is a programming language and computing platform first released by Sun Microsystems in 1995. It has evolved from humble beginnings to power a large share of today's digital world, by providing the reliable platform upon which many services and applications are built. New, innovative products and digital services designed for the future continue to rely on Java, as well.

Python

Python is a programming language that lets you work quickly and integrate systems more effectively. Python is an interpreted, object-oriented (not fully) programming language that's gained popularity for big data professionals due to its readability and clarity of syntax. Python is relatively easy to learn and highly portable, as its statements can be interpreted in several operating systems.

Tuples in Python

Python Tuple is a collection of objects separated by commas. Tuples are used to store multiple items in a single variable. Tuple is one of 4 built-in data types in Python used to store collections of data, the other 3 are List, Set, and Dictionary, all with different qualities and usage. A tuple is a collection which is ordered and unchangeable. In a nutshell, a tuple is a collection of things/objects, enclosed in `( )` and separated by commas.

Tuple Examples:

```
# tuple as a (key, value):
# tuple is immutable
v = ('fox', 23)
# v[0] : 'fox'
# v[1] : 23
# len(v) : 2

# tuple of 4 values:
# tuple is immutable
t = (2, 1.5, 'alex', [1, 2, 3])
# t[0] : 2
# t[1] : 1.5
# t[2] : 'alex'
# t[3] : [1, 2, 3]
# len(t) : 4
```

In PySpark, if your RDD elements are in the form of `(key, value)` tuple, then you may apply reduction transformations such as `groupByKey()`, `reduceByKey()` and `combineByKey()`.

Lists in Python

Lists are used to store multiple items in a single variable. Lists are one of 4 built-in data types in Python used to store collections of data. Python Lists are just like dynamically sized arrays. In a nutshell, a list is a collection of things/objects, enclosed in `[ ]` and separated by commas.

List Examples:

```
>>> things = ['alex', 'jane', 'mary', 8, 9]
>>> things
['alex', 'jane', 'mary', 8, 9]
>>> len(things)
5
>>> # add an element to the end of  list
>>> things.append('jeff')
>>> things
['alex', 'jane', 'mary', 8, 9, 'jeff']
>>> len(things)
6
>>> things[0]
'alex'
>>> things[1]
'jane'
>>> things[2]
'mary'
>>> things[3]
8
>>> things[4]
9
>>> things[5]
'jeff'
>>> # add an element to the beginning of  list
>>> things.insert(0, 100)
>>> things
[100, 'alex', 'jane', 'mary', 8, 9, 'jeff']
```

Difference between Tuples and Lists in Python

The primary difference between tuples and lists is that tuples are immutable as opposed to lists which are mutable. Therefore, it is possible to change a list but not a tuple. The contents of a tuple cannot change once they have been created in Python due to the immutability of tuples.

JavaScript

A scripting language designed in the mid-1990s for embedding logic in web pages, but which later evolved into a more general-purpose development language.

What is JavaScript used for? JavaScript is a scripting language that enables you to create dynamically updating content, control multimedia, animate images, and pretty much everything else.

A JavaScript engine is a software component that executes JavaScript code. Notable Java Script engines:

- V8 from Google is the most used JavaScript engine.
- SpiderMonkey is developed by Mozilla for use in Firefox.
- JavaScriptCore is Apple's engine for its Safari browser.
- Chakra is the engine of the Internet Explorer browser.
- Node.js is a JavaScript runtime built on Chrome's V8 JavaScript engine.

In-memory

A database management system stores data on the main memory instead of the disk, resulting is very fast processing, storing and loading of the data Internet of Things – ordinary devices that are connected to the internet at any time anywhere via sensors

Latency

A measure of time delayed in a system

Location data

GPS data describing a geographical location

Machine Learning

Part of artificial intelligence where machines learn from what they are doing and become better over time. Apache Spark offers a comprehensive Maching Learning library for big data. In a nutshell, Machine learning is an application of AI that enables systems to learn and improve from experience without being explicitly programmed.

There are many ML packages for experimentation (partial list):

- scikit-learn - Machine Learning in Python

- Apache Spark Machine Learning

- PyTorch - An open source machine learning framework in Python

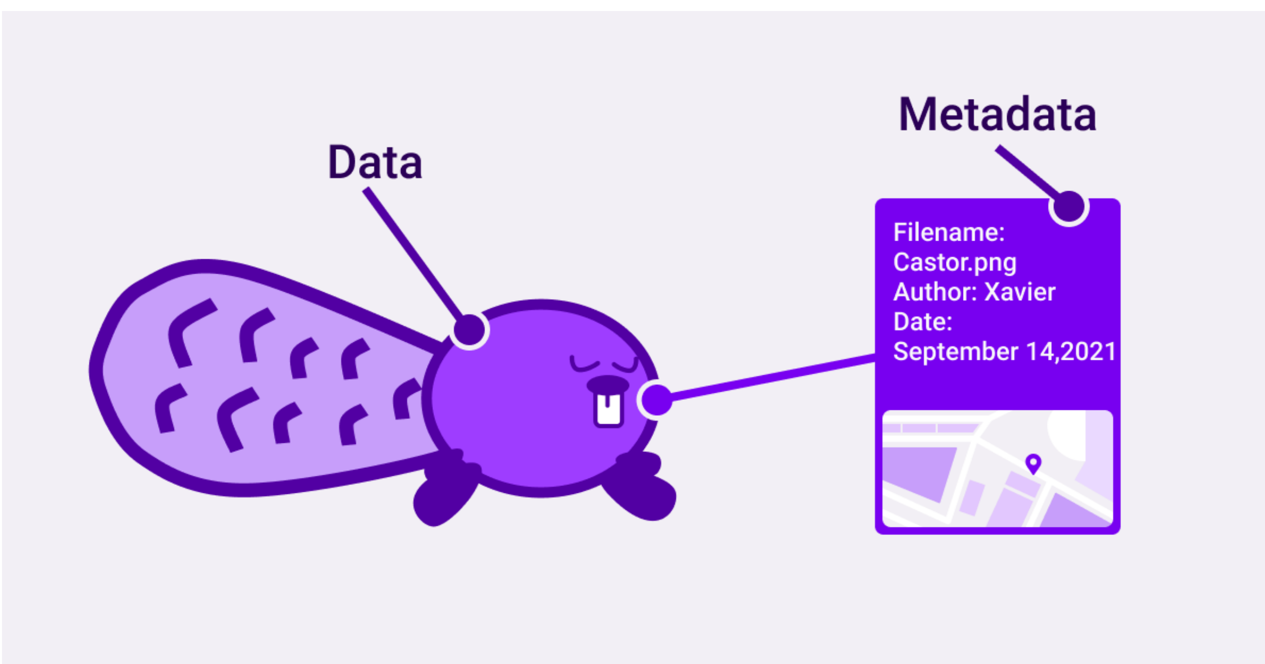
Internet of Things

Internet of things, IoT, in short, is a conception of connecting devices, such as house lighting, heating or even fridges to a common network. It allows storing big amounts of data, which can later be used in real-time analytics. This term is also connected with a smart home, a concept of controlling house with phone etc.

According to Wiki: The Internet of things (IoT) describes physical objects (or groups of such objects) with sensors, processing ability, software and other technologies that connect and exchange data with other devices and systems over the Internet or other communications networks. Internet of things has been considered a misnomer because devices do not need to be connected to the public internet, they only need to be connected to a network and be individually addressable.

Metadata

Data about data; gives information about what the data is about. Metadata is information that describes and explains data. It provides context with details such as the source, type, date, owner, and relationships to other data sets, thus helping you understand the relevance of a particular data set and guiding you on how to use it.



For example, author, date created, date modified and file size are examples of very basic document file metadata.

Table definition for a relational table is an example of metadata.

HTML files and websites frequently use metadata to provide information about the content of a webpage to search engines. HTML files contain meta tags that include information about the page — its author, a description, some keywords, or even special instructions that tell a web browser how to display the page contents. Search engines can use these tags when organizing and displaying search results.

Natural Language Processing (NLP)

A field of computer science involved with interactions between computers and human languages.

Open source software for NLP: [The Stanford Natural Language Processing]

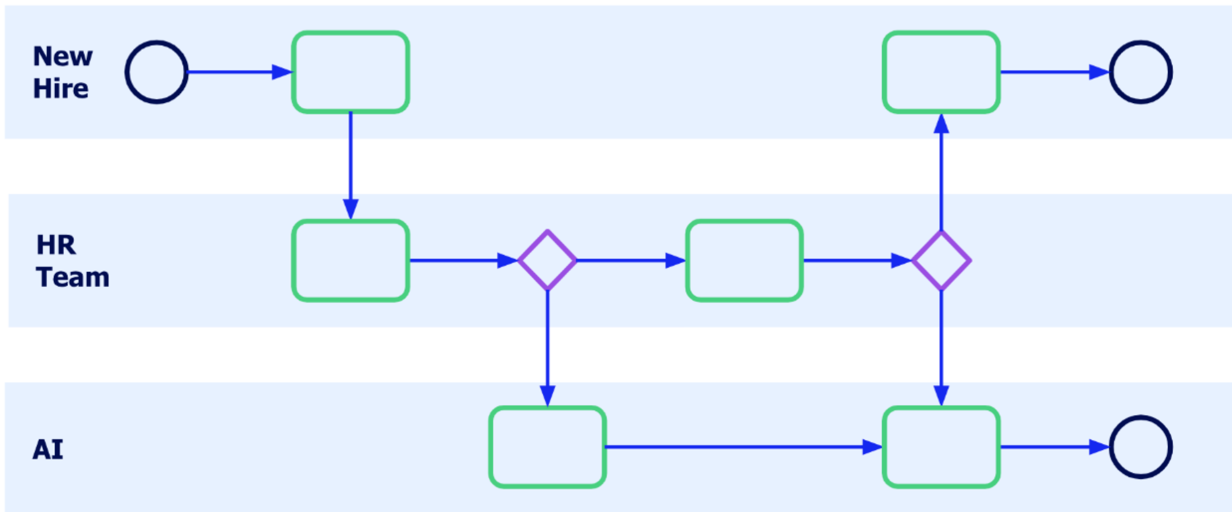
Network analysis

Viewing relationships among the nodes in terms of the network or graph theory, meaning analysing connections between nodes in a network and the strength of the ties.

Workflow

What is a workflow? A workflow is a standardized series of tasks you complete to achieve a specific goal.

HR onboarding workflow.



A graphical representation of a set of events, tasks, and decisions that define a business process (example: vacation approval process in a company; purchase approval process). You use the developer tool to add objects to a workflow and to connect the objects with sequence flows. The Data Integration Service uses the instructions configured in the workflow to run the objects.

Schema

In computer programming, a schema (pronounced `SKEE-mah`) is the organization or structure for a database, while in artificial intelligence (AI) a schema is a formal expression of an inference rule. For the former, the activity of data modeling leads to a schema.

- Example, Database schema:

```
CREATE TABLE product (
    id INT AUTO_INCREMENT PRIMARY KEY,
    product_name VARCHAR(50) NOT NULL,
    price VARCHAR(7) NOT NULL,
    quantity INT NOT NULL
)
```

- Example, DataFrame schema in PySpark

```
from pyspark.sql.types import StructType, StructField
from pyspark.sql.types import StringType, IntegerType

schema = StructType([ \
    StructField("firs_tname", StringType(),True), \
    StructField("last_name", StringType(),True), \
    StructField("emp_id", StringType(), True), \
    StructField("gender", StringType(), True), \
    StructField("salary", IntegerType(), True)
])
```

Difference between Tuple and List in Python

The primary difference between tuples and lists is that tuples are **immutable** as opposed to lists which are **mutable**. Therefore, it is possible to change a list but not a tuple. The contents of a tuple cannot change once they have been created in Python due to the immutability of tuples.

Examples in Python3:

```
# create a tuple
>>> t3 = (10, 20, 40)
>>> t3
(10, 20, 40)

# create a list
>>> l3 = [10, 20, 40]
>>> l3
[10, 20, 40]

# add an element to a list
>>> l3.append(500)
>>> l3
[10, 20, 40, 500]

# add an element to a tuple
>>> t3.append(600)
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
AttributeError: 'tuple' object has no attribute 'append'
```

Object Databases

An object database store data in the form of objects, as used by object-oriented programming. They are different from relational or graph databases and most of them offer a query language that allows object to be found with a declarative programming approach.

Pattern Recognition

Pattern Recognition identifies patterns in data via algorithms to make predictions of new data coming from the same source.

Predictive analysis

Analysis within big data to help predict how someone will behave in the (near) future. It uses a variety of different data sets such as historical, transactional, or social profile data to identify risks and opportunities.

Privacy

To seclude certain data / information about oneself that is deemed personal Public data – public information or data sets that were created with public funding

Query

Asking for information to answer a certain question. What Is a Query? A database query is a request for data from a database. The request should come in a database table or a combination of tables using a code known as the query language. This way, the system can understand and process the query accordingly.

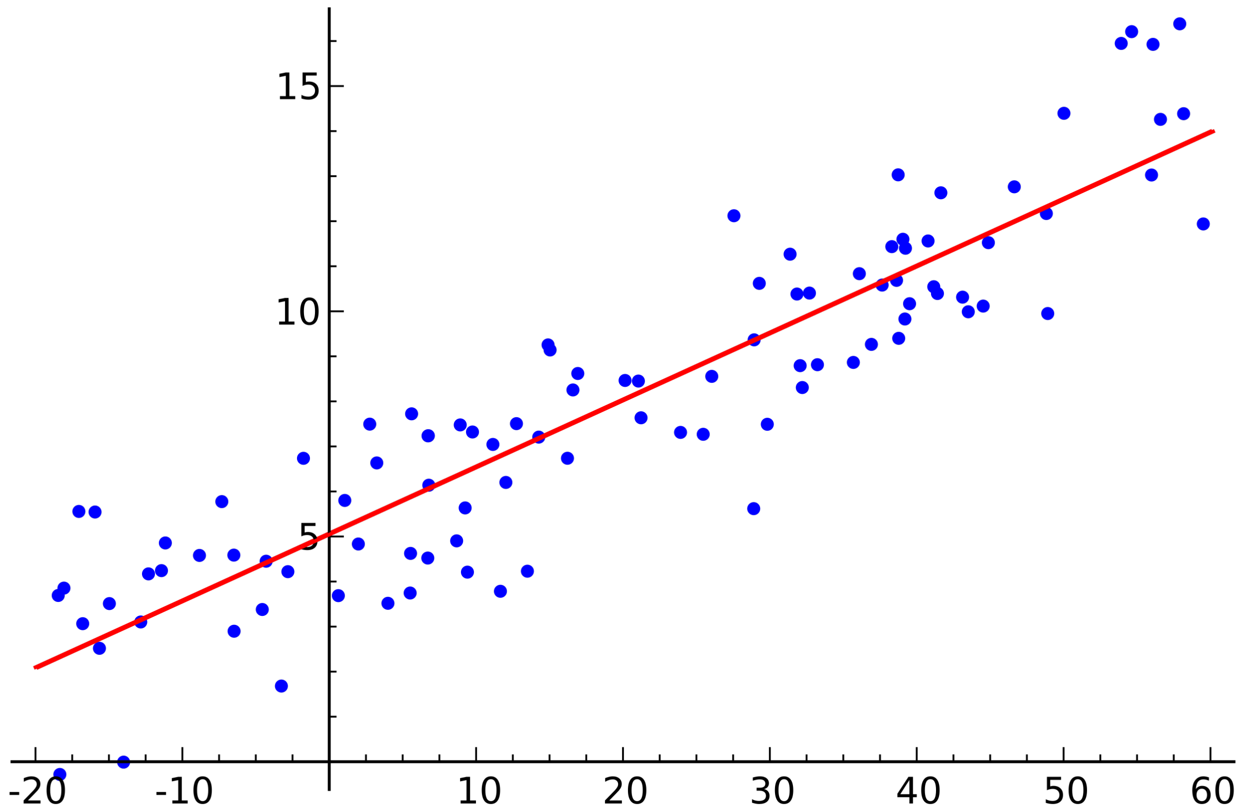
SQL is the most common language to query data from relational databases. Also, some big data platforms (such as Amazon Athena, Snowflake, Google BigQuery) support SQL for big data queries.

Regression analysis

To define the dependency between variables. It assumes a one-way causal effect from one variable to the response of another variable.

Regression analysis is a powerful statistical method that allows you to examine the relationship between two or more variables of interest. While there are many types of regression analysis, at their core they all examine the influence of one or more independent variables on a dependent variable.

Illustration of linear regression on a data set:



Real-time data

Real-time data is data that is available as soon as it's created and acquired. Real-time data is data that is created, processed, stored, analysed and visualized within milliseconds.

What is an example of real-time data processing? Good examples of real-time data processing systems are bank ATMs, traffic control systems and modern computer systems such as the PC and mobile devices. In contrast, a batch data processing system collects data and then processes all the data in bulk in a later time, which also means output is received at a later time.

Scripting

The use of a computer language where your program, or script, can be run directly with no need to first compile it to binary code. Semi-structured data - a form a structured data that does not have a formal structure like structured data. It does however have tags or other markers to enforce hierarchy of records.

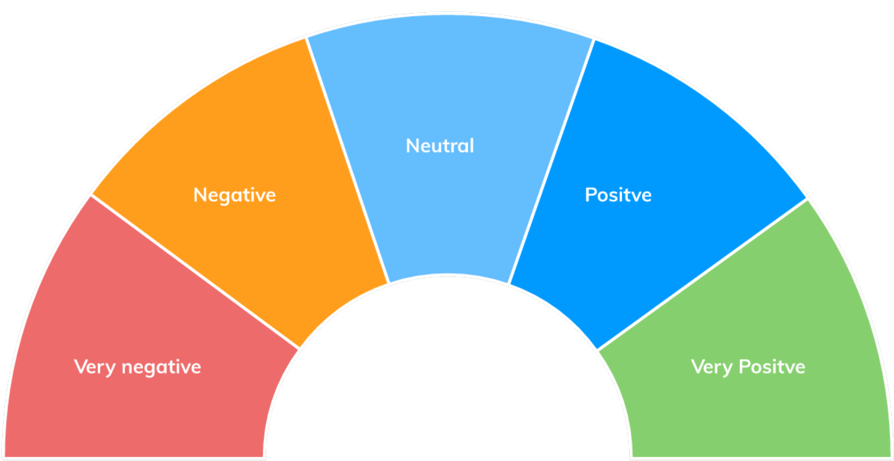
Scripting Languages (partial list):

- JavaScript
- PHP
- Python
- Ruby
- Groovy
- Perl
- Lua
- Bash
- Shell

Sentiment Analysis

Using algorithms to find out how people feel about certain topics or events.

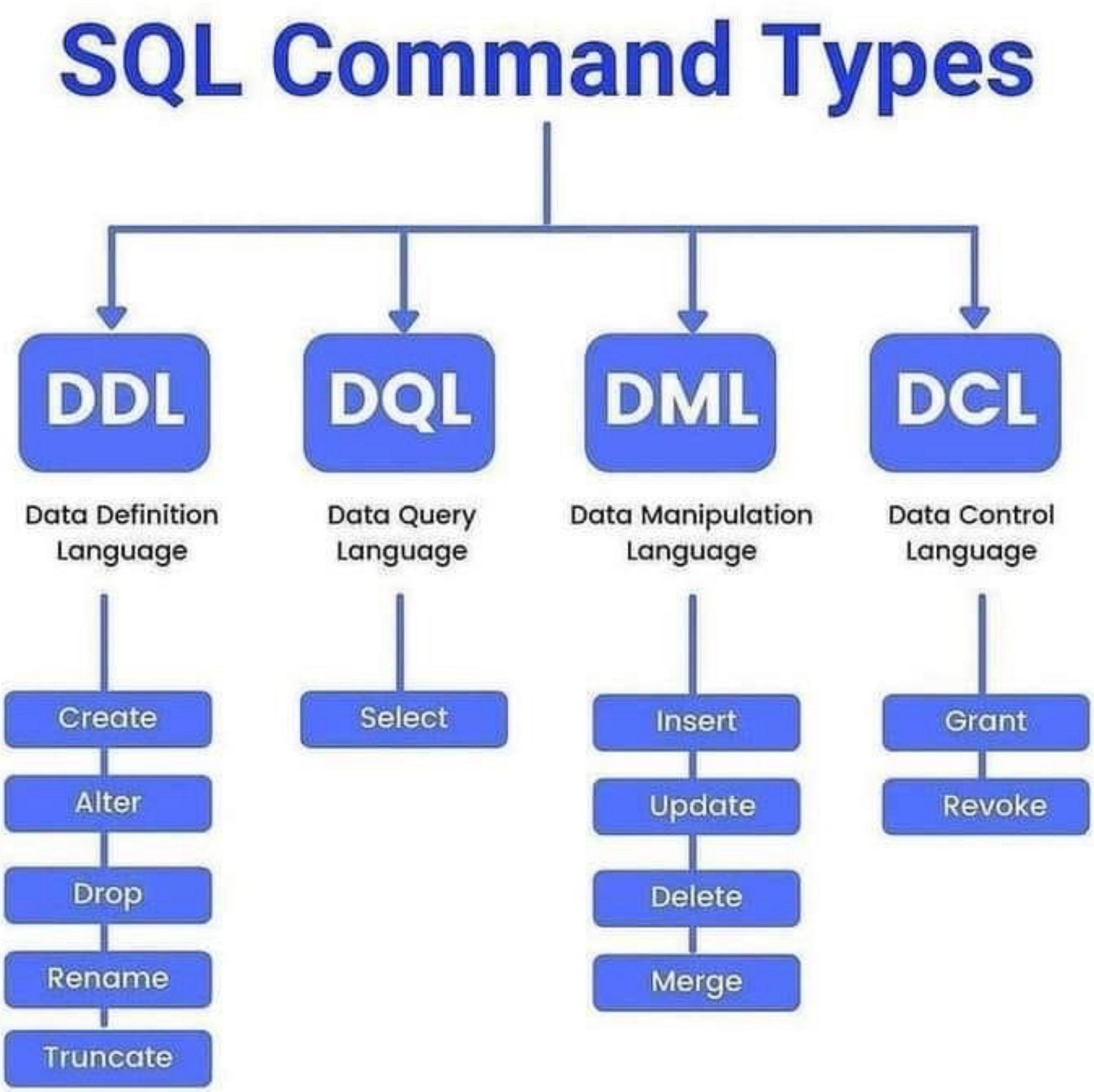
Sentiment analysis (or opinion mining) is a natural language processing (NLP) technique used to determine whether data is positive, negative or neutral. Sentiment analysis is often performed on textual data to help businesses monitor brand and product sentiment in customer feedback, and understand customer needs.



SQL

A programming language for retrieving data from a relational database. Also, SQL is used to retrieve data from big data by translating query into mappers, filters, and reducers.

SQL is a standard language for accessing and manipulating databases (relational and non-relational). Also, SQL is used to query big data (examples are: Spark, Snowflake, Amazon Athena, Google BigQuery).



What is SQL?

- SQL stands for Structured Query Language
- SQL lets you access and manipulate databases
- SQL became a standard of the American National Standards Institute (ANSI) in 1986, and of the International Organization for Standardization (ISO) in 1987

What Can SQL do?

- SQL can execute queries against a database
- SQL can retrieve data from a database
- SQL can insert records in a database
- SQL can update records in a database
- SQL can delete records from a database
- SQL can create new databases
- SQL can create new tables in a database
- SQL can create stored procedures in a database
- SQL can create views in a database
- SQL can set permissions on tables, procedures, and views

Time series analysis

Analysing well-defined data obtained through repeated measurements of time. The data has to be well defined and measured at successive points in time spaced at identical time intervals.

Variability

It means that the meaning of the data can change (rapidly). In (almost) the same tweets for example a word can have a totally different meaning

What are the 4 Vs of Big Data?

- Volume (i.e., the size of the dataset)
- Velocity (i.e., rate of flow)
- Variety (i.e., data from multiple repositories, domains, or types)
- Veracity (i.e., refers to the accuracy of the data)

Variety

Data today comes in many different formats: structured data, semi-structured data, unstructured data and even complex structured data

Velocity

The speed at which the data is created, stored, analysed and visualized

Veracity

Ensuring that the data is correct as well as the analyses performed on the data are correct.

Volume

The amount of data, ranging from megabytes to gigabytes to petabytes to …

XML Databases

XML Databases allow data to be stored in XML format. The data stored in an XML database can be queried, exported and serialized into any format needed.

Big Data Scientist

Someone who is able to develop the distributed algorithms to make sense out of big data.

Classification analysis

A systematic process for obtaining important and relevant information about data, also meta data called; data about data.

Cloud computing

Cloud Computing is a distributed computing system hosted and running on remote servers and accessible from anywhere on the internet.
A distributed computing system over a network used for storing data off-premises. This can include ETL, data storage, application development, and data analytics. Examples: Amazon Cloud and Google Cloud.

Cloud computing is one of the must-known big data terms. It is a new paradigm computing system which offers visualization of computing resources to run over the standard remote server for storing data and provides IaaS, PaaS, and SaaS. Cloud Computing provides IT resources such as Infrastructure, software, platform, database, storage and so on as services. Flexible scaling, rapid elasticity, resource pooling, on-demand self-service are some of its services.

Distributed computing

Distributed computing is a computing system in which components located on networked computers communicate and coordinate their actions by passing messages.

Clustering analysis

Cluster analysis or clustering is the task of grouping a set of objects in such a way that objects in the same group (called a cluster) are more similar (in some sense) to each other than to those in other groups (clusters).

Database-as-a-Service

A database hosted in the cloud on a pay per use basis, for example Amazon Web Services

Database Management System (DBMS)

Database Management System is software that collects data and provides access to it in an organized layout. It creates and manages the database. DBMS provides programmers and users a well-organized process to create, update, retrieve, and manage data.

Distributed File System

Distributed File System is a system that offer simplified, highly available access to storing, analysing and processing data.

A Distributed File System (DFS) as the name suggests, is a file system that is distributed on multiple file servers or multiple locations. It allows programs to access or store isolated files as they do with the local ones, allowing programmers to access files from any network or computer.

What is DFS? The main purpose of the Distributed File System (DFS) is to allows users of physically distributed systems to share their data and resources by using a Common File System. A collection of workstations and mainframes connected by a Local Area Network (LAN) is a configuration on Distributed File System. A DFS is executed as a part of the operating system. In DFS, a namespace is created and this process is transparent for the clients.

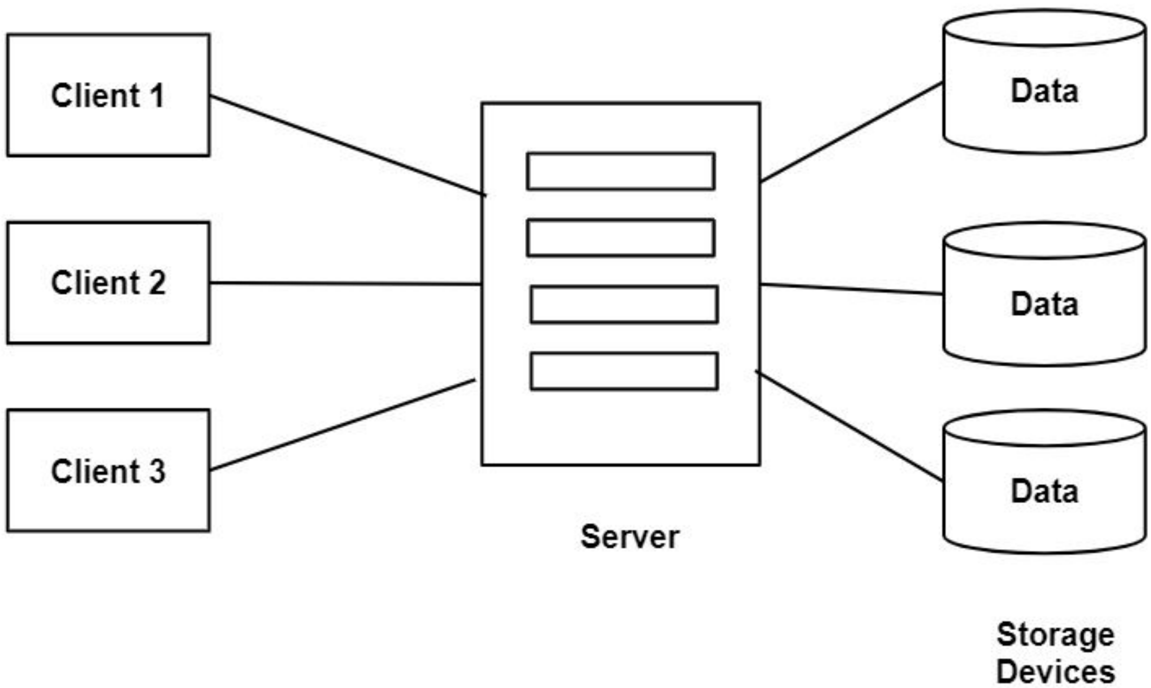
DFS has two components:

- **Location Transparency**: Location Transparency achieves through the namespace component.
- **Redundancy**: Redundancy is done through a file replication component.

In the case of failure and heavy load, these components together improve data availability by allowing the sharing of data in different locations to be logically grouped under one folder, which is known as the "DFS root".

Examples of DFS are:

- Hadoop Distributed File System (HDFS)
- Amazon S3 (a distributed object storage system)



[Features of DFS](#):

> **Transparency**: Structure transparency – There is no need for the client to know about the number or locations of file servers and the storage devices. Multiple file servers should be provided for performance, adaptability, and dependability.
>
> **Access transparency** – Both local and remote files should be accessible in the same manner. The file system should be automatically located on the accessed file and send it to the client's side.
>
> **Naming transparency** – There should not be any hint in the name of the file to the location of the file. Once a name is given to the file, it should not be changed during

transferring from one node to another.

Replication transparency – If a file is copied on multiple nodes, both the copies of the file and their locations should be hidden from one node to another.

User mobility – It will automatically bring the user's home directory to the node where the user logs in.

Performance : Performance is based on the average amount of time needed to convince the client requests. This time covers the CPU time + time taken to access secondary storage + network access time. It is advisable that the performance of the Distributed File System be similar to that of a centralized file system.

Simplicity and ease of use : The user interface of a file system should be simple and the number of commands in the file should be small.

High availability : A Distributed File System should be able to continue in case of any partial failures like a link failure, a node failure, or a storage drive crash. A high authentic and adaptable distributed file system should have different and independent file servers for controlling different and independent storage devices.

Scalability : Since growing the network by adding new machines or joining two networks together is routine, the distributed system will inevitably grow over time. As a result, a good distributed file system should be built to scale quickly as the number of nodes and users in the system grows. Service should not be substantially disrupted as the number of nodes and users grows.

High reliability : The likelihood of data loss should be minimized as much as feasible in a suitable distributed file system. That is, because of the system's unreliability, users should not feel forced to make backup copies of their files. Rather, a file system should create backup copies of key files that can be used if the originals are lost. Many file systems employ stable storage as a high-reliability strategy.

Data integrity : Multiple users frequently share a file system. The integrity of data saved in a shared file must be guaranteed by the file system. That is, concurrent access requests from many users who are competing for access to the same file must be correctly synchronized using a concurrency control method. Atomic transactions are a high-level concurrency management mechanism for data integrity that is frequently offered to users by a file system.

Security : A distributed file system should be secure so that its users may trust that their data will be kept private. To safeguard the information contained in the file system from

> unwanted & unauthorized access, security mechanisms must be implemented.
>
> **Heterogeneity** : Heterogeneity in distributed systems is unavoidable as a result of huge scale. Users of heterogeneous distributed systems have the option of using multiple computer platforms for different purposes.

For more information refer to What is DFS (Distributed File System)? .

Document Store Databases

A document-oriented database that is especially designed to store, manage and retrieve documents, also known as semi structured data.

NoSQL

NoSQL sometimes referred to as 'Not only SQL' as it is a database that doesn't adhere to traditional relational database structures. It is more consistent and can achieve higher availability and horizontal scaling. NoSQL is an approach to database design that can accommodate a wide variety of data models, including key-value, document, columnar and graph formats. NoSQL, which stands for "not only SQL," is an alternative to traditional relational databases in which data is placed in tables and data schemais carefully designed before the database is built. NoSQL databases are especially useful for working with large sets of distributed data.

Scala

A software programming language that blends object-oriented methods with functional programming capabilities. This allows it to support a more concise programming style which reduces the amount of code that developers need to write. Another benefit is that Scala features, which operate well in smaller programs, also scale up effectively when introduced into more complex environments.

Apache Spark is written in Scala. Hence, many if not most data engineers adopting Spark are also adopting Scala, while Python and R remain popular with data scientists. Fortunately, you don't need to master Scala to use Spark effectively.

Columnar Database

A database that stores data column by column instead of the row is known as the column-

oriented database.
Columnar Databases organize and store data by columns rather than rows. They optimize data for aggregate functions (such as `sum()` and `avg()`) and operations on columns of data, by storing data values contiguously, with the same data type and semantic meaning.

The following are partial list of columnar databases:

- Apache Cassandra
- Amazon Redshift
- Snowflake
- Hbase
- Vertica
- MariaDB
- Apache Kudu
- Google Cloud BigTable

Data Analyst

The data analyst is responsible for collecting, processing, and performing statistical analysis of data. A data analyst discovers the ways how this data can be used to help the organization in making better business decisions. It is one of the big data terms that define a big data career. Data analyst works with end business users to define the types of the analytical report required in business.

Data Scientist

Data Scientist is also a big data term that defines a big data career. A data scientist is a practitioner of data science. He is proficient in mathematics, statistics, computer science, and/or data visualization who establish data models and algorithms for complex problems to solve them.

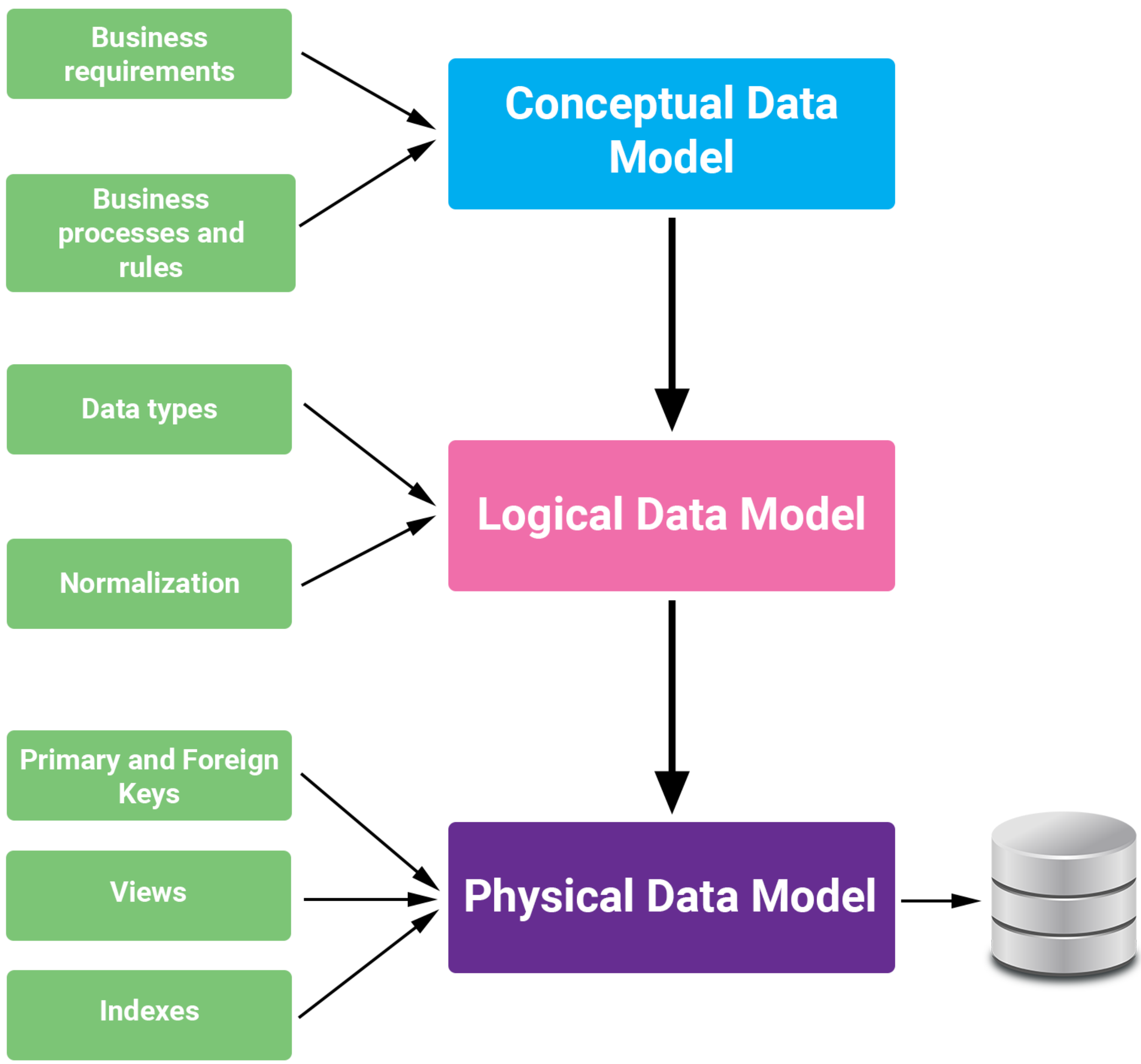
Data Model and Data Modelling

Data Model is a starting phase of a database designing and usually consists of attributes, entity types, integrity rules, relationships and definitions of objects.

Data modeling is the process of creating a data model for an information system by using certain formal techniques. Data modeling is used to define and analyze the requirement of data for supporting business processes.

Data Model

According to Wikipedia: a data model is an abstract model that organizes elements of data and standardizes how they relate to one another and to the properties of real-world entities. For instance, a data model may specify that the data element representing a car be composed of a number of other elements which, in turn, represent the color and size of the car and define its owner.



A data model explicitly determines the structure of data. Data models are specified in a data modeling notation, which is often graphical in form.

Hive

The Apache Hive data warehouse software facilitates reading, writing, and managing large datasets residing in distributed storage and queried using SQL syntax.

Hive is an open source Hadoop-based data warehouse software project for providing data summarization, analysis, and query. Users can write queries in the SQL-like language known as HiveQL. Hadoop is a framework which handles large datasets in the distributed computing environment.

Load Balancing

Load balancing is a tool which distributes the amount of workload between two or more computers over a computer network so that work gets completed in small time as all users desire to be served faster. It is the main reason for computer server clustering and it can be applied with software or hardware or with the combination of both.

Load balancing refers to distributing workload across multiple computers or servers in order to achieve optimal results and utilization of the system

Log File

A log file is the special type of file that allows users keeping the record of events occurred or the operating system or conversation between the users or any running software.

Log file is a file automatically created by a computer program to record events that occur while operational.

Examples:

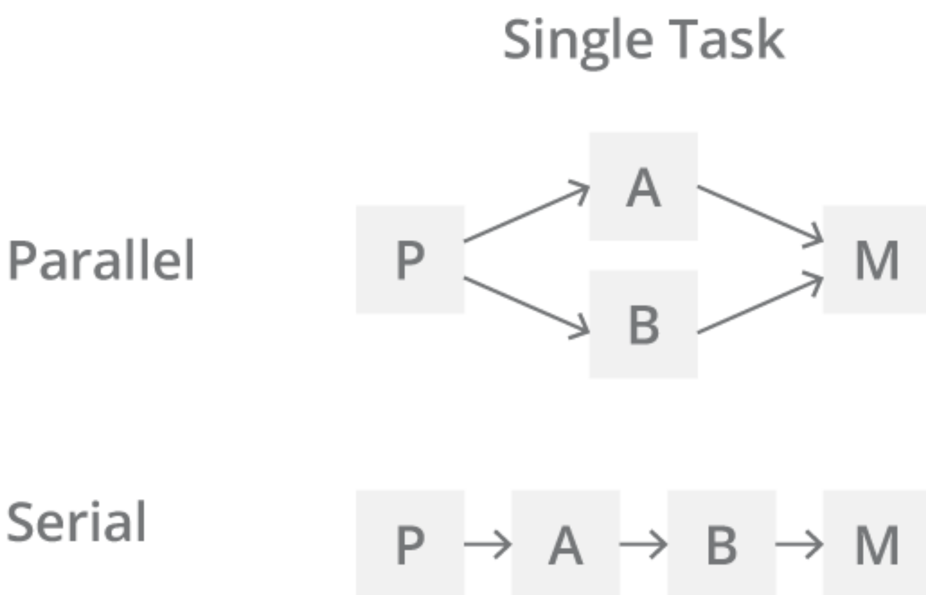
- A search engine might create records of search query, response, response time, data and time
- A financial company web server might create details of every transaction (such as data and time, account number, transaction type, transaction amount, account number, …)
- Amazon.com might create records for every transcation: date and time, transaction typem item sold, amount, state and city shipped, …

Parallel Processing

It is the capability of a system to perform the execution of multiple tasks simultaneously (at the same time)

In parallel processing, we take in multiple different forms of information at the same time. This is especially important in vision. For example, when you see a bus coming towards you, you see its color, shape, depth, and motion all at once.

Parallel processing is a method in computing of running two or more processors (CPUs) to handle separate parts of an overall task. Breaking up different parts of a task among multiple processors will help reduce the amount of time to run a program.



For example, Spark uses Resilient Distributed Datasets (RDD) to perform parallel processing across a cluster or computer processors.

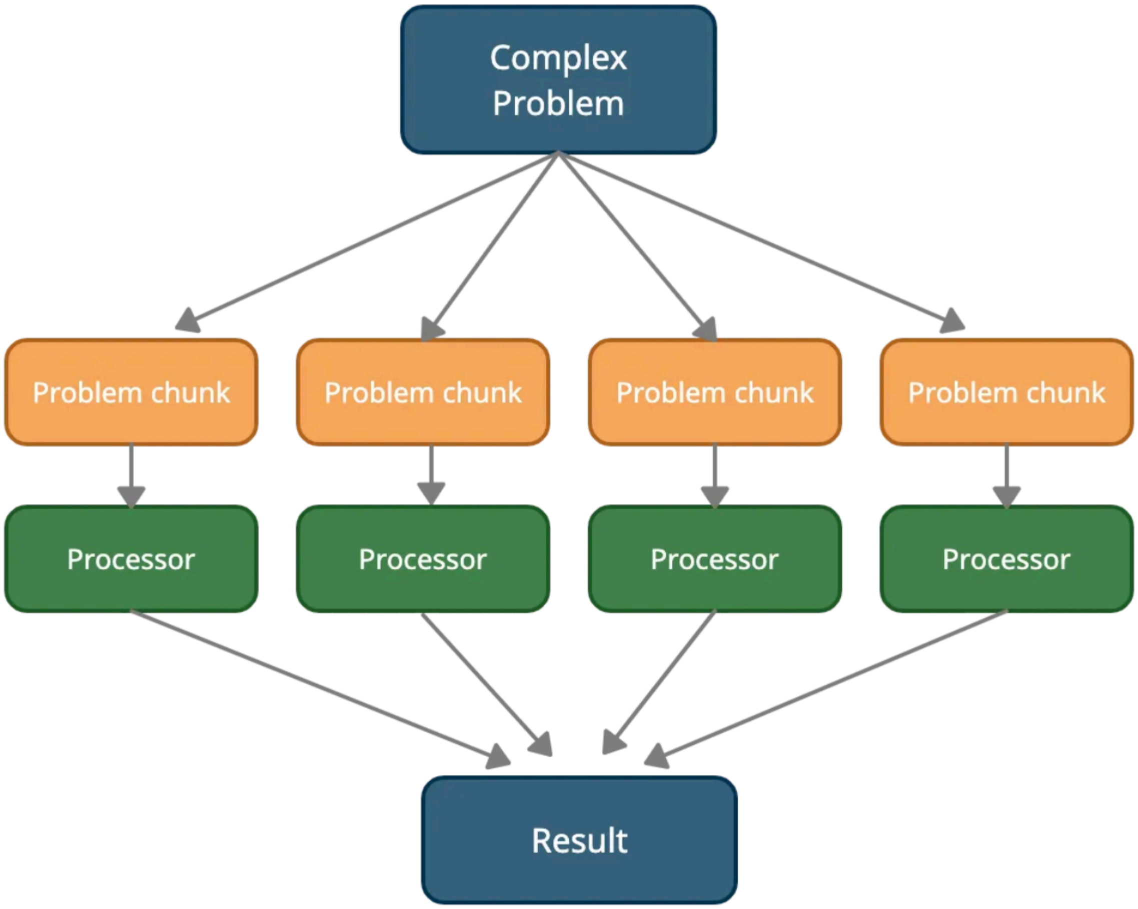


Diagram: high-level concept of parallelism

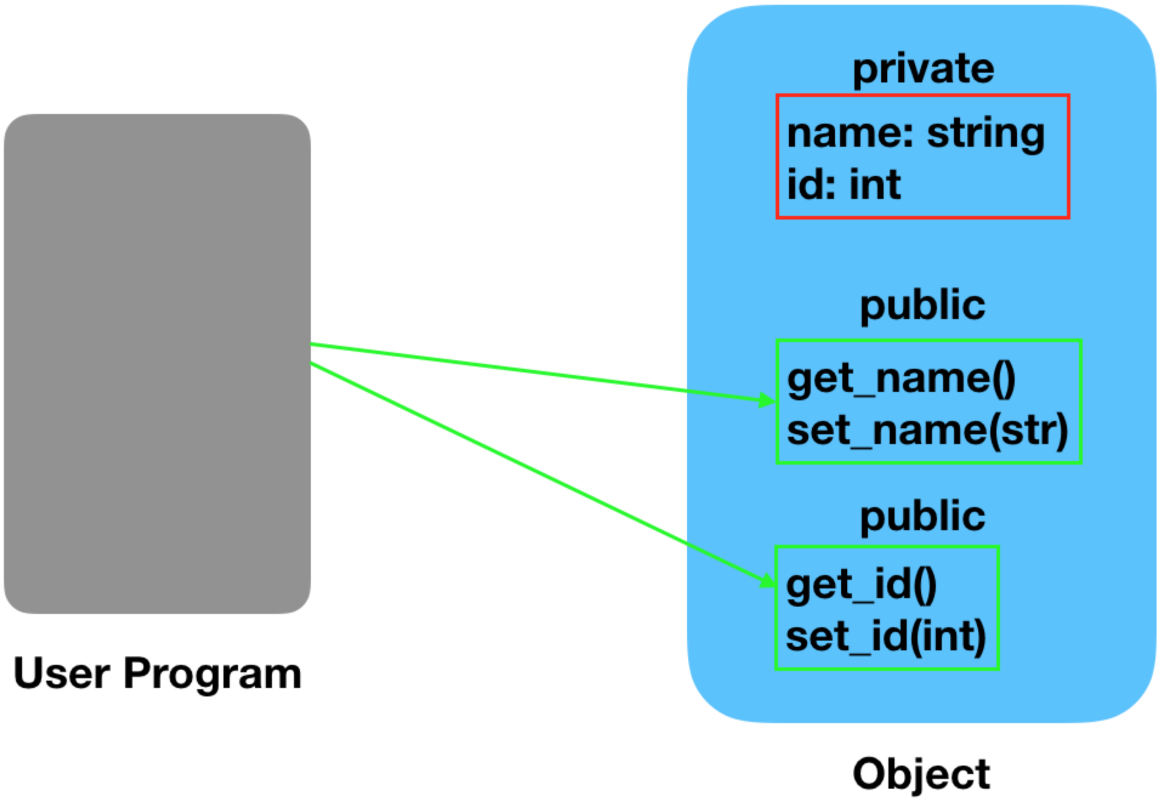
Server (or node)

The server is a virtual or physical computer that receives requests related to the software application and thus sends these requests over a network. It is the common big data term used almost in all the big data technologies.

Abstraction layer

A translation layer that transforms high-level requests into low-level functions and actions. Data abstraction sees the essential details needed to perform a function removed, leaving behind the complex, unnecessary data in the system. The complex, unneeded data is hidden from the client, and a simplified representation is presented. A typical example of an abstraction layer is an API (application programming interface) between an application and an operating system.

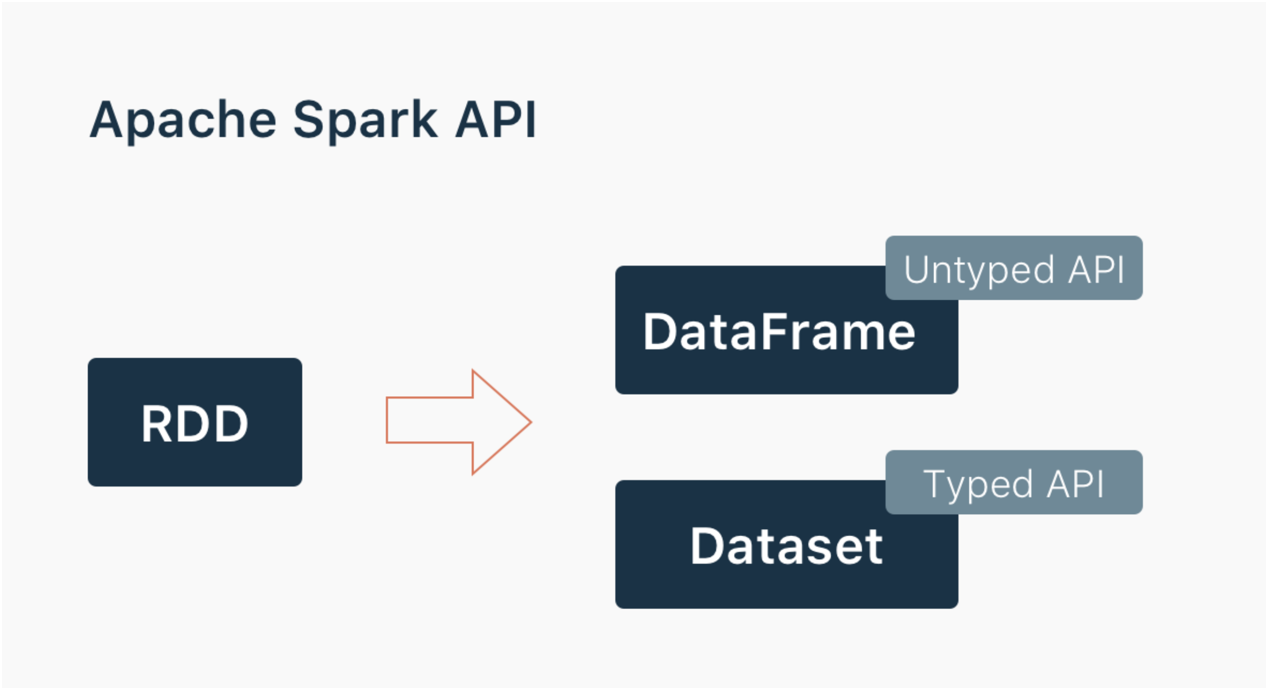
Data Abstraction



For example, relational databases offer table of rows and columns as an abstraction for your structured data.

For example, Spark offers three types of data abstractions (it means that your data can be represented in RDD, DataFrame, and Dataset):

- **RDD** (supported by PySpark)
- **DataFrame** (supported by PySpark)
- Dataset (not supported by PySpark)
    - supported in Java and Scala



Cloud

Cloud technology, or The Cloud as it is often referred to, is a network of servers that users access via the internet and the applications and software that run on those servers. Cloud computing has removed the need for companies to manage physical data servers or run software applications on their own devices - meaning that users can now access files from almost any location or device.

The cloud is made possible through virtualisation - a technology that mimics a physical server but in virtual, digital form, A.K.A virtual machine.

If you've heard of cloud computing at all, then you've heard of Amazon Web Services (AWS), Microsoft Azure, and Google Cloud.

Data Ingestion

Data ingestion is the process of moving data from various sources into a central repository such as a data warehouse where it can be stored, accessed, analysed, and used by an organisation.

Common examples of data ingestion include:

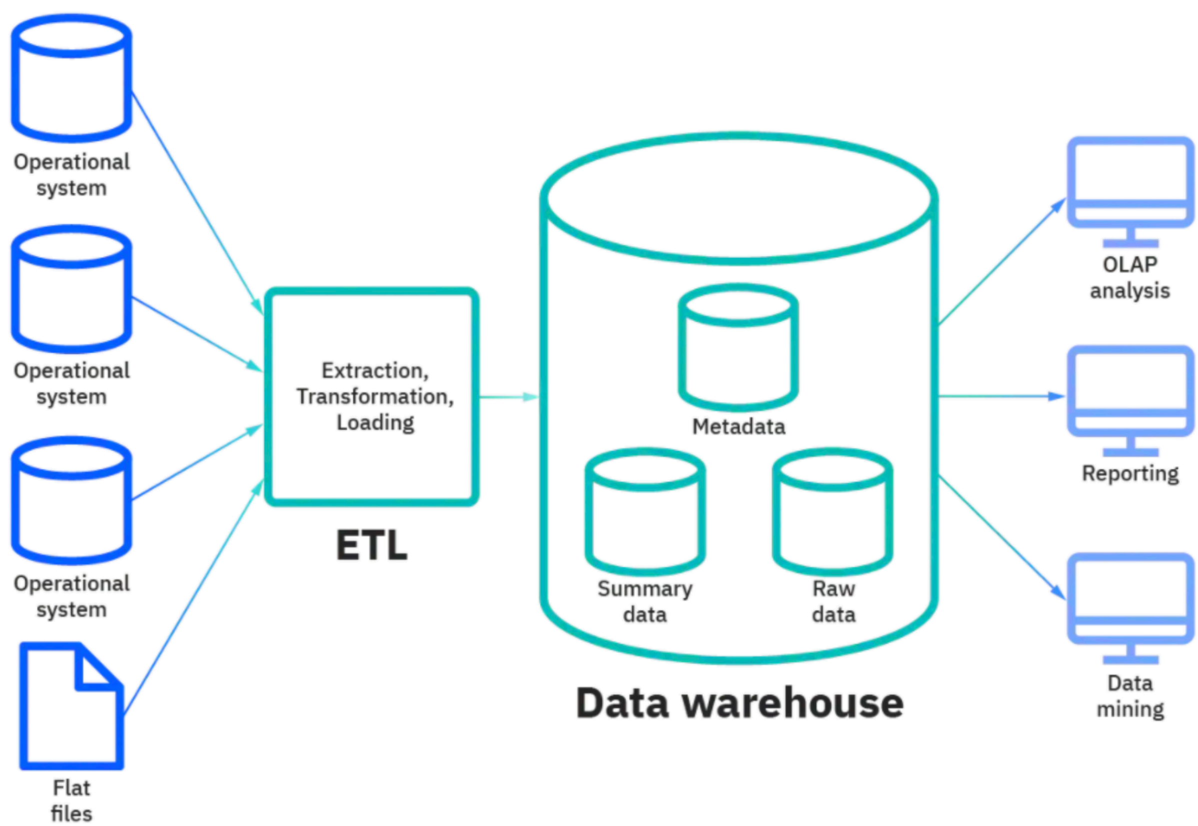
- Move data from DNA laboratory to a data warehouse then analyze with variant analyzer.
- Capture data from a Twitter feed for real-time sentiment analysis.

- Acquire data for training machine learning models and experimentation.

Data Warehouse

A centralised repository of information that enterprises can use to support business intelligence (BI) activities such as analytics. Data warehouses typically integrate historical data from various sources.

It is a system that stores data in order to analyze and process it in the future. The source of data can vary, depending on its purpose. Data can be uploaded from the company's CRM (Customer relationship management) systems as well as imported from external files or databases.



For big data, these are the data warehouse platforms on the market:

- Snowflake
- Google BigQuery
- Amazon Redshift
- Amazon Athena
- Azure Synapse Analytics
- IBM Db2 Warehouse

- Firebolt

Open-Source

Open-source refers to the availability of certain types of code to be used, redistributed and even modified for free by other developers. This decentralised software development model encourages collaboration and peer production.

The most popular open-source software is from Apache Software Foundation.

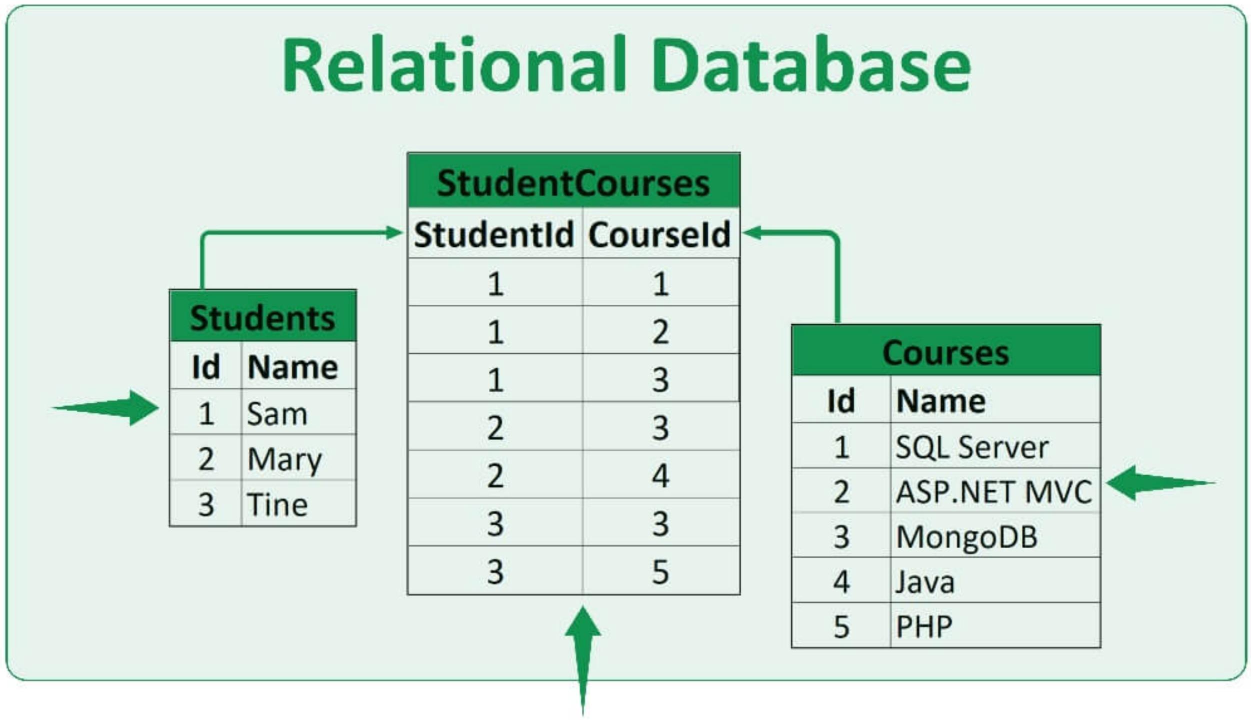
Prime examples of open-source products are:

- Apache HTTP Server
- Apache Hadoop
- Apache Spark
- Presto

Relational Database

The `relational` term here refers to the relations (also commonly referred to as tables) in the database - the tables and their relationships to each other. The tables ‘relate’ to each other. It is these relations (tables) and their relationships that make it `relational`.

A relational database exists to house and identify data items that have pre-defined relationships with one another. Relational databases can be used to gain insights into data in relation to other data via sets of tables with columns and rows. In a relational database, each row in the table has a unique ID referred to as a key.



What do you mean by relational database? a relational database is a collection of information (stored as rows) that organizes data in predefined relationships where data is stored in one or more tables (or "relations") of columns and rows, making it easy to see and understand how different data structures relate to each other.

There are 3 different types of relations in the database:

- one-to-one
- one-to-many
- many-to-many

RDBMS

- RDBMS stands for Relational DataBase Management System. The following are examples of system, which implement RDBMS:
  - Oracle database
  - MySQL
  - MariaDB
  - PostgreSQL
  - Microsoft SQL Server
- It is a database, which stores data in a structured format using rows and columns

- RDBMS is a multi-tenant and can manage many databases, where each database may have many tables
- RDBMS is built in such a way to respond to SQL queries in seconds
- With RDBMS, you can create databases, and within a database, you can create tables, which you may insert/update/delete/query records
- The relational structure makes it possible to run queries against many tables
- SQL (structured query langiage) is the standard programming language used to access database

How does Hadoop perform Input Splits?

The Hadoop's `InputFormat<K, V>` is responsible to provide the input splits. The `InputFormat<K,V>` describes the input-specification for a MapReduce job. The interface `InputFormat` 's full name is `org.apache.hadoop.mapred.InputFormat<K,V>` .

According to Hadoop: the MapReduce framework relies on the `InputFormat` of the job to:

1. Validate the input-specification of the job.
2. Split-up the input file(s) into logical `InputSplit` (s), each of which is then assigned to an individual Mapper.
3. Provide the `RecordReader` implementation to be used to glean input records from the logical `InputSplit` for processing by the Mapper.

The [`InputFormat`] interface has 2 functions:

```
// 1. Get the RecordReader for the given InputSplit.
RecordReader<K,V>   getRecordReader(InputSplit split, JobConf job, Reporter r

// 2. Logically split the set of input files for the job.
InputSplit[]    getSplits(JobConf job, int numSplits)
```

In general, if you have `N` nodes, the HDFS will distribute the input file(s) over all these `N` nodes. If you start a job, there will be `N` mappers by default. The mapper on a machine will process the part of the data that is stored on this node.

MapReduce/Hadoop data processing is driven by this concept of input splits. The number of input splits that are calculated for a specific application determines the number of mapper tasks.

The number of maps is usually driven by the number of DFS blocks in the input files. Each of these mapper tasks is assigned, where possible, to a worker node where the input split (`InputSplit`) is stored. The Resource Manager does its best to ensure that input splits are processed locally (for optimization purposes).

Sort & Shuffle function in MapReduce/Hadoop

Shuffle phase in Hadoop transfers the map output (in the form of `(key, value)` pairs) from Mapper to a Reducer in MapReduce. Sort phase in MapReduce covers the merging and sorting of mappers outputs. Data from the mapper are grouped by the `key`, split among reducers and sorted by the key. Every reducer obtains all values associated with the same `key`.

For example, if there were 3 input chunks/splits, (and each chunk go to a different server) then mappers create `(key, value)` pairs per split (also called partitions), consider all of the output from all of the mappers:

```
    Partition-1  Partition-2  Partition-3
    (A, 1)       (A, 5)       (A, 9)
    (A, 3)       (B, 6)       (C, 20)
    (B, 4)       (C, 10)      (C, 30)
    (B, 7)       (D, 50)
  (A, 100)
```

Then the output of Sort & Shuffle phase will be (note that the values of keys are not sorted):

```
    (A, [1, 3, 9, 5, 100])
    (B, [4, 7, 6])
    (C, [10, 20, 30])
    (D, [50])
```

Output of Sort & Shuffle phase will be input to reducers.

Therefore, Sort & Shuffle creates its outputs in the following form:

```
(key_1, [a_1, a_2, a_3, ...]),
(key_2, [b_1, b_2, b_3, ...]),
(key_3, [c_1, c_2, c_3, ...]),
...
```

where all mappers (for all input) have created:

```
(key_1, a_1),    (key_2, b_1),    (key_3, c_1),
(key_1, a_2),    (key_2, b_2),    (key_3, c_2),
(key_1, a_3),    (key_2, b_3),    (key_3, c_3),
...              ...              ...
```

NoSQL Database

NoSQL databases (aka “not only SQL”) are non-tabular databases and store data differently than relational tables. NoSQL databases come in a variety of types. Redis, HBase, CouchDB and MongoDB, … are examples of NoSQL databases.

PySpark

What is PySpark? PySpark is the Python API for Apache Spark, an open source, distributed computing frameworkand set of libraries for near-real-time, large-scale data processing. If you’re already familiar with Python and libraries such as Pandas, then PySpark is a good language to learn to create more scalable analyses and pipelines. According to Spark documentation: “PySpark is an interface for Apache Spark in Python. It not only allows you to write Spark applications using Python APIs, but also provides the PySpark shell for interactively analyzing your data in a distributed environment. PySpark supports most of Spark’s features such as Spark SQL, DataFrame, Streaming, MLlib (Machine Learning) and Spark Core.”

PySpark Data Abstractions:

PySpark supports two types of data abstractions:

- RDDs
- DataFrames

Note that PySpark does not support `Dataset` data abstraction (the `Dataset` data abstraction is only supported in Java and Scala). A `Dataset` is a strongly typed collection of domain-specific objects that can be transformed in parallel using functional or relational operations. Each `Dataset` also has an untyped view called a `DataFrame`, which is a `Dataset` of `Row`.

PySpark Documentation:

- PySpark Documentation

PySpark Usage:

PySpark can be used in two modes (The `SPARK_HOME` is an environment variable which denotes the directory/folder where Spark is installed):

- Interactive mode: by invoking:

```
${SPARK_HOME}/bin/pyspark
```

- Batch mode: by invoking

```
${SPARK_HOME}/bin/spark-submit <pyspark-program> [optional-parameters]
```

PySpark Graph Analysis:

You may use GraphFrames (a DataFrame-based dolution) package to build and analyze graphs at scale.

Boolean Predicate

A Boolean predicate returns the truth value of a Boolean expression (boolean-expression: an expression that returns the Boolean value: `True` or `False`).

For example, in Spark, `RDD.filter(f: Callable[[T], bool])` returns a new RDD containing only the elements that satisfy a boolean predicate.

For example, a Python function is a boolean predicate if it only returns `True` or `False`.

Example of a boolean predicate in Python:

```python
# Python function to check if the input parameter is even.
# A number is even if division by 2 gives a remainder of 0.
# If the remainder is 1, it is an odd number.
def is_even(num):
  if (num % 2) == 0:
    return True
  else:
   return False
#end-def
```

Boolean predicates can be used in PySpark's `RDD.filter()`:

```python
# sc : SparkContext
rdd = sc.parallelize([1, 2, 3, 4, 5, 6, 7])
# keep the even numbers
rdd2 = rdd.filter(is_even)
rdd2.collect()
[2, 4, 6]
```

Cartesian Product

In mathematics, specifically set theory, the Cartesian product of two sets `A` and `B`, denoted `A × B`, is the set of all ordered pairs `(a, b)` where `a` is in `A` and `b` is in `B`:

```
A x B = {(a,b) /  a in A and  b in B }
```

Cartesian Product in Python:

```python
>>> A = [1, 2, 3]
>>> B = [4, 5]
>>> cartesian_product = [(a, b) for a in A for b in B]
>>> cartesian_product
[(1, 4), (1, 5), (2, 4), (2, 5), (3, 4), (3, 5)]
```

Cartesian Product in PySpark:

```python
# sc : SparkContext
rdd = sc.parallelize([1, 2, 3])
rdd2 = sc.parallelize([4, 5])
rdd.cartesian(rdd2).collect())
[(1, 4), (1, 5), (2, 4), (2, 5), (3, 4), (3, 5)]
```

Python Lambda

A lambda function is a small anonymous function.

A lambda function can take any number of arguments, but can only have one expression.

You should use lambda functions when an anonymous function is required for a short period of time. You should use the lambda function to create simple expressions. For example, expressions that do not include complex structures such as `if-else`, `for-loops`, and so on.

Syntax:

```python
lambda argument(s) : expression
```

where

- `lambda` is a keyword in Python for defining the anonymous function.
- `expression` is the code you want to execute in the lambda function.

Example:

```
x = lambda a: a + 10
print(x(5))
15

x = lambda a, b, c : a + b + c
print(x(2, 3, 4))
9

def my_func(n):
    return lambda a : a * n

my_tripler = my_func(3)
print(my_tripler(11))
33

my_list = [1, 2, 3, 4, 5, 6, 7, 8, 9]
list(filter(lambda x: x % 2 == 0, my_list))
[2, 4, 6, 8]
```

Data transformation

Data transformation is the process to convert data from one form to the other.

Note that data transformation in Python is sequential (and can handle small to meium size data) and single threaded, while in PySpark, data is partitioned and processed in parallel and there is no limit on the size of data.

Data transformation in Python:

```
>>> A = [1, 2, 3]
>>> B = [x*x for x in A]
>>> B
[1, 4, 9]
```

Data transformation in Python using map():

```
>>> map(lambda n: n * 2, [1, 2, 3, 4, 5])
[2, 4, 6, 8, 10]
```

Data transformation in Python using filter():

```
>>> strs = ['apple', 'and', 'a', 'donut']
>>>
>>> list(filter(lambda s: len(s) > 3, strs))
['apple', 'donut']
```

Data transformation in PySpark using map():

```
# sc : SparkContext
rdd = sc.parallelize([1, 2, 3, 4])
rdd.map(lambda x: x * x).collect()
[1, 4, 9, 16]
```

Data transformation in PySpark using filter():

```
# sc : SparkContext
rdd = sc.parallelize([1, 2, 3, 4])
rdd.filter(lambda x: x > 2).collect()
[3, 4]
```

Data transformation in PySpark using flatMap():

```
# sc : SparkContext
>>> rdd = sc.parallelize([ [], [1, 2, 3, 9], [], [4, 5, 6] ])
>>> rdd.count()
4
>>> rdd.collect()
[ [], [1, 2, 3, 9], [], [4, 5, 6] ]
>>> # note that flatMap() will drop empty lists
>>> rdd2 = rdd.flatMap(lambda x: x)
>>> rdd2.count()
7
>>> rdd2.collect()
[1, 2, 3, 9, 4, 5, 6]
```

Data transformation in PySpark using reduceByKey():

```
# sc : SparkContext
>>> pairs = [ ('A', 2), ('A', 3), ('B', 5), ('B', 6), ('B', 7), ('C', 9)]
>>> rdd = sc.parallelize()
>>> rdd.count()
6
>>> rdd.collect()
>>> rdd2 = rdd.reduceByKey(lambda x, y: x+y)
>>> rdd2.count()
3
>>> rdd2.collect()
[
 ('A', 5),
 ('B', 18),
 ('C', 9
]
```

Data transformation in PySpark using groupByKey():

```
# sc : SparkContext
>>> pairs = [ ('A', 2), ('A', 3), ('B', 5), ('B', 6), ('B', 7), ('C', 9)]
>>> rdd = sc.parallelize()
>>> rdd.count()
6
>>> rdd.collect()
>>> rdd2 = rdd.groupByKey()
>>> rdd2.count()
3
>>> rdd2.mapValues(lambda values: list(values)).collect()
[
 ('A', [2, 3]),
 ('B', [5, 6, 7]),
 ('C', [9]
]
```

Data Curation

Curation is the process of validating and managing discovered metadata of a data source so that the metadata is fit for use and reporting. Data curation is the process of creating, organizing and maintaining data sets so they can be accessed and used by people looking for information. It involves collecting, structuring, indexing and cataloging data for users in an organization, group or the general public.

What is Bioinformatics?

- Bioinformatics is a mutually beneficial collaboration between Biology and Computer Science (CS).
- For CS, Biology provides a motivation for studing new challenging problems and developing new algorithms.
- For Biology, CS offers effective and cheap (as in silico experiments are typically cheaper than wet-lab ones) solutions to many tough problems

Software Framework

From Wikipedia: in computer programming, a software framework is an abstraction in which software, providing generic functionality, can be selectively changed by additional user-written code, thus providing application-specific software. It provides a standard way to build and deploy applications and is a universal, reusable software environment that provides particular functionality as part of a larger software platform to facilitate the development of software applications, products and solutions.

Example of Software Frameworks:

- Spring is an open-source application
  framework for developing Java enterprise applications. It offers an infrastructure that enables developing well-structured and easily-testable Java applications, web applications, applets, etc.
- Spark: is a unified engine for large-scale data analytics. Spark is a multi-language (Java, Python, Scala, R, SQL) engine for executing data engineering, data science, and machine learning on single-node machines or clusters.
- Django is an open source and high-level Python web framework that encourages rapid development and clean, pragmatic design. Built by experienced developers, it takes care of much of the hassle of web development, so you can focus on writing your application without needing to reinvent the wheel.
- JUnit is a unit testing open-source framework for the Java programming language. Java Developers use this framework to write and execute automated tests. In Java, there are test cases that have to be re-executed every time a new code is added. This is done to make sure that nothing in the code is broken.

- Hadoop is an open-source framework by Apache that stores and distributes large data sets across several servers, operating parallel. One of the major benefits of Hadoop over traditional RDBMS is its cost-effective system for storing giant data sets. The core of Apache Hadoop is Hadoop Distributed File System (the storage part) and MapReduce Programming Model (the processing part). Hadoop is written in Java, the widely used language by developers, which makes it easy for developers to handle tasks and process data efficiently. Hadoop's MapReduce enables processing terabytes of data in minutes in a cluster environment.

- FastAPI is a Web framework for developing RESTful APIs in Python. FastAPI is based on Pydantic and type hints to validate, serialize, and deserialize data, and automatically auto-generate OpenAPI documents.

- Swagger: is an "API Development for Everyone". You can simplify API development for users, teams, and enterprises with the Swagger open source and professional toolset.

Software Library

A software library is a suite of data and programming code that is used to develop software programs and applications. It is designed to assist both the programmer and the programming language compiler in building and executing software. In computer science, a library is a collection of non-volatile resources used by computer programs, often for software development. These may include configuration data, documentation, help data, message templates, pre-written code and subroutines, classes, values or type specifications.

Example of Software Libraries:

- Java Date and Time API: It is a set of classes and interfaces that define properties and methods that developers can use to format dates, perform time zone conversions and provide global calendar support.

- Pandas: it is a fast, powerful, flexible and easy to use open source data analysis and manipulation tool, built on top of the Python programming language.

- Node.js is an open-source, cross-platform JavaScript runtime environment.

- scikit-learn is an Open-source Machine Learning in Python:
  - Simple and efficient tools for predictive data analysis
  - Built on NumPy, SciPy, and matplotlib

- TensorFlow: a free and open-source software library for machine learning and artificial intelligence.

Difference between a Library and Framework

The framework provides the flow of a software application and tells the developer what it needs and calls the code provided by the developer as required. If a library is used, the application calls the code from the library.

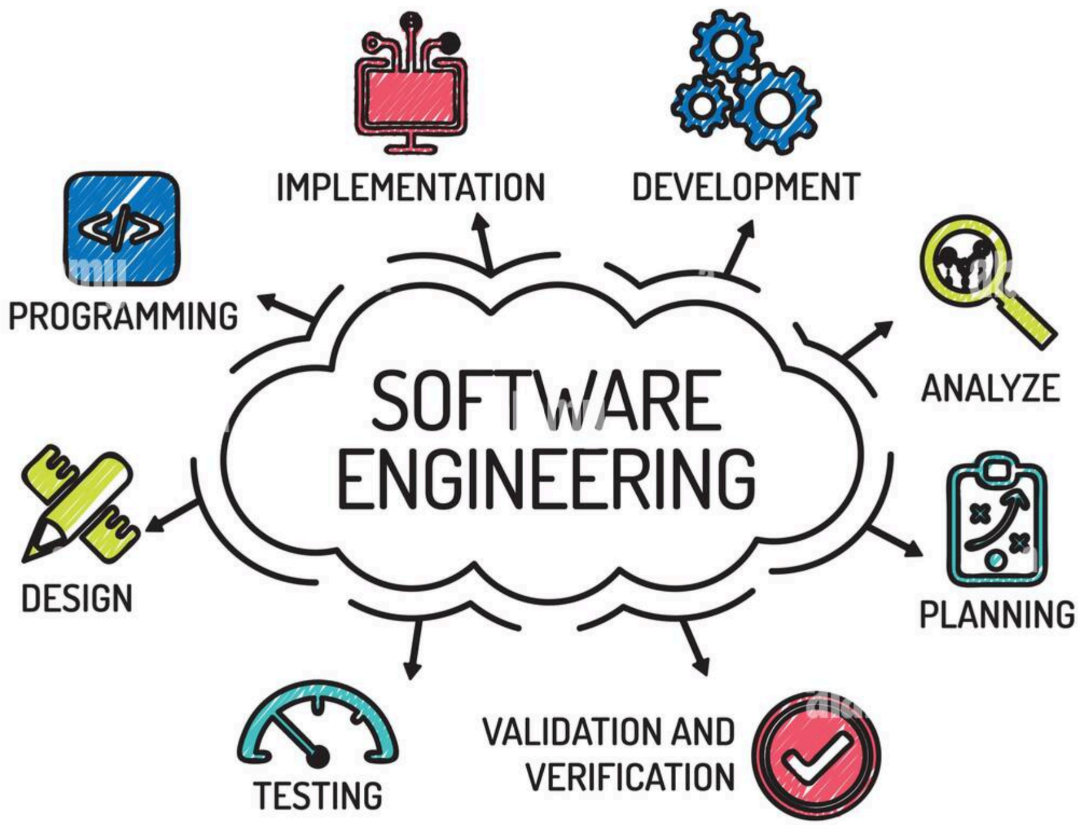
Developers often use the terms “library” and “framework” interchangeably. But there is a difference. Both frameworks and libraries are code written by someone else that is used to help solve common problems.

According to FreeCodeCamp:

> A library is like going to IKEA (a store which sells many things - it’s a global home furnishing). You already have a home, but you need a bit of help with furniture. You don’t feel like making your own table from scratch. IKEA allows you to pick and choose different things to go in your home. You are in control. A framework, on the other hand, is like building a model home. You have a set of blueprints and a few limited choices when it comes to architecture and design. Ultimately, the contractor and blueprint are in control. And they will let you know when and where you can provide your input.
>
> The Technical Difference: The technical difference between a framework and library lies in a term called inversion of control. When you use a library, you are in charge of the flow of the application. You are choosing when and where to call the library. When you use a framework, the framework is in charge of the flow. It provides some places for you to plug in your code, but it calls the code you plugged in as needed.

Software Engineering

Software Engineering is a systematic approach to the analysis, design, implementation and maintenance of software. It often involves the use of CASE tools. There are various models of the software life-cycle, and many methodologies for the different phases. A software engineer is a person (usually knows multiple programming languages) who applies the principles of software engineering to design, develop, maintain, test, and evaluate computer software.



Is big data related to software engineering? Big Data Systems (BDSs) are an emerging class of scalable software technologies whereby massive amounts of heterogeneous data are gathered from multiple sources, managed, analyzed (in batch, stream or hybrid fashion), and served to end-users and external applications.

spark-packages.org

spark-packages.org is a community package index to track the growing number of open source packages and libraries that work with Apache Spark. Spark Packages makes it easy for users to find, discuss, rate, and install packages for any version of Spark and makes it easy for developers to contribute packages.

For example, GraphFrames package is located here.

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Mahmoud Parsian's List of Books:

Data Algorithms with Spark

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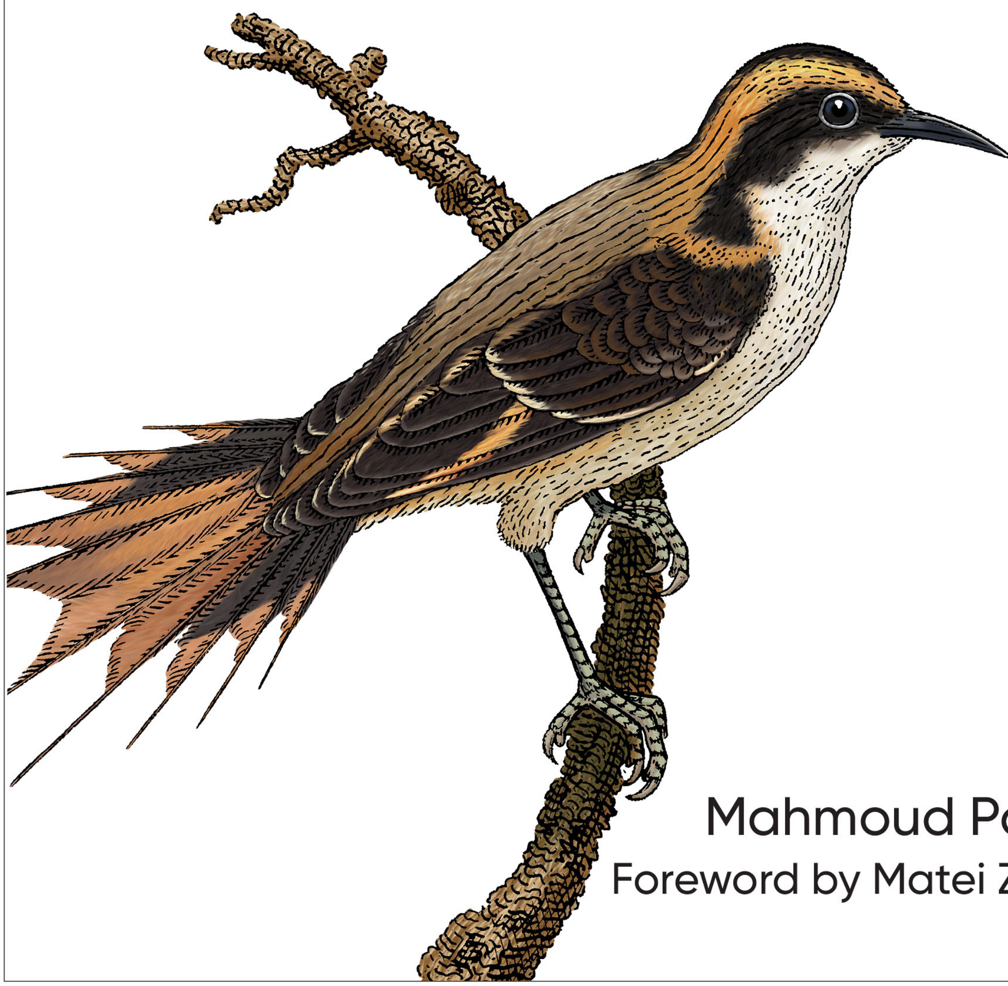
Recipes and Design Patterns for Scaling Up Using PySpark



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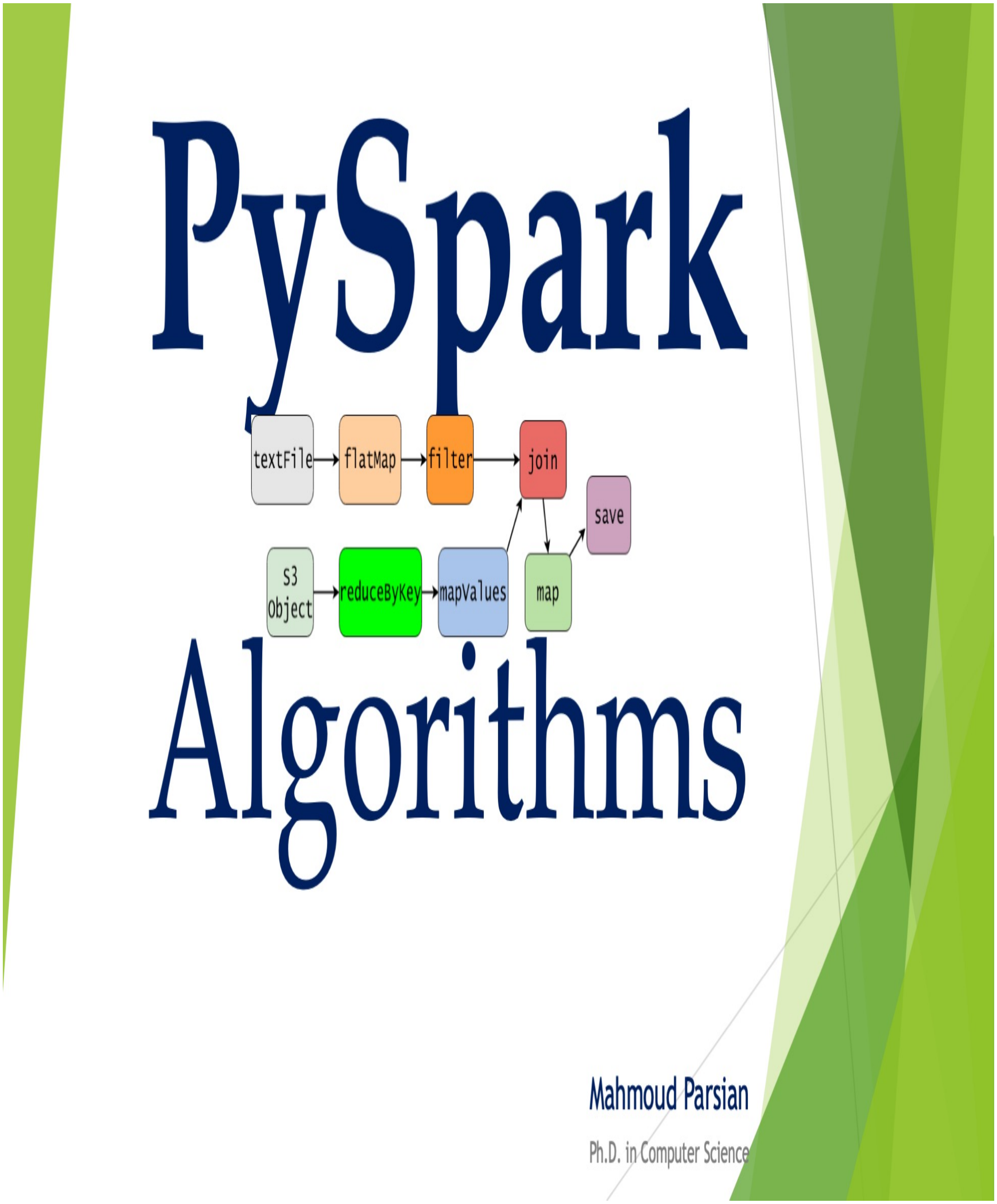
PySpark Algorithms



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