University of Djillali Bounaama – Khemis Miliana

Implementation and Evaluation of a Frequent Subgraph Mining Algorithm with Hadoop an Iterative MapReduce Based Method

A Thesis

Submitted to the Computer Science Department

Faculty of Science and Technology - Khemis Miliana University

in Partial Fulfillment of the Requirements for the Degree of

Master in Computer Science

Authors:

Abdelkader RALEM AHMED

Abdellatif BOUBEKEUR

Supervisor:

Prof. O.HARBOUCHE

June 2017-2018

Abstract

Frequent subgraph mining (FSM) is an important task for exploratory data analysis on graph data. Over the years, many algorithms have been proposed to solve this task. These algorithms assume that the data structure of the mining task is small enough to fit in the main memory of a computer. However, as the real-world graph data grows, both in size and quantity, such an assumption does not hold any longer. To overcome this, some graph database-centric methods have been proposed in recent years for solving FSM; however, a distributed solution using MapReduce paradigm has not been explored extensively. Since, MapReduce is becoming the de-facto paradigm for computation on massive data, an efficient FSM algorithm on this paradigm is of huge demand. In this work we study frequent subgraph mining algorithm called FSM-H which uses an iterative MapReduce based framework. FSM-H is complete as it returns all the frequent subgraphs for a given user-defined support, and it is efficient as it applies all the optimizations that the latest FSM algorithms adopt, our experiments of with real life and large synthetic datasets validate the effectiveness of FSM-H for mining frequent subgraphs from large graph datasets.

Résumé:

La fouille des sous graphes fréquent est une tâche importante lorsqu'il s'agit de l'analyse exploratoire des données de graphe. Au cours des années, de nombreux algorithmes ont été proposés pour résoudre cette tâche. Ces algorithmes supposent que la structure de données sujet de l'exploration est petite et peut tenir dans la mémoire principale d'un ordinateur, cependant, à mesure que les données du graphe qu'on trouvent dans la vie réelle augmentent, en taille et en quantité,une telle hypothèse ne tient plus, Pour surmonter ce probléme, ces dernières années certaines méthodes centrées sur les bases de données du graphe ont été proposées pour résoudre la fouille des sous-graphe fréquent (FSF), Cependant, une solution distribuée utilisant le paradigme MapReduce n'a pas été largement explorée. Ces derniéres années le modèle de programmation MapReduce est devenu la norme lorsque il s'agit de l'exploration des données massives,donc une solution basé sur ce paradigme est très aprécié.Dans ce travail nous étudions une méthode pour la fouille des sous graphe fréquent qui adopte une approche itérative basé sur le modèle Map Reduce qui s'appelle FSM-H.cet algorithme est complet puisque il retourne tous les sous graphes fréquents qui ont un minimum support donnée par l »utilisateur, de plus cet algorithme est efficace car il applique toutes les optimisations qui sont adoptés par les algorithmes de fouille de graphes. Nos expériences et tests sur des données de graphe de la vie réelle et des données synthétiques valident l'efficacité de FSM-H pour la fouille des sous graphes fréquents dans un ensemble de données massives.

Acknowledgments

There are no words to express our gratitude to Prof. O.HARBOUCHE, our adviser who helped us to improve nearly every aspect of this current work, The study presented in this thesis would not have happened without his support, guidance, and encouragement.

It was an honor to have Prof. S.HADJ SADOK, Prof. N.AZZOUZA, and Prof. R.MEGHATRIA as committee members for examining this work.

Special thanks are directed to Dr.N.BELKHIER for having hosted us at the FIMA Lab and allowed us to work in comfortable conditions.

We would also like to thank our families, they were always supporting and encouraging us with their best wishes.

Contents

List of Figures

List of Tables

Introduction

Introduction:

We live in the era where almost everything surrounding us is generating some kind of data, a search on a search engine is being logged, a heartbeat of a patient in the hospital generates data, the flipping of channels when watching TV is being captured by cable companies, Data this valuable asset is created constantly, and at an ever-increasing rate, and so must be stored somewhere for some purpose.

Organizations and institutions have been storing huge volumes of data that is of various types and in different forms for several years now. the data remained on backup tapes or drives, and so it could only be used in case of emergency to retrieve important data, This is changing, Organizations want now to use this data to get insight to help understand existing problems, seize new opportunities, and be more profitable, the study and analysis of these volumes of data that have the unique feature of being “massive, high dimensional, heterogeneous, complex, unstructured, incomplete, noisy, and erroneous” has given birth to a term called big data.

It is important to mention that the move to big data is not exclusively driven just by businesses, Science, Research and Government activities have also helped to derive it forward, just think about analyzing the human genome, or dealing with all the astronomical data collected at observatories to advance our understanding of the world around us, that being said big data find its application in several different domains ranging from web, computational biology, astronomy, chemoinformatics, medicine, e-commerce just to name a few, in these domains, analyzing and mining of massive data for extracting novel insights has become a routine task, thus giving rise obviously to various basic and advanced data analytics methods appropriate to the problem in question like data mining , social network analysis for social websites, discourse-level analysis for text , …. etc.

Data mining for instance is an analytics method which have a basic objective of discovering hidden and useful data pattern from very large datasets. Graph mining is a data mining technique that gained much attention in the last few decades as novel approach when it comes to exploratory data analysis for mining datasets represented by a graph datastructure.

Graphs are common data structures used to represent and model real-world systems, e.g. social networks, chemical molecules, map of roads in a country. Frequent sub graph mining which is the subject of this report is considered as a sub section of graph mining domain which is extensively used to identify subgraphs in large graph datasets whose occurrences counts are above a specified minimum support threshold, also used for graph classification, building indices and graph clustering purposes. The frequent sub graph mining is addressed from various perspectives and viewed in different directions based upon the domain expectations.

Mining patterns from graph databases is challenging since graph related operations, such as subgraph testing, generally have higher time complexity than the corresponding operations on item sets, sequences, and trees, moreover the tremendously increasing size of existing graph databases makes the mining even much harder. hence processing or analyzing such data to get insight efficiently was very difficult in the past, because traditional methods for analysis and mining are not designed to handle massive data and complex operation on it, and so do not withstand the requirements, therefore in recent years, many such methods are re-designed and re-implemented under a computing framework that is better equipped to handle big data idiosyncrasies.

Among the recent effort for building a suitable computing platform for analyzing massive data, the Map Reduce framework of distributed computing has been the most successful. Because it adopts a data centric approach of distributed computing with the ideology of “moving computation to data”, besides it uses a distributed file system that is particularly optimized to improve the IO performance, while handling massive data, another main reason for this framework to gain attention of many admirers is the high level of abstraction that it provides, which keeps many system level details hidden from the programmers and allow them to concentrate more on the problem specific computational logic.

In this report we propose an implementation and a detailed evaluation of a novel iterative map reduce based frequent subgraph mining algorithm "FSM-H", in the Hadoop platform.

The report is organized in five chapters as follows:

In chapter 01, we define big data, and review its evolution in the past 20 years. we present the underlying technology architecture that support it, as well as various data analytics methods.

Chapter 02 is divided in two parts:

Part 01 : discusses the Graphs data structure, means of representing them on machines, Graph theory terminology.

Part 02 : gives the state of the art of frequent subgraph mining approaches, a survey on different FSM algorithms and their classification with respect to different considerations, as well as solutions addressing the major issues that one may encounter when enumerating subgraphs in large datasets.

Chapter 03 covers the internals of the Apache Hadoop ecosystem, the platform in which the algorithm is implemented, review its features and capabilities, runs into the technical details of the Hadoop distributed file system HDFS and the MapReduce programming model.

Chapter 04 present a thorough explanation of the FSM-H algorithm studied, giving the implementation details, describing for instance the map and the reduce functions, covering the techniques used for the purpose of carrying out isomorphism checking, candidate subgraph generation and support counting.

In Chapter 05 we present the experiments and analyses the results, and so empirically demonstrate the performance of FSM-H on real world chemical compounds datasets.

Chapter I:

Big Data Principles and Techniques

I. Chapter 01

Big Data Principles and techniques

Context:

The term big data is now well understood for its well-defined characteristics. more the usage of big data is now looking promising. this chapter being an introduction draws a comprehensive picture on the history and progress of big data, it defines the big data characteristics, and then presents the big data technology stack, a discussion on the state of the art of big data analytics techniques including data mining is also presented.

I.1 Brief History:

Although the term big data itself is relatively new, when it was first coined by a ***Silicon Graphics Inch SGI*** chief scientist called ***John Mashey*** in 1990, the origins of large data sets go back to the 1960s and '70s when the world of data was just getting started, with the first data centers and the development of the relational database.

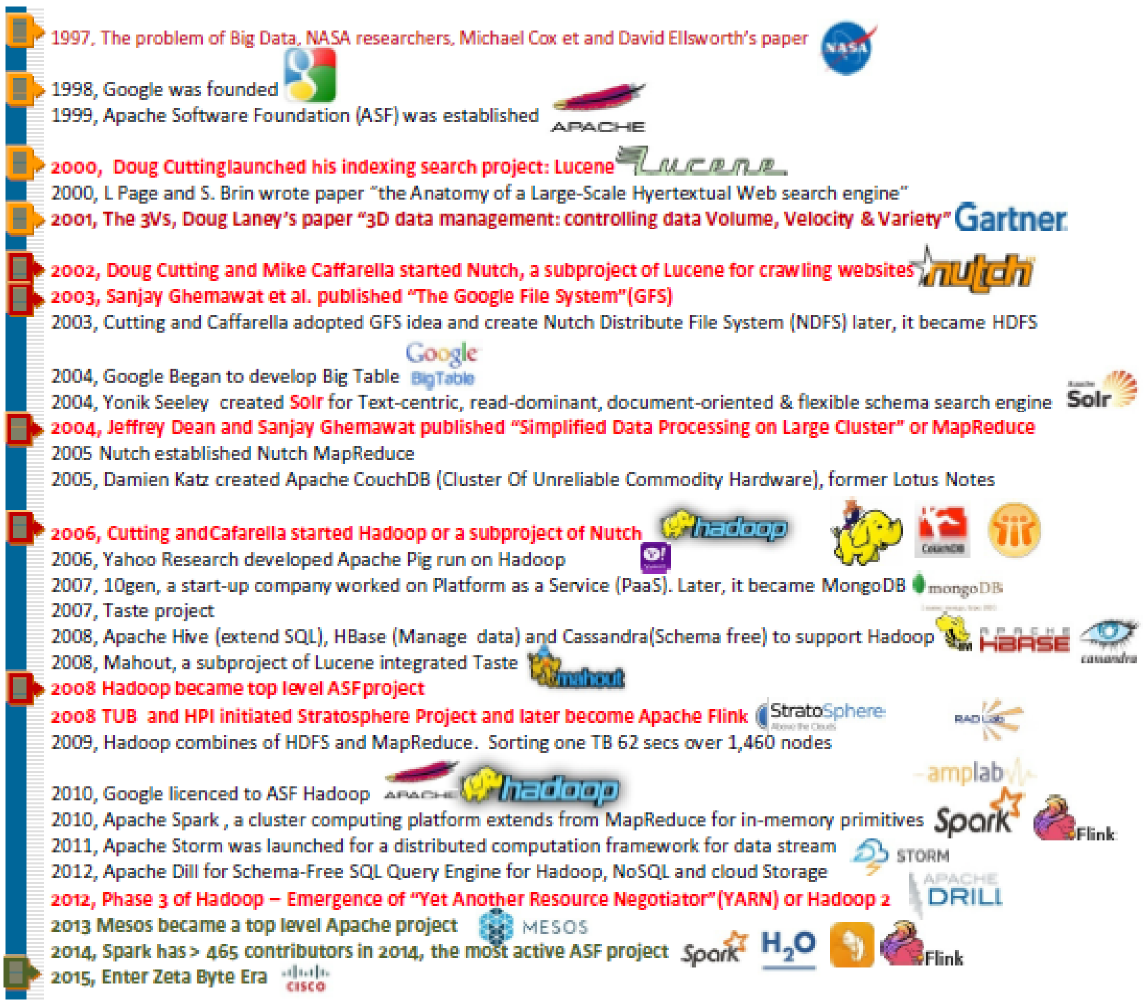
Around 2005, people began to realize just how much data users generated through Facebook, YouTube, and other online services. Hadoop an open-source framework created specifically to store and analyze big data sets was developed that same year. NoSQL databases also began to gain popularity during that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

In the years since then, the volume of big data has skyrocketed. Users are still generating huge amounts of data but it’s not just humans who are doing it.

With the advent of the IoT more objects and devices are connected to the internet, gathering data on customer usage patterns and product performance.

While big data has come far, its usefulness is only just beginning. Cloud computing has expanded big data possibilities even further. The cloud offers truly elastic scalability, where developers can simply spin up ad hoc clusters to test a subset of data.(1)

Figure I-1 Highlights the most important technical events in the history of big data:



1997, The problem of Big Data, NASA researchers, Michael Cox et and David Ellsworth's paper
1998, Google was founded
1999, Apache Software Foundation (ASF) was established
2000, Doug Cuttinglaunched his indexing search project: Lucene
2000, L Page and S. Brin wrote paper "the Anatomy of a Large-Scale Hyertextual Web search engine"
2001, The 3Vs, Doug Laney's paper "3D data management: controlling data Volume, Velocity & Variety"
2002, Doug Cutting and Mike Caffarella started Nutch, a subproject of Lucene for crawling websites
2003, Sanjay Ghemawat et al. published "The Google File System"(GFS)
2003, Cutting and Caffarella adopted GFS idea and create Nutch Distribute File System (NDFS) later, it became HDFS
2004, Google Began to develop Big Table
2004, Yonik Seeley created Solr for Text-centric, read-dominant, document-oriented & flexible schema search engine
2004, Jeffrey Dean and Sanjay Ghemawat published "Simplified Data Processing on Large Cluster" or MapReduce
2005 Nutch established Nutch MapReduce
2005, Damien Katz created Apache CouchDB (Cluster Of Unreliable Commodity Hardware), former Lotus Notes
2006, Cutting andCafarella started Hadoop or a subproject of Nutch
2006, Yahoo Research developed Apache Pig run on Hadoop
2007, 10gen, a start-up company worked on Platform as a Service (PaaS). Later, it became MongoDB
2007, Taste project
2008, Apache Hive (extend SQL), HBase (Manage data) and Cassandra(Schema free) to support Hadoop
2008, Mahout, a subproject of Lucene integrated Taste
2008 Hadoop became top level ASFproject
2008 TUB and HPI initiated Stratosphere Project and later become Apache Flink
2009, Hadoop combines of HDFS and MapReduce. Sorting one TB 62 secs over 1,460 nodes
2010, Google licenced to ASF Hadoop
2010, Apache Spark , a cluster computing platform extends from MapReduce for in-memory primitives
2011, Apache Storm was launched for a distributed computation framework for data stream
2012, Apache Dill for Schema-Free SQL Query Engine for Hadoop, NoSQL and cloud Storage
2012, Phase 3 of Hadoop – Emergence of "Yet Another Resource Negotiator"(YARN) or Hadoop 2
2013 Mesos became a top level Apache project
2014, Spark has > 465 contributors in 2014, the most active ASF project
2015, Enter Zeta Byte Era

Figure I-1 : A short history of big data.

I.2 Definition:

Big data is an abstract concept. Apart from masses of data, it also has some other features, which determine the difference between itself and "massive data" At present, although the importance of big data has been generally recognized, when you read articles about big data, it becomes clear that there are varying definitions of it, this looseness leads to considerable confusion. In general, big data refers to the datasets that could not be perceived, acquired, managed, and processed by traditional IT and software/hardware tools within a tolerable time.(2) Because of different concerns, scientific and technological enterprises, research scholars, data analysts, and technical practitioners have different definitions of big data. In 2010, Apache Hadoop defined big data as "datasets which could not be captured, managed, and processed by general computers within an acceptable scope."(3), On the basis of this definition, in May 2011, ***McKinsey & Company***, a global consulting agency announced Big Data as "the Next Frontier for Innovation, Competition, and Productivity."(1)

As a matter of fact, the wider and most used definition of big data, has been proposed as early as 2001 when ***Doug Laney***, an analyst of ***META (***presently ***Gartner)*** defined challenges and opportunities brought by the increased data in terms of a 3 Vs attributes.

I.3 Big Data 3V's :

Volume – This is big data's most identifiable aspect. It refers to the mind-boggling amount of data generated each second by users, sensors, and server. just think of all the emails, Twitter messages, photos, video clips that we produce and share every second. We are not talking terabytes, but zettabytes or brontobytes of data. On Facebook alone we send 10 billion messages per day, click the like button 4.5 billion times and upload 350 million new pictures each and every day. If we take all the data generated in the world between the beginning of time and the year 2000, it is the same amount we now generate every minute.

Velocity – refers to the speed at which new data is generated and the speed at which data moves around. This covers everything from emails to real-time monitoring, to online financial transactions. Consider that more than 100 million emails are composed every minute, and Just think of social media messages going viral in minutes. Velocity therefore suggest two kind of analytics batch and real time.

Variety – refers to the different types of data we can now use. In the past we focused on structured data that neatly fits into tables or relational databases such as financial data (for example, sales by product or region). But now Nearly all the data generated is in an unstructured format, in fact, 80 percent of the world's data is now unstructured and therefore can't easily be put into tables or relational databases, just think of sensor data or social media posts to get an idea of the variety of content.(4)

The below figure highlights several sources that drives the big data deluge:

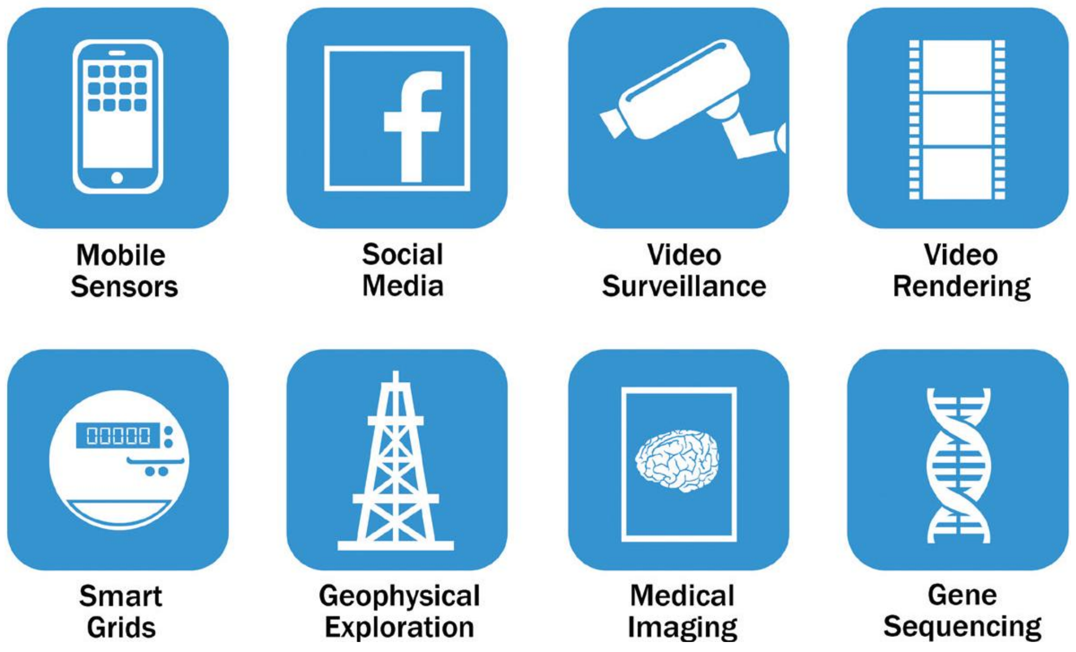


Figure I-2 : What's driving the data deluge.(5)

Over the years, large enterprises like IBM have expanded the definition to include five V's, incorporating:

Veracity – Big Data Veracity refers to the biases, noise and abnormality in data, this is a highly significant factor that only really became apparent as data analysts began to work with big data. The trustworthiness of the data source and the time necessary to clean up the data before it could be used deeply impact how useful the data is to an enterprise. The length of time between when the data is collected and the time it is analyzed contributed to a new plague of "data rot."(2)

Value – As the above suggests, the complexity of converting raw data into useful insights and actionable conclusions influences whether it should be considered big data or merely a big headache, the purpose of the value characteristic is to answer the following question:

"Does the data contain any valuable information for my needs".

Really, there's no reason to stop at five. The number of Vs that could be added continue to increase as more people begin exploring the possibilities. Data experts have suggested adding ***vulnerability*** to stress the growing security concerns over the use of big data and ***viability*** to highlight the fact that not all data, even if accurate, will have a meaningful impact on desired outcomes.

Figure I-3 shows the progress of big data from 2V's attributes up to 6V's.

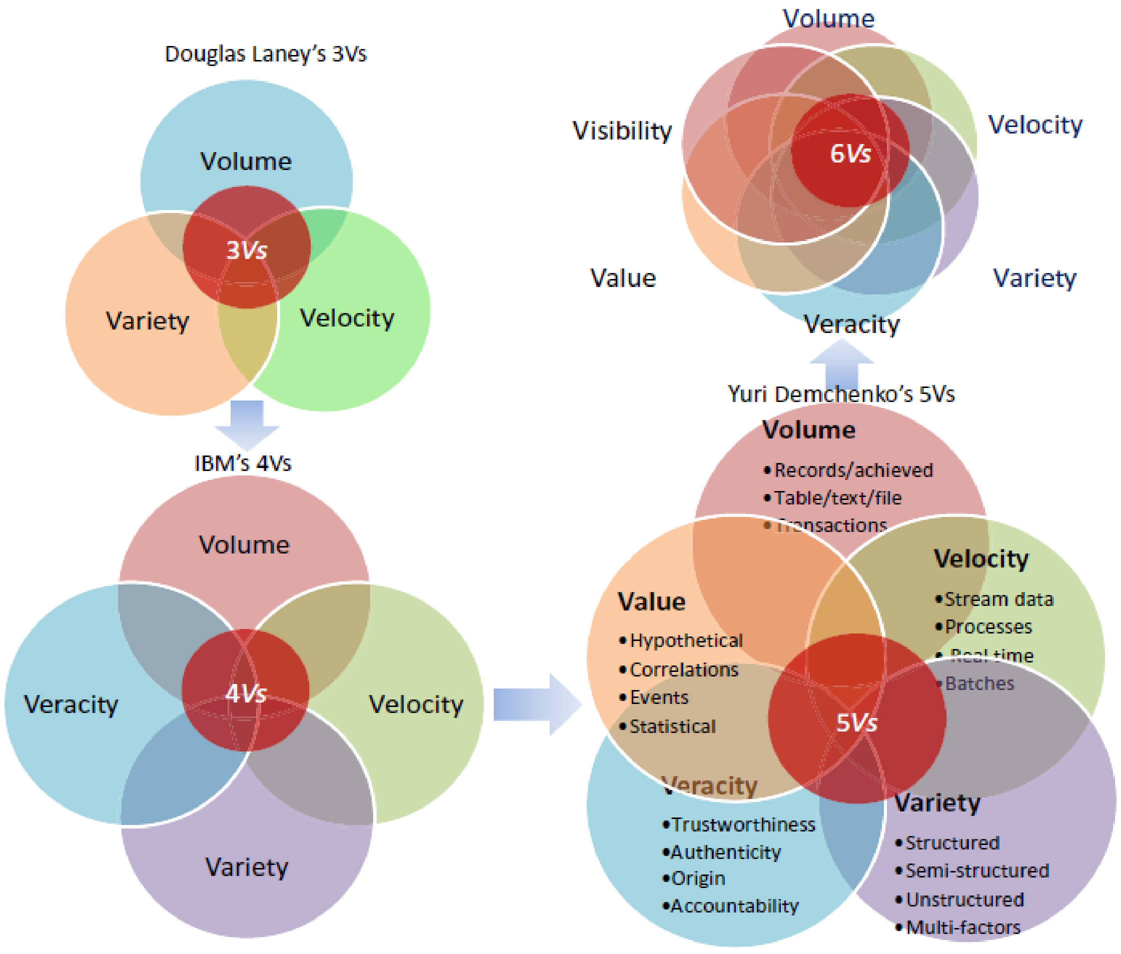


Figure I-3 : From 3Vs, 4Vs, 5Vs, and 6Vs big data definition.

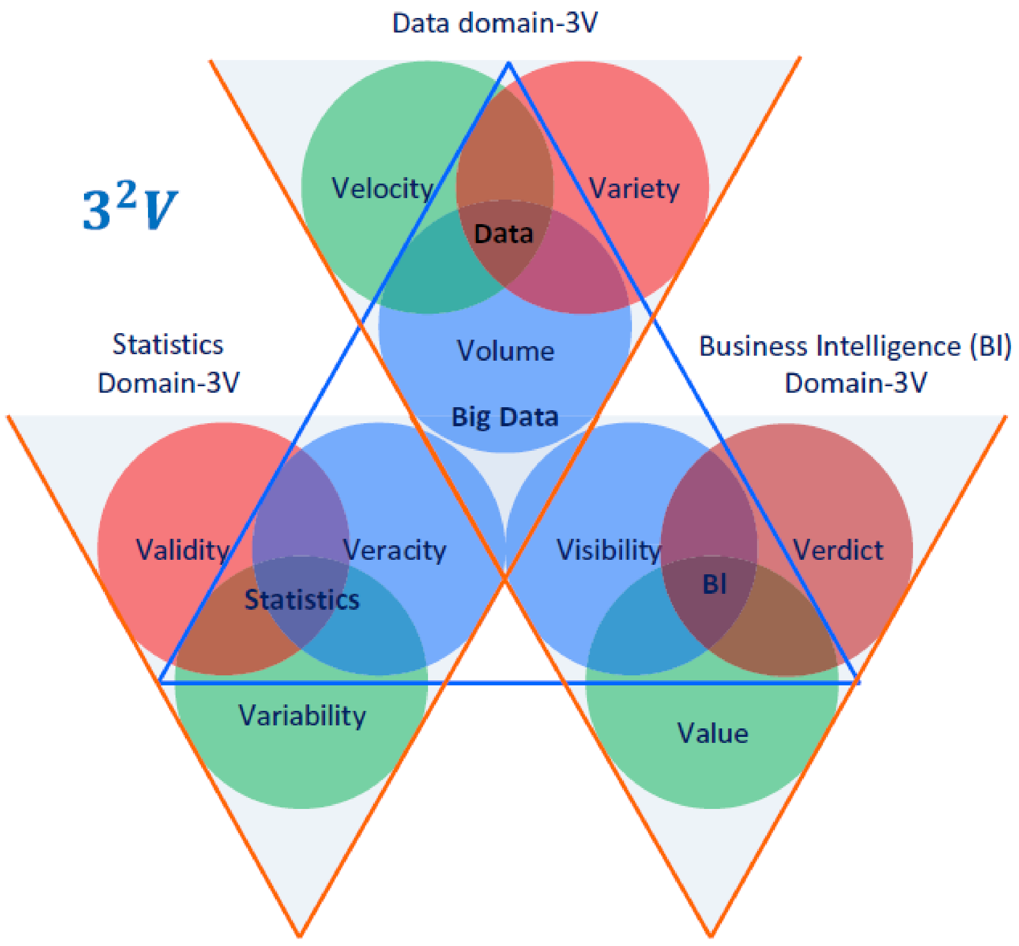
I.4 3^2 Vs Definition and Big Data VENN DIAGRAM:

Laney's 3Vs have captured the importance of Big Data characteristics reflecting the pace and exploration phenomena of data growth during the last few years. these 3V's however represented just a syntactic or logical meaning of Big Data, therefore for a more precise and semantic meaning the relationship of data, business intelligence, and statistics have to be included incorporating all attributes of these three domains, which in fact represent a hierarchical model for a variety of complex problems and applications.(6)

The Figure below presents a venn diagram showing all logical relations of Data, BI, Statistics in terms of their 3^2V's (9V's) attributes considered for big data as follows:

- Data Attributes: Volume, Variety, Velocity.
- BI Attributes: Visibility, Verdict, Value.
- Statistics Attributes: Veracity, Validity, Variability.

This is actually considered as the most accurate definition of big data.



.

Figure I-4 : 3^2 Vs Venn diagrams hierarchical model.

I.5 Data Types:

Big data can come in multiple forms, including structured and non-structured data such as financial data, text files, multimedia files, and genetic mappings, Figure I-5 shows four types of data structures, with 80–90% of future data growth coming from non-structured data types.

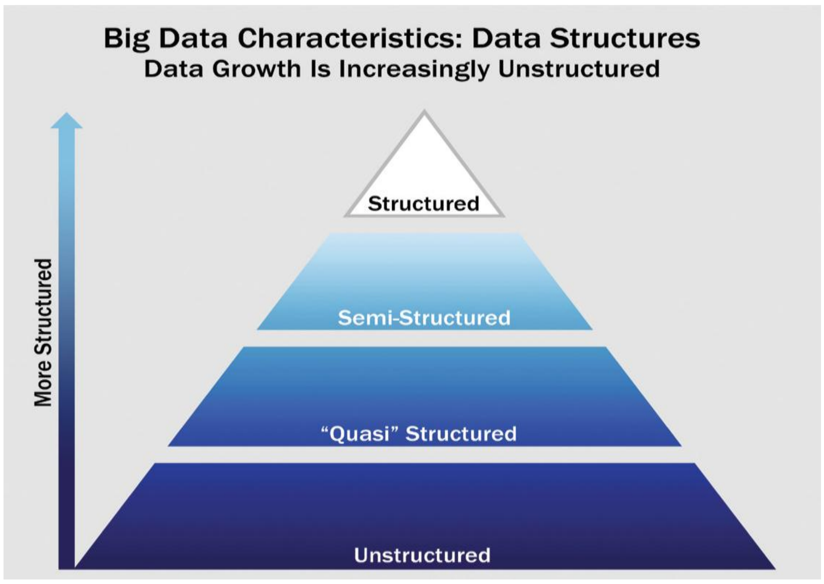
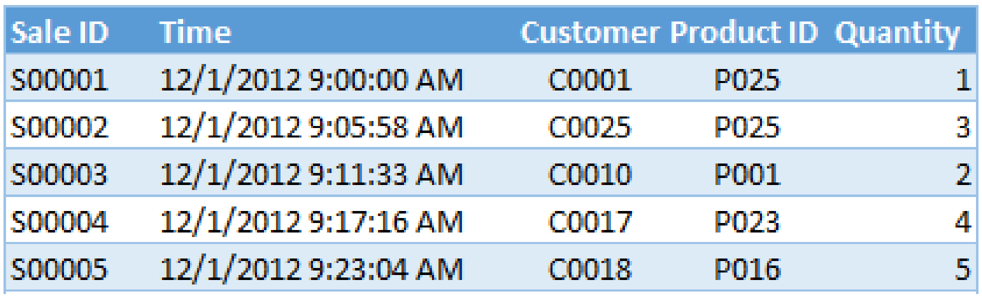

Big Data Characteristics: Data Structures
Data Growth Is Increasingly Unstructured
More Structured
Structured
Semi-Structured
"Quasi" Structured
Unstructured

Figure I-5 : Big data growth is increasingly unstructured.

I.5.1 Structured Data:

The term structured data generally refers to data containing a defined data type, format, and structure, examples of structured data include numbers, dates, and strings (for example, a customer's name, address), transaction data, online analytical processing (OLAP) data cubes, CSV files, and even simple spreadsheets, this kind of data accounts for about 20 percent of the data that is out there, most of structured data resides in relational databases (RDBMS). And it is eminently searchable using a language like structured query language (SQL).



Sale ID	Time	Customer	Product ID	Quantity
S00001	12/1/2012 9:00:00 AM	C0001	P025	1
S00002	12/1/2012 9:05:58 AM	C0025	P025	3
S00003	12/1/2012 9:11:33 AM	C0010	P001	2
S00004	12/1/2012 9:17:16 AM	C0017	P023	4
S00005	12/1/2012 9:23:04 AM	C0018	P016	5

Figure I-6 : Example of structured data.

The sources of structured data are divided into two categories:

- **Computer or machine-generated**: Machine-generated data generally refers to data that is created by a machine without human intervention.
- **Human-generated**: This is data that humans, in interaction with computers, supply.

Machine-generated structured data could include the following:

- ✓ **Sensor data**: Examples include radio frequency ID (RFID) tags, smart meters, medical devices, and Global Positioning System (GPS) data.
- ✓ **Web log data**: When servers, applications, networks, and so on operate, they capture all kinds of data about their activity.
- ✓ **Point-of-sale data**: When the cashier swipes the bar code of any product that you are purchasing, all that data associated with the product is generated.

Examples of structured human-generated data might include the following:

- ✓ **Input data**: This is any piece of data that a human might input into a computer, such as name, age, income, non-free-form survey responses, and so on.
- ✓ **Gaming-related data**: Every move you make in a game can be recorded.(7)

I.5.2 Unstructured Data:

Data that has no inherent structure, which may include text documents, PDFs, images, and video. Unstructured data is really most of the data that we may encounter as it represents 80% of the whole data out there, it may be human or machine-generated. It may also be stored within a non-relational database. Until recently, however, the technology didn't really support doing much with it except storing it or analyzing it manually.

The term unstructured data is misleading because each document may contain its own specific internal structure or formatting based on the software that created it. However, what is internal to the document is truly unstructured.

Examples of machine-generated unstructured data include:

- ✓ **Satellite images:** This includes weather data or the data that the government captures in its satellite surveillance imagery, i.e. Google Earth.
- ✓ **Scientific data:** This includes seismic imagery, atmospheric data, and high energy physics.
- ✓ **Photographs and video:** This includes security, surveillance, and traffic video.
- ✓ **Radar or sonar data:** This includes vehicular, meteorological, and oceanographic seismic profiles.

The following list shows a few examples of human-generated unstructured data:

- ✓ **Social media data:** This data is generated from the social media platforms such as YouTube, Facebook, Twitter, LinkedIn, and Flickr.
- ✓ **Mobile data:** This includes data such as text messages and location information.(7)

Figure I-7 : Example of unstructured data : Video about Antarctica expedition.

I.5.3 Structured vs. Unstructured Data: What's the Difference?

The biggest difference is the ease of analyzing structured data vs. unstructured data. Mature analytics tools exist for structured data, but analytics tools for mining unstructured data are nascent and developing.

The following table depicts some of their differences:

Table I-1 : Structured vs. unstructured data.

	Structured Data	**Unstructured Data**
Characteristics	• Pre-defined data models • Usually text only • Easy to search	• No pre-defined data model • May be text, images, sound, video or other formats • Difficult to search
Resides in	• Relational databases • Data Warehouses	• Applications • NoSQL databases • Data Warehouses • Data lakes
Generated by	Humans or machines	Human or machines
Typical applications	• Airplane reservations systems • Inventory control • CRM systems • ERP systems	• Word Processing • Presentation software • Email clients • Tools for viewing or editing media

I.5.4 Semi-Structured Data:

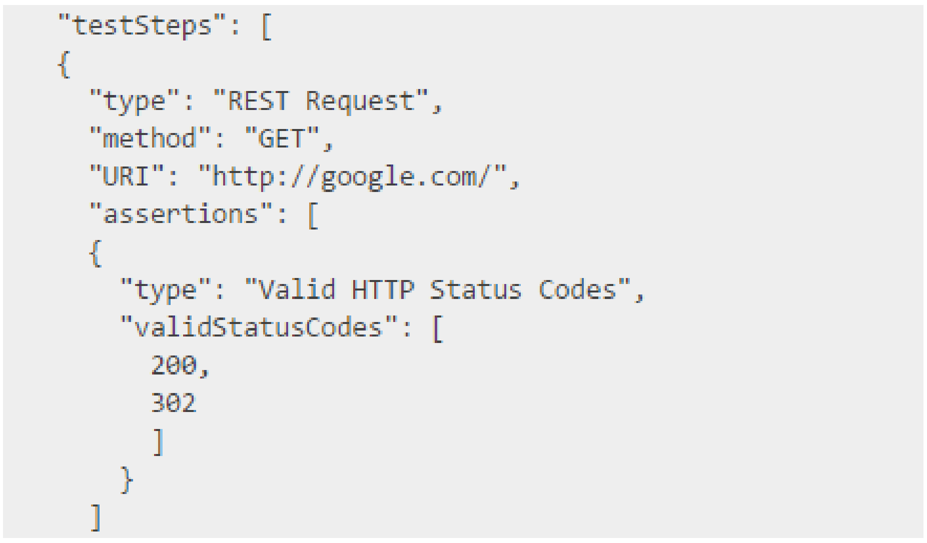
Semi-structured data is a kind of data that falls between structured and unstructured data. Semi-structured data does not necessarily conform to a fixed schema (that is, structure) but may be self-describing and may have simple label/value pairs. It maintains internal tags and markings that identify separate data elements, which enables information grouping and hierarchies. Both documents and databases can be semi-structured. This type of data only represents about 5-10% of the structured/semi-structured/unstructured data pie, but has critical business usage cases.

Email is a very common example of a semi-structured data type. Although more advanced analysis tools are necessary for thread tracking, near-dedupe, and concept searching; email's native metadata enables classification and keyword searching without any additional tools.

Examples of Semi-Structured Data:

- **Extensible markup language XML:** This is a semi-structured document language, it is a set of document encoding rules that defines a human- and machine-readable format, XML data files are self-describing, and has a discernible pattern that enables parsing.

- **Open standard JavaScript Object Notation JSON**: this is another semi-structured data interchange format.

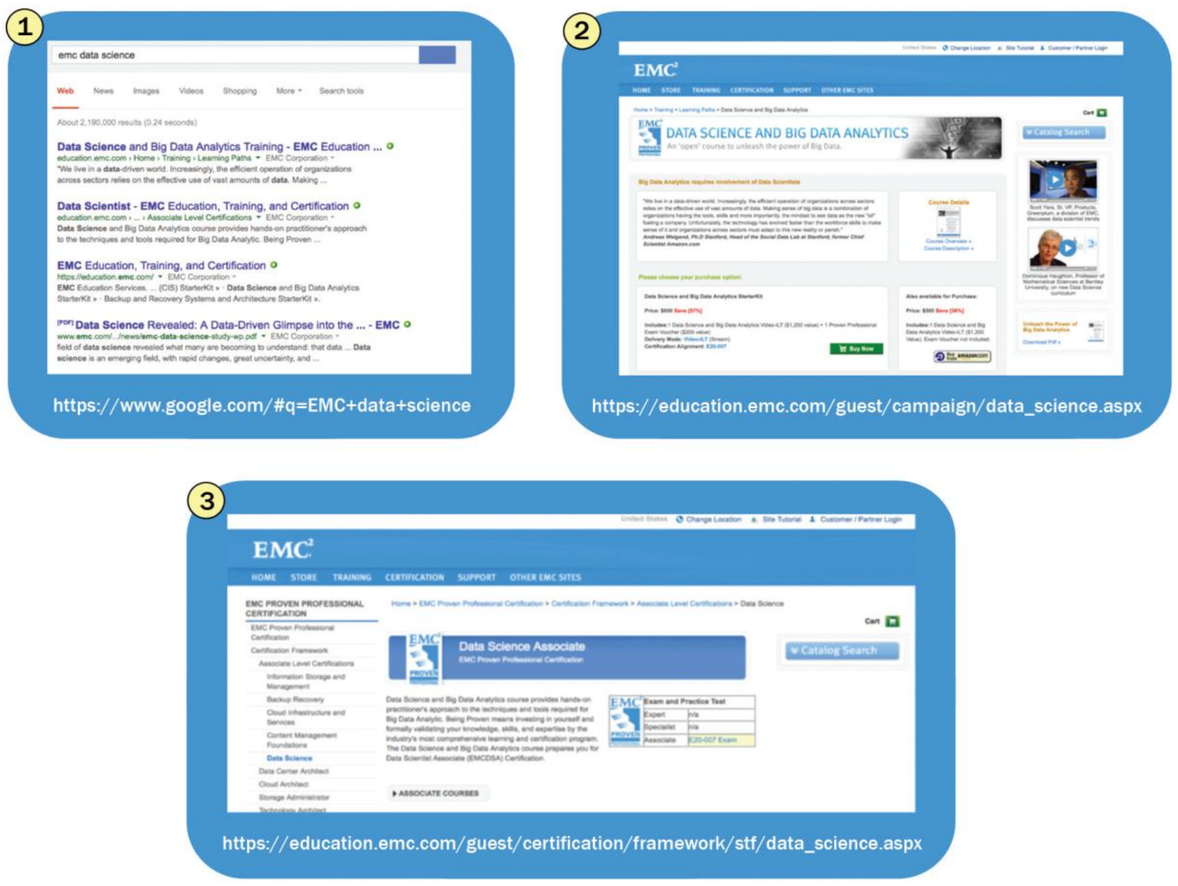


```
"testSteps": [
{
  "type": "REST Request",
  "method": "GET",
  "URI": "http://google.com/",
  "assertions": [
  {
    "type": "Valid HTTP Status Codes",
    "validStatusCodes": [
      200,
      302
      ]
    }
  ]
```

Figure I-8 : Excerpt from semi-structured data JSON File.

I.5.5 Quasi-Structured Data:

Textual data with erratic data formats that can be formatted with effort, tools, and time for instance, web clickstream data that may contain inconsistencies in data values and formats.(5)



emc data science

Web News Images Videos Shopping More Search tools

About 2,190,000 results (0.24 seconds)

Data Science and Big Data Analytics Training - EMC Education ...
education.emc.com › Home › Training › Learning Paths ▾ EMC Corporation ▾
"We live in a data-driven world. Increasingly, the efficient operation of organizations across sectors relies on the effective use of vast amounts of data. Making ...

Data Scientist - EMC Education, Training, and Certification
education.emc.com › ... › Associate Level Certifications ▾ EMC Corporation ▾
Data Science and Big Data Analytics course provides hands-on practitioner's approach to the techniques and tools required for Big Data Analytic. Being Proven ...

EMC Education, Training, and Certification
https://education.emc.com/ ▾ EMC Corporation ▾
EMC Education Services. ... (CIS) StarterKit » · Data Science and Big Data Analytics StarterKit » · Backup and Recovery Systems and Architecture StarterKit ».

[PDF] Data Science Revealed: A Data-Driven Glimpse into the ... - EMC
www.emc.com/.../news/emc-data-science-study-wp.pdf ▾ EMC Corporation ▾
field of data science revealed what many are becoming to understand: that data ... Data science is an emerging field, with rapid changes, great uncertainty, and ...

https://www.google.com/#q=EMC+data+science

United States Change Location Site Tutorial Customer / Partner Login

EMC²

HOME STORE TRAINING CERTIFICATION SUPPORT OTHER EMC SITES

Home > Training > Learning Paths > Data Science and Big Data Analytics

Cart

DATA SCIENCE AND BIG DATA ANALYTICS
An 'open' course to unleash the power of Big Data.

Catalog Search

Big Data Analytics requires involvement of Data Scientists

"We live in a data-driven world. Increasingly, the efficient operation of organizations across sectors relies on the effective use of vast amounts of data. Making sense of big data is a combination of organizations having the tools, skills and more importantly, the mindset to see data as the new "oil" fueling a company. Unfortunately, the technology has evolved faster than the workforce skills to make sense of it and organizations across sectors must adapt to this new reality or perish."
Andreas Weigend, Ph.D Stanford, Head of the Social Data Lab at Stanford, former Chief Scientist Amazon.com

Course Details
Course Overview »
Course Description »

Scott Yara, Sr. VP, Products, Greenplum, a division of EMC, discusses data scientist trends

Dominique Haughton, Professor of Mathematical Sciences at Bentley University, on new Data Science curriculum

Please choose your purchase option:

Data Science and Big Data Analytics StarterKit
Price: $600 Save (57%)
Includes: 1 Data Science and Big Data Analytics Video-ILT ($1,200 value) + 1 Proven Professional Exam Voucher ($200 value)
Delivery Mode: Video-ILT (Stream)
Certification Alignment: E20-007

Buy Now

Also available for Purchase:
Price: $500 Save (58%)
Includes: 1 Data Science and Big Data Analytics Video-ILT ($1,200 Value). Exam Voucher not included.

Unleash the Power of Big Data Analytics
Download Pdf »

https://education.emc.com/guest/campaign/data_science.aspx

United States Change Location Site Tutorial Customer / Partner Login

EMC²

HOME STORE TRAINING CERTIFICATION SUPPORT OTHER EMC SITES

EMC PROVEN PROFESSIONAL CERTIFICATION
EMC Proven Professional Certification
Certification Framework
Associate Level Certifications
Information Storage and Management
Backup Recovery
Cloud Infrastructure and Services
Content Management Foundations
Data Science
Data Center Architect
Cloud Architect
Storage Administrator
Technology Architect

Home > EMC Proven Professional Certification > Certification Framework > Associate Level Certifications > Data Science

Cart

Data Science Associate
EMC Proven Professional Certification

Catalog Search

Data Science and Big Data Analytics course provides hands-on practitioner's approach to the techniques and tools required for Big Data Analytic. Being Proven means investing in yourself and formally validating your knowledge, skills, and expertise by the industry's most comprehensive learning and certification program. The Data Science and Big Data Analytics course prepares you for Data Scientist Associate (EMCDSA) Certification.

Exam and Practice Test	
Expert	n/a
Specialist	n/a
Associate	E20-007 Exam

ASSOCIATE COURSES

https://education.emc.com/guest/certification/framework/stf/data_science.aspx

Figure I-9 : Example of Click Stream Data , EMC data science website search results.

I.6 Data at Rest and Data in Motion:

Apart from being classified as structured and unstructured, big data is also categorized as data at rest and data in motion, each of these categorizes has different infrastructure requirements.

I.6.1 Data at Rest:

Data at rest refers to the data that is captured at asynchronous intervals, this data can be stored in hard disk and flash storage, and can be retrieved and analyzed after the data creating events occurs, let us understand this better with an example of a retail store:

A retailer uses the analysis of the previous month sales data (data at rest), to decide marketing strategy and business activities for the present month, using this data the retailer can decide on the kind of the marketing strategies that will entice its customers and increases sales, while the data provide value, the business impact is limited and dependent on the customer coming back to the store to take advantages of the marketing strategies and activities.(8)

Data at rest is usually managed by batch processing or online transaction processing methods OTLP (which will be covering later in the chapter), and therefore does not need an on demand infrastructure, however the infrastructure must be scalable to support large data sets for both transaction, that is RDBMS and the analysis which means:

- Data warehousing
- Business Intelligence

The two latter concepts will be covered in details later when presenting the big data technology stack.

I.6.2 Data in motion:

Data in motion (real-time data) is the term used for data as it is in transit over the network, often there is a need to manage and process large volume of data that is continuously flowing, such data captured at frequent intervals typically from electronic sensors and devices is called data in motion.

The volume and velocity of such data type will be very high and we need various tools to process such continuous streams of data.

Picture the scenario of a hospital ICU for example:

In a hospital ICU Electronic devices continuously monitors various medical parameters of a patient, however there are multiple patients with various medical conditions in the ICU, considering the criticality of the patient conditions, doctors need to be alerted if there is a branch in the threshold value of any parameter at any given point in time, in this scenario there are vast amounts of data in a form of parameter values flowing continuously into a computer system, such data is a real-time data, so for alerts to be raised such data need to be processed and analyzed to check for any breach within small time windows within the computer memory and when it is flowing, this is done by various big data stream processing technologies.(8)

I.6.3 Data at Rest vs. Data in Motion:

How is data in motion different from data at rest?

The key difference between the two data sets is at the point of analytics unlike data at rest data in motion analytics occurs in real time as the event happens and organizations stand to gain tremendous opportunity to improve business results in real time from insights gained from streaming data.

The figure below highlights some workload requirements for both data at rest and data in motion.

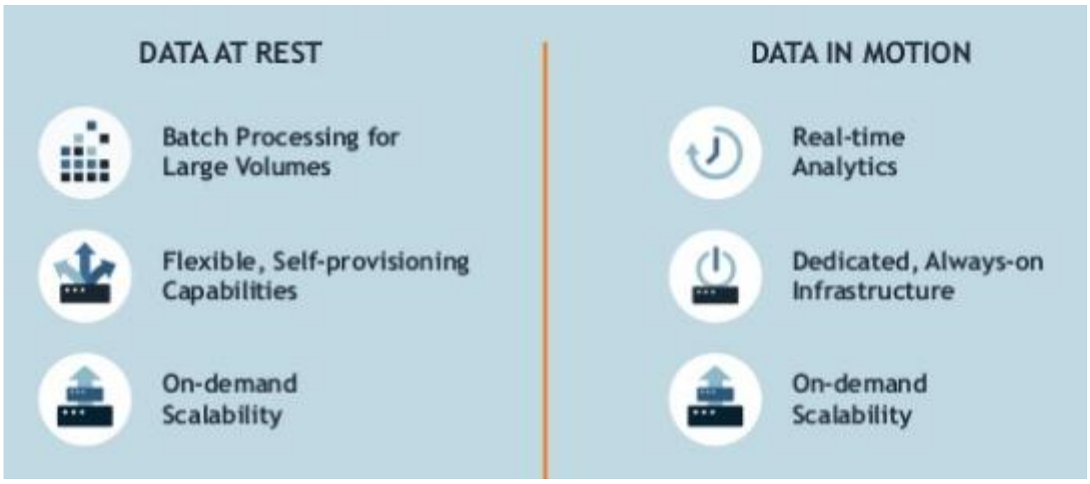

DATA AT REST
Batch Processing for Large Volumes
Flexible, Self-provisioning Capabilities
On-demand Scalability
DATA IN MOTION
Real-time Analytics
Dedicated, Always-on Infrastructure
On-demand Scalability

Figure I-10 : Workload requirements (Data at rest vs Data in motion).

I.7 Functional and infrastructure requirements:

Before we examine the big data technology stack and its component let first discuss the different architectural considerations associated with big data. This architectural foundation must take into account the functional requirements as well as the infrastructure requirements, these will form the design principles that are critical for creating a strong environment that is conducive for big data, so what are those functional requirements.

The architecture design must support the following:

First data is captured, and then organized and integrated, after this phase is successfully implemented, data can be analyzed then based on the problem being addressed, finally we act on the results of the analysis, although this sounds straightforward, certain nuances of these functions are complicated. Validation when capturing data is particularly an important issue, for instance when combining data sources, it is critical that we have the ability to validate that these sources make sense when combined. Also, certain data sources may contain sensitive information, therefore the implementation of sufficient levels of security and governance is of high importance.(7)

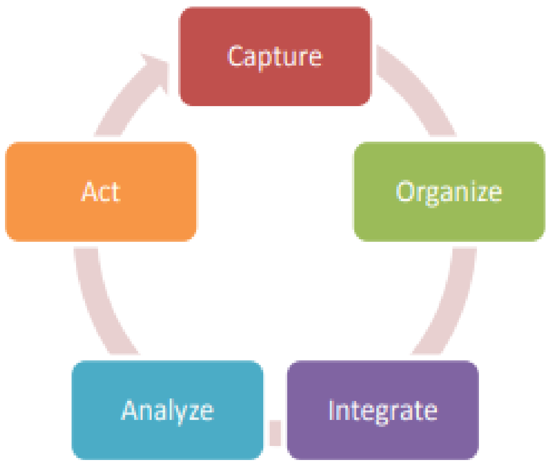


Figure I-11 : The cycle of Big data Management.

In addition to the functional requirements it is important that the architecture supports:

- High power and high speed computation.
- High data storage.
- Right redundancy, etc.

I.8 Data characteristics:

As we discuss earlier, big data consists of structured, semi-structured, and unstructured data. And we often have a lot of it, and it can be quite complex. When you think about analyzing it, you need to be aware of the potential characteristics of it:

- **It can come from untrusted sources:** Big data analysis (which will be covering a bit later in the chapter) often involves aggregating data from various sources, these may include both internal and external data sources. How trustworthy are these external sources?

The information may be coming from an unverified source, so the integrity of this data needs to be considered in the analysis of information.

- **It can be dirty**: Dirty data refers to inaccurate, incomplete, or erroneous data. This may include the misspelling of words; a sensor that is broken, not properly calibrated, or corrupted in some way; or even duplicated data, of course, one might say that the dirty data should be cleaned, but in reality it may contain interesting outliers so the cleansing strategy will probably depend on the source and type of data and the goal of your analysis.

- **The signal-to-noise ratio can be low**: In other words, the signal (usable information) may only be a tiny percent of the data; the noise is the rest. Being able to extract a tiny signal from noisy data is part of the benefit of big data analytics.

- **It can be real-time:** In many cases, you'll be trying to analyze real-time data streams from social media websites like Facebook or Twitter for instance.(7)

I.9 Big data Challenges:

Big data promises to be transformative, the effective use of this data cannot only deliver substantial top and bottom line profits but also improve the performance of existing functions and also create opportunities for growth and expansion, yet very few organizations are able to reap these benefits, the main reason being the lack of the right infrastructure to handle big data leading to poor data management and consequent loss of revenue. one of the challenges that businesses and organization face while delivering big data capabilities is the strain that it puts on their existing IT infrastructure due to the huge data influx and thereby slowing the systems, businesses will need to invest in a more robust architecture that can handle the size and dynamic nature of big data, but before looking at the technology architecture supporting big data, let us review some of the challenges which are primarily divided into three groups, (i) data, (ii) processing and (iii) management challenges.(9)

I.9.1 Data Challenges:

while dealing with large amounts of information we face such challenges as *volume*, *variety*, *velocity* and *veracity*.

***Volume*:** refers to the large amount of data, especially, machine-generated. This characteristic defines a size of the data set that makes its storage and analysis problematic utilizing conventional database technology.

Variety: Multiplicity of the various data implied by variety results in the issue of its handling.

***Velocity**:* the speed of new data generation and distribution requires the implementation of real-time processing for the streaming data analysis (e.g. on social media, different types of transactions or trading systems, etc.)

***Veracity**:* refers to the complexity of data which may lead to a lack of quality and accuracy.

This characteristic reveals several challenges: uncertainty, imprecision, missing values, misstatement and data availability. There is also a challenge regarding data discovery that is related to the search of high quality data in data sets.

I.9.2 Processing Challenges:

The second branch of Big Data challenges is called processing challenges. It includes data collection, resolving similarities found in different sources, modification data to a type acceptable for the analysis, the analysis itself and the output representation, i.e. the results must be visualized in a form that is most suitable for human perception.(9)

I.9.3 Management Challenges:

The last type of challenges offered by this classification is related to data management. Management challenges usually refer to secured data storage, its processing and collection. Here the main focuses of study are: data privacy, its security, governance and ethical issues. Most of them are controlled based on policies and rules provided by information security institutes on state or international levels.(9)

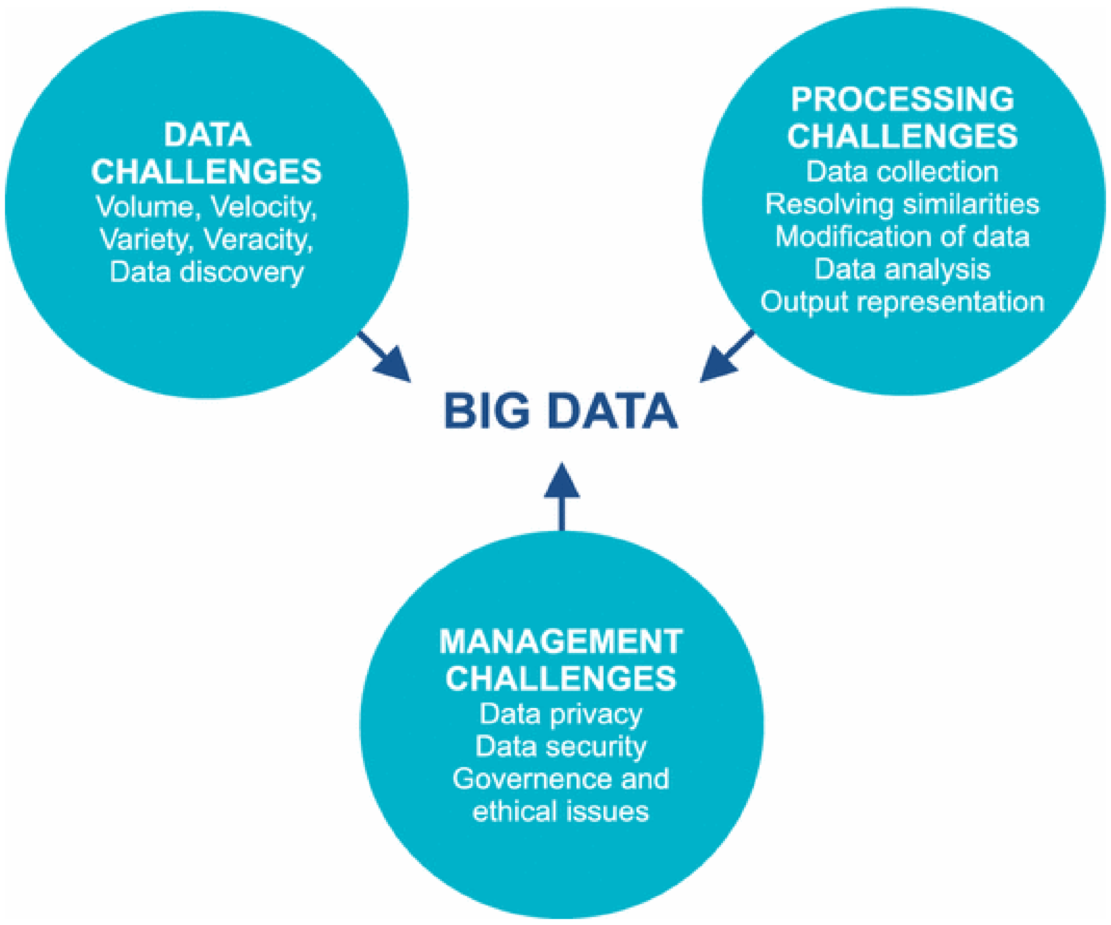


Figure I-12 : Big Data Challenges.

I.10 Big Data Technology Stack:

The task of getting useful insights out of Big Data is not easy. It is a matter of developing comprehensive environment that includes hardware, infrastructure software, operational software, management software and application programming interface (API) to provide fully functional model managing the Big Data requirements. the conceptual representation of this environment represented as layered reference architecture is called big data technology stack, as shown in Figure I-13, this technology stack is a comprehensive stack that has several components that address specific functions of managing big data and tackle the special need and challenges of it, these components are grouped in layers where each layer performs a different function.(10) These layers work on the big data in tandem to produce the desired results, these eight key layers of architecture are as follows:

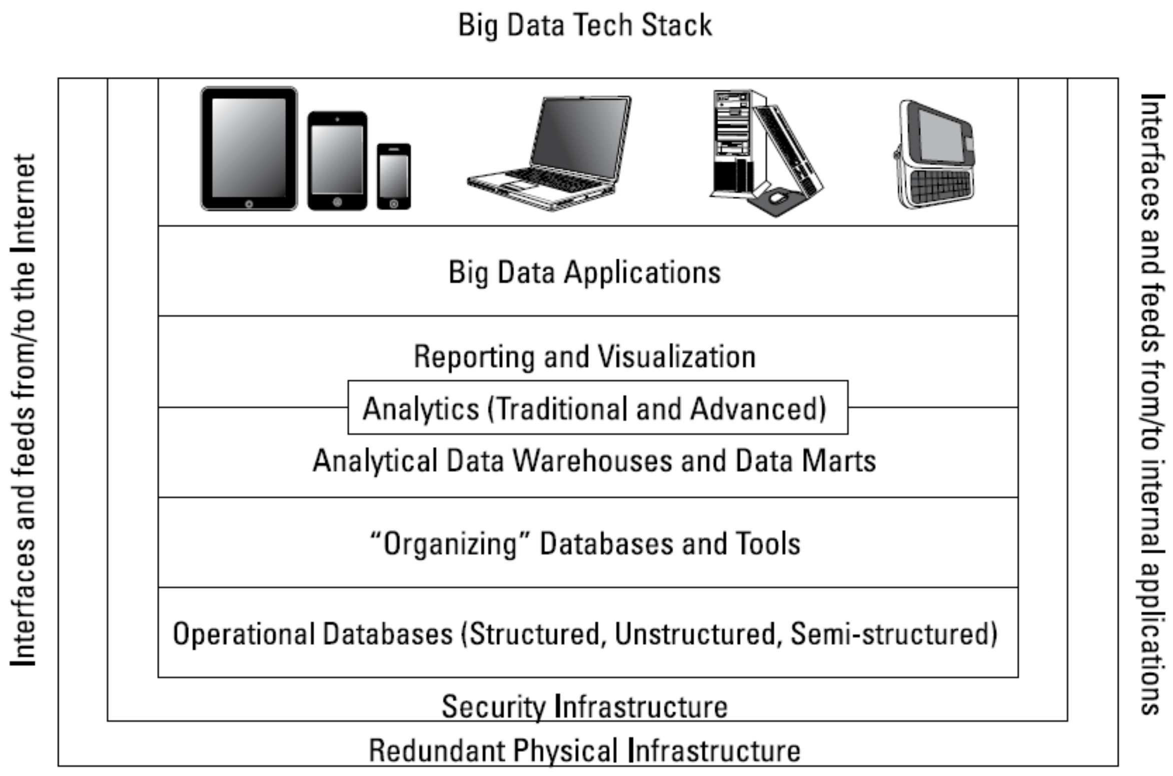

Big Data Tech Stack
Interfaces and feeds from/to the Internet
Interfaces and feeds from/to internal applications
Big Data Applications
Reporting and Visualization
Analytics (Traditional and Advanced)
Analytical Data Warehouses and Data Marts
"Organizing" Databases and Tools
Operational Databases (Structured, Unstructured, Semi-structured)
Security Infrastructure
Redundant Physical Infrastructure

Figure I-13 : Big Data technology stack.(7)

I.10.1 Layer 1 - Redundant Physical Infrastructure:

It is mainly about the new technology infrastructure to overcome the challenges arising from data characteristics like high-volume, high data-variety, high-velocity. IT physical infrastructure will provide necessary hardware systems with adequate storage, processing power and communication speed matching the requirements of Big Data. the optimal IT infrastructure which will suffice your Big Data implementation will be clearly determined after you set your requirements against each of the following criteria:

- ***Performance***: this measure the responsive degree of system, as the system performance increases the cost of infrastructure increases.
- ***Availability***: Do you need your system to be up and running for 24/7 with no interruption? If yes, this means you need high availability infrastructure which is also expensive.
- ***Scalability***: You need to set the size of your infrastructure, the storage capacity and the computing power. Also you need to consider additional scale for future challenges.

- ***Flexibility***: this relates to how fast you can add more resources to infrastructure or you can recover from failures. the flexibility degree is pragmatically proportional with the cost, the most flexible infrastructures can be costly, but we can control the costs with cloud services. Due to the non-stop flow of data for Big Data projects the physical infrastructure must be both redundant and resilient. Resiliency and redundancy are interrelated. An infrastructure, or a system, is resilient to failure or changes when sufficient redundant resources are in place, ready to jump into action.

I.10.2 Layer 2 – Security Infrastructure:

Security and privacy requirements for big data are similar to the requirements for conventional data environments. The security requirements have to be closely aligned to specific business needs. The following list describe briefly Some of the unique challenges that arise when big data becomes part of the strategy:

1. **Data access:** User access to raw or computed big data has about the same level of technical requirements as non-big data implementations. The data should be available only to those who have a legitimate need for examining or interacting with it.

2. **Application access:** Application access to data is also relatively straightforward from a technical perspective. Most application programming interfaces (APIs) offer protection from unauthorized usage or access.

3. **Data encryption**: The main solution to ensure the data remains protected is to apply encryption however this is the most challenging aspect of security in a big data environment, in traditional environments, encrypting and decrypting data really stresses the system's resources, With the volume, velocity, and varieties associated with big data, this problem is exacerbated, the simplest (brute-force) approach is to provide more and faster computational capability. However, this comes with a steep price tag especially when you have to accommodate resiliency requirements. A more temperate approach is to identify the data elements requiring this level of security and to encrypt only the necessary items.

4. **Threat detection:** The inclusion of mobile devices and social networks as sources of big data exponentially increases both the amount of data and the opportunities for security threats. It is therefore important that organizations take a multi-perimeter approach to security.

I.10.3 Interfaces and Feeds to and from Applications and the Internet (API's):

So, the physical infrastructure enables everything and security infrastructure protects all the elements in your big data environment. The next level in the stack is the layer of interfaces and feeds to applications and the internet.

This layer manages the feed of data into and out of both internally managed data and data feeds from external sources, since big data relies on the fact that data from lots of sources are picked, this layer becomes critical for the big data solutions, interfaces also exist at every level and between each layer of the stack, without this layer big data cannot happen.

I.10.4 Layer 3 – Operational Databases:

At the heart of a big data environment are fast, scalable, and rock solid database engines that contains the collections of data elements relevant to a business. A choice has to be made between engines and database languages, a mix of engines cloud also coexist within this layer.

For a long time, most of data management functionalities used to be provided only by relational database management systems (RDBMS) and SQL, However, in the last decades, new applications emerged and new requirements were raised by big data that could hardly be met by relational databases thus the appearance of NoSQL databases.

Let first consider Relational SQL Databases.

I.10.4.1 Relational Databases and RDBMS:

A relational database is a data store that organizes data using the relational model, data is stored in database objects called tables. A table is a collection of related data entries and it consists of columns and rows, and a schema strictly defines the tables, columns, indexes, relationships between tables, and other database elements.

SQL is the most widely used mechanism for creating, querying, maintaining, and operating relational databases. These tasks are referred to as CRUD: Create, retrieve, update, and delete, Optimization of queries, indexes and tables structure is required to achieve peak performance, still this property however dependent of the disk subsystem.

Relational databases management systems (RDBMS) support a set of properties defined by the acronym ACID: Atomicity, Consistency, Isolation and Durability.

Atomicity: A transaction is "all or nothing" when it is atomic. If any part of the transaction or the underlying system fails, the entire transaction fails.

Consistency: Only transactions with valid data will be performed on the database. If the data is corrupt or improper, the transaction will not complete and the data will not be written to the database, data must conform to the schema.

Isolation: Multiple, simultaneous transactions will not interfere with each other. All valid transactions will execute until completed and in the order they were submitted for processing.

Durability: The ability to recover from an unexpected system failure or power outage to the last known state.

A relational database is mostly suited when there is a need on gathering business intelligence reports or in-depth analytics of large volumes of structured data. Example of RDBMS include: *SQL Server*, *MySQL*, *Oracle*, *PostgreSQL*,

Even with all the features, relational databases are not capable to provide the scale and agility needed to meet the challenges that face modern applications, nor were they designed to take advantage of the inexpensive storage and processing power that have become so readily available today.

Actually the features of such databases limit the feasibility and scalability of it, as in order for example to maintain the ACID properties the database has to pass through various parameters which limits its performance and also the schema part is lacking, therefore the need for a new design that overcome those limits, that brings us to talk about NoSQL databases.

I.10.4.2 NoSQL (Not Only SQL) databases:

NoSQL is the term used to describe high-performance, non-relational databases which typically do not enforce a tabular schema of rows and columns found in most traditional database systems, instead non-relational databases use a storage model that is optimized for the specific requirements of the type of data being stored.

Performance is generally a function of the underlying hardware cluster size, network latency, and the calling application, NoSQL databases are designed to scale out using distributed clusters of low-cost hardware to increase throughput without increasing latency.

While RDBMS uses ACID (Atomicity, Consistency, Isolation, Durability) as a mechanism for ensuring the consistency of data, non-relational DBMS use BASE, which stands for Basically Available, Soft state, and Eventual Consistency. Of these, eventual consistency is the most important, because it is responsible for conflict resolution when data is in motion between nodes in a distributed implementation. The data state is maintained by the software and the access model relies on basic availability.

NoSQL is a better choice for businesses whose data workloads are more geared toward the rapid processing and analyzing of vast amounts of varied and unstructured data, e.g.: *Big Data.*

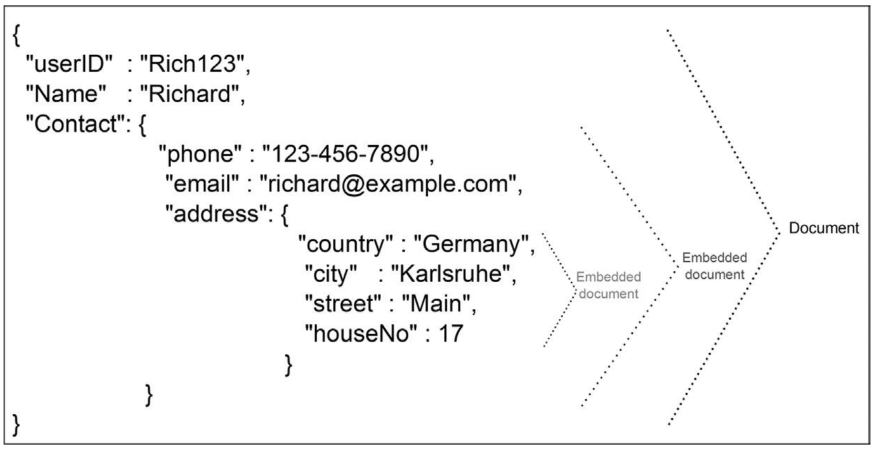
NoSQL databases do not use SQL for queries, and instead use other programming languages and constructs to query the data, even though many of these databases do support SQL-compatible queries. However, the underlying query execution strategy is usually very different from the way a traditional RDBMS would execute the same SQL query.

The following sections describe the major categories of NoSQL database:

• Document Databases:

A document data store manages a set of named string fields and object data values in an entity referred to as a *document*. These data stores typically store data in the form of *JSON* documents. Each field value could be a scalar item, such as a number, or a compound element, such as a list or a parent-child collection. The data in the fields of a document can be encoded in a variety of ways, including *XML*, *YAML*, *JSON*, *BSON* or even stored as *plain text*, document store does not require that all documents have the same structure. This free-form approach provides a great deal of flexibility. Documents are almost equivalent to records in relational term, and collections are more similar to tables, whereas fields are similar to attributes (columns) in each relation.(11)

Example of Document databases implementation include: ***MongoDB***, ***CouchDB***.

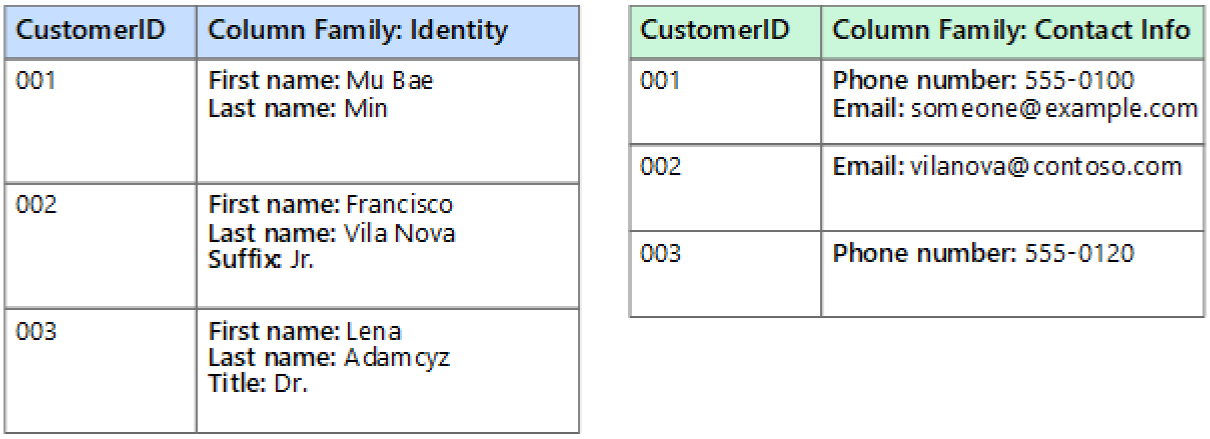


```
{
  "userID"  : "Rich123",
  "Name"   : "Richard",
  "Contact": {
                 "phone" : "123-456-7890",
                  "email" : "richard@example.com",
                  "address": {
                                   "country" : "Germany",
                                    "city"   : "Karlsruhe",
                                    "street" : "Main",
                                    "houseNo" : 17
                                 }
                 }
}
```

Figure I-14 : A document can have many types of values : scalar , lists and nested documents.

• Columnar databases:

A columnar or column-family data store organizes data into columns and rows. In its simplest form, a column-family data store can appear very similar to a relational database, at least conceptually. The real power of a column-family database lies in its denormalized approach to structuring sparse data, which stems from the column-oriented approach to storing data, you can think of a column-family data store as holding tabular data with rows and columns, but the columns are divided into groups known as column families. Each column family holds a set of columns that are logically related and are typically retrieved or manipulated as a unit.



CustomerID	Column Family: Identity
001	**First name:** Mu Bae **Last name:** Min
002	**First name:** Francisco **Last name:** Vila Nova **Suffix:** Jr.
003	**First name:** Lena **Last name:** Adamcyz **Title:** Dr.

CustomerID	Column Family: Contact Info
001	**Phone number:** 555-0100 **Email:** someone@example.com
002	**Email:** vilanova@contoso.com
003	**Phone number:** 555-0120

Figure I-15 : Columnar data store

The above diagram shows an example with two column families, `Identity` and `Contact Info`. The data for a single entity has the same row key in each column family. This structure, where the rows for any given object in a column family can vary dynamically, is an important benefit of the column-family approach, making this form of data store highly suited for storing data with varying schemas.

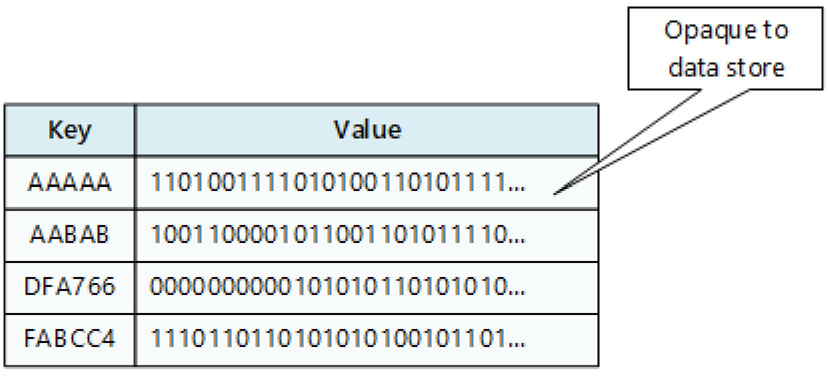
The most popular columnar databases are ***HBase*** databases which relies mainly on Hadoop file system and MapReduce for its operations. we will be covering Hadoop and MapReduce in more details later in chapter 04, other example of columnar databases include : ***Cassandra***, ***AmazonSimpleDB***.

- ## Key/value databases:

A key/value store is essentially a large hash table. You associate each data value with a unique key, and the key/value store uses this key to store the data by using an appropriate hashing function. The hashing function is selected to provide an even distribution of hashed keys across the data storage.

Key/value stores are highly optimized for applications performing simple lookups using the value of the key, or by a range of keys, but are less suitable for systems that need to query data across different tables of keys/values, such as joining data across multiple tables.

One widely used open source key-value pair database is called **Riak,** other examples include: **Aerospike**, **LevelDB**, **DynamoDB**.



Key	Value
AAAAA	1101001111010100110101111...
AABAB	10011000010110011010111110...
DFA766	0000000000101010110101010...
FABCC4	1110110110101010100101101...

Opaque to data store

Figure I-16 : Key/Value data store

• Graph databases:

A graph data store manages two types of information, nodes and edges. Nodes represent entities, and edges specify the relationships between these entities. Both nodes and edges can have properties that provide information about that node or edge, similar to columns in a table. Edges can also have a direction indicating the nature of the relationship.

The purpose of a graph data store is to allow an application to efficiently perform queries that traverse the network of nodes and edges, and to analyze the relationships between entities. The following diagram shows an organization's personnel data structured as a graph. The entities are employees and departments, and the edges indicate reporting relationships and the department in which employees work. In this graph, the arrows on the edges show the direction of the relationships.(11)

Neo4J is the most widely used graph databases, other examples include : ***ArangoDB***, ***OrientDB***, ***BrightstarDB***, ***Meronymy.***

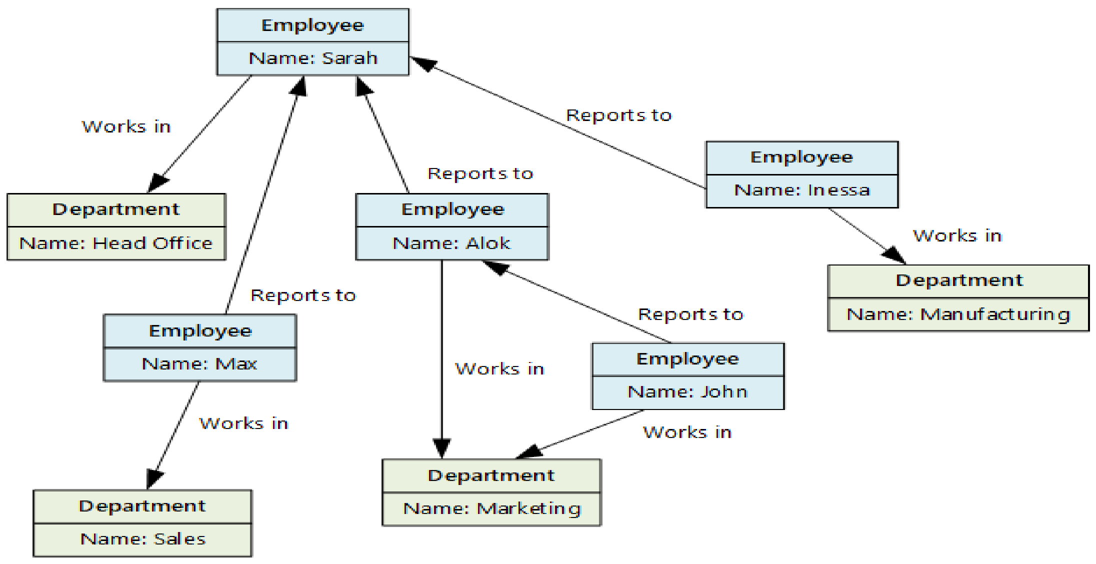


Figure I-17 : Graph data store

Other examples of NoSQL database types include:

- ✓ Multimodel Databases
- ✓ Object Databases
- ✓ Grid & Cloud Database Solutions
- ✓ XML Databases
- ✓ Multidimensional Databases
- ✓ Time Series / Streaming Databases
- ✓ Scientific and Specialized DBs

I.10.5 Layer 4 – Organizing Data Services and Tools:

Once you have understood what you need, what data you are gathering, where to store it, and how to use it, you need to organize it so it can be consumed for analytics, reporting, or specific applications, this is where this layer comes into the picture.

Organizing data services and tools layer capture, validate, and assemble various big data elements into contextually relevant collections, because big data is massive, techniques have evolved to process the data efficiently and seamlessly.

Organizing data services are, in reality, an ecosystem of tools and technologies that can be used to gather and assemble data in preparation for further processing. As such, the tools need to provide integration, translation, normalization, and scale. Technologies in this layer has to include the following:

- **A distributed file system:** Necessary to accommodate the decomposition of data streams and to provide scale and storage capacity
- **Serialization services:** Necessary for persistent data storage and Multilanguage remote procedure calls (RPCs)
- **Coordination services:** Necessary for building distributed applications (locking and so on).
- **Extract, transform, and load (ETL) tools:** Necessary for the loading and conversion of structured and unstructured data.
- **Workflow services:** Necessary for scheduling jobs and providing a structure for synchronizing process elements across layers.

In Chapters 4, we examine Hadoop, the most widely used set of products for organizing big data.

I.10.6 Layer 5 – Analytical Data Warehouses and Data marts:

A data warehouse is a storage architecture designed to hold data extracted from transaction systems, operational data stores, and external sources, the warehouse then combines that data in an aggregate, summary form suitable for enterprise-wide data analysis and reporting.

Before we present the component of a data warehouse, let review some important concepts related to data warehousing for instance: OTLP and OLAP and DataMarts.

IT systems could be divided into transactional systems (Online Transactions Systems: OLTP) and analytical systems (Online Analytical Processing Systems: OLAP). In general, we can assume that OLTP systems provide source data to data warehouses, whereas OLAP systems help to analyze it.

OTLP: OLTP systems record business interactions as they occur in the day-to-day operation of the organization, and support querying of this data to make inferences, they are characterized by a large number of short on-line transactions (INSERT, UPDATE, DELETE). The main emphasis for OLTP systems is put on very fast query processing, maintaining data integrity in multi-access environments and an effectiveness measured by number of transactions per second. In OLTP database there is detailed and current data, and schema used to store transactional databases is the entity model (usually 3NF), The databases that are used for OLTP, however, were not designed for analysis.

OLAP: These Systems are characterized by relatively low volume of transactions. Queries are often very complex and involve aggregations. For OLAP systems a response time is an effectiveness measure. OLAP applications are widely used by Data Mining techniques. OLAP enables the effectiveness use of data warehouses for online analysis, their Key aspect approach is to achieve a multi-dimensional analysis of organization data.

Data marts : A data mart is a subset of data stored within the overall data warehouse, for the needs of a specific team, section or department within the business enterprise. Data marts make it much easier for individual departments to access key data insights more quickly and helps prevent departments within the business organization from interfering with each other's data.

I.10.6.1 Components of a Data Warehouse:

The components of a data warehouse are:

1. **ETL**: Extract Transform and Load or ETL are Toolsets that help acquire variety of data from multiple sources
2. **Warehouse**: The storage component which store data of facts and multiple perspective from which these facts can be analyzed and which are called dimensions.
3. **Metadata**: Attributes that could be associated with facts, including source, format, update frequency, etc.
4. **Cube**: Olap data structure (which is considered as a staging area) that is extracted from the data warehouse for specific subject analysis like sales for example.

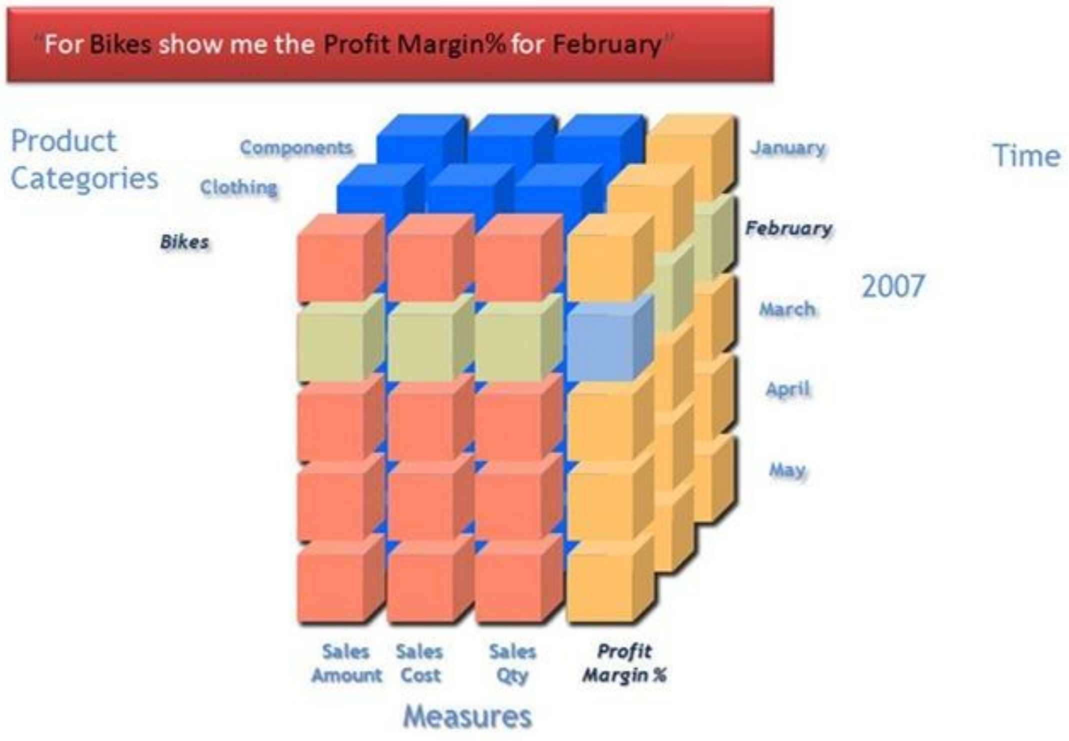


Figure I-18 : OLAP Cube Sales Data Example.

5. **Reports and dashboard**: The visualization that provide business insights.

Figure I-19 highlights the relationships between the components in the analytical datawarehouse layer :

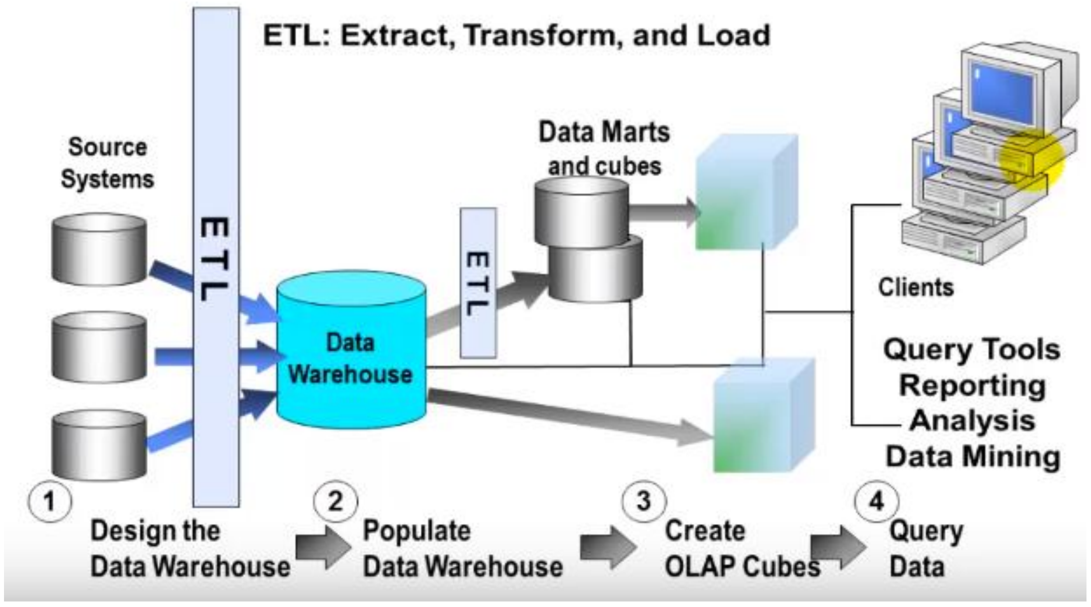


Figure I-19 : Data Warehouse Component.

Data is complementary to become like a hybrid structure. This hybrid structure will include highly structured data managed by traditional data warehouse and the highly distributed and prone to change data is managed by Hadoop-controlled solution.

I.10.7 Layer 6 – Analytics (Traditional and Advanced):

This layer contains analytics methods that reach into the data warehouses and process the data for revealing insights, it contains business intelligence traditional techniques as well as advanced data analytics methods.

I.10.7.1 BI vs. Analytics:

The increasing complexity of businesses problems, the possibility of several alternatives solutions and the limited time available for making the right call in a business scenario demands a highly structured decision-making process, most businesses use huge amount of historical facts, figures, and data available for informed decision making. This is called fact-based decision making and collectively the set of tools, technique, and framework that allowed this is called business intelligence or BI.

Organizations rely heavily on BI to run efficiently, and reducing decision cycle time, however just making the right decision to run operations smartly is not enough today, as a fiercely competitive world require businesses to use data available beyond organizational data, and to foresee future trends, this is where advanced analytics come into the picture.

I.10.7.2 Data Analytics Techniques:

Businesses today analyzes the growing volumes of unstructured and semi-structured data available from multiple new sources such as machines, sensors, logs, and social media, so let’s discuss a bit more about analytics.

Data analytics essentially include a set of statistical, mathematical modeling methods and machine learning techniques and tools to analyze various types of data in huge amounts.

I.10.7.3 Types of Analytical Applications and Techniques:

Analytical applications traditional and advanced typically fall under these four categories depending on the level of answers:

- ✓ Discovery analytics or BI.
- ✓ Exploratory analysis or data mining.
- ✓ Predictive analytics.
- ✓ Prescriptive analyti

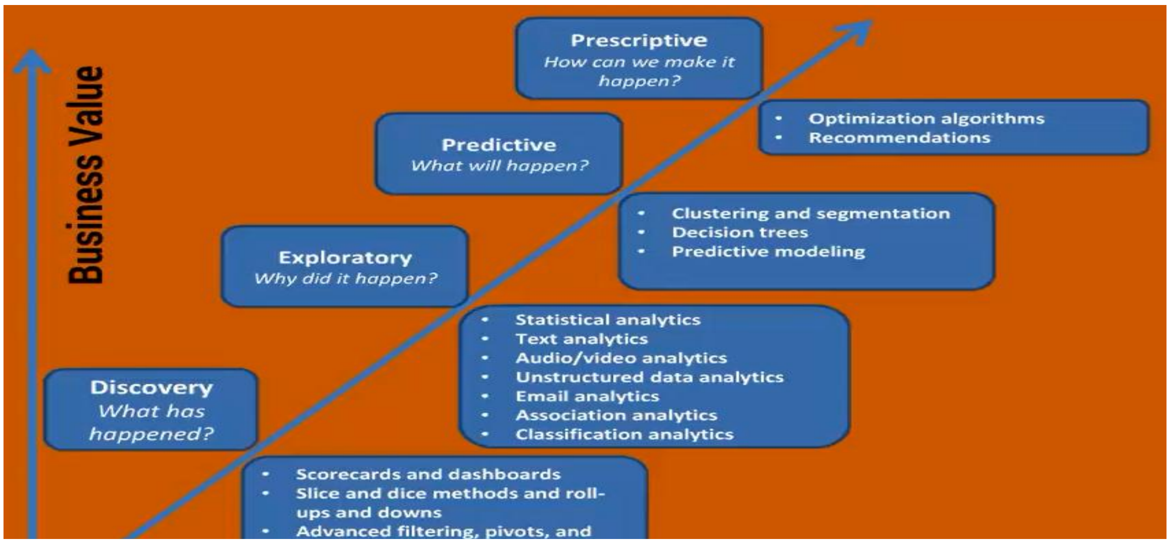


Figure I-20 : Categories of Data Analytics Techniques.

Let's cover each of these briefly:

1. **Discovery analytics:**

DA is the study of huge organizational data sets, some techniques that fall into this category includes: *slicing* and *dicing*, *roll ups* and *downs* and *business graphics*.

2. **Exploratory analytics:**

Goes a step further to analyze data deeper with techniques such as:

a. ***Statistical analytics***: which involves collecting samples of data from a bigger stat and scrutinizing it. this aims at identifying trends such as the primary buyers of a certain brand of products over the last five years for example.

b. ***Text Analytics***: this is the process of analyzing unstructured text, extracting relevant information and transforming it into structured information, that can then be leveraged in various ways, this can be used to detect plagiarism in research papers.

c. ***Audio/Video Analytics***: analyses audio and video data such as those from traffic surveillance cameras, for security or vehicle classification purposes or to analyses traffic density.

d. ***Unstructured data analytics***: this helps extract structured information from unstructured data, an example of this is fraud detection by analyzing credit card data.

e. ***Email analytics***: analyses the email data of customers or organization which can help enhance marketing efforts, for instance use can use email analytics applications to track the customers who read your emails and the ones who delete it.

f. ***Association analytics***: help finds interesting relationships in large data sets for instance, analyses the purchases of consumers on a grocery store and identify the goods they tend to buy together, this can help alter the layout of the store to stock related items in one location.

g. ***Classification analytics***: helps classify data, for instance, a marketing manager can analyses customer profiles and classify the customers into categories of the ones who will make a purchase and the ones who will not

h. ***Graph mining***: graph mining along with subgraph mining are the subject of this report and so will be covering them in much more details in the next chapter.

3. **Predictive analytics:**

This is an advanced technique that aims to predict the probability of occurrence of a future event such as loan defaults, stock market fluctuations and so on, and thus taking preventive actions accordingly, some techniques that fall into this category include:

Clustering and *segmentation*, *creating decisions trees*, *predictive modeling*.

4. **Prescriptive analytics:**

This helps analyze future trends to create strategies and find an optimal solution to a problem or select an appropriate decision form multiple alternatives, unlike predictive analytics that shows the probability of a future event prescriptive analytics helps identify a solution to an existing problem for example inventory management.

I.10.8 Layer 7 – Reporting and Visualization:

- **Reporting and dashboards**: these are user-friendly tools used to represent information collected from various sources. this area is still evolving to support Big Data needs and currently it accesses new database technology

- **Visualization**: these can be seen as advanced reporting tools which provide pictorial or graphical representation for data and help users to easily understand the data and relationship of several variables at the same time. the output of these tools is greatly interactive and dynamic. these tools have employed new techniques to enable users to watch the data as being changing in real time.

Visualization techniques include: *mind maps*, *heap maps*, *infographic* and *connection diagrams*.

I.10.9 Layer 8 – Big Data Applications:

Users are most interested with the technology products relevant to this layer as they are the end products which they interact with. these products can be third-party applications or in-house applications which can fulfill common requirements of multiple industries or the requirement of particular industry. Some examples of well-known groups are log data application (***Splunk***, ***Loggly***), marketing applications (***Bloomreach***, ***Myrrix***) and advanced Media applications (**Bluefin**, **DataXu**). Building custom products for Big Data should follow up proper software development standards, for example to include well-defined API interface which will help the developers to access the functionalities exposed by each layer through those interfaces

I.11 Virtualization and Cloud Computing in Big Data:

With the advent of big data, the nature and volume of data that the organization received and needed to handle increased by multiple times this required for constant upgradation of hardware and software to handle and analyze the data effectively and efficiently.(12)

Traditionally businesses were incurring huge capital investments year-on-year for purchasing and maintaining IT infrastructure and software to meet their business needs, however this approach was not sustainable in the long run businesses can no longer afford to start over and build all new applications every time, a solution for this problem was found in the evolution of virtualization and cloud computing technologies, these technologies enabled the system to support:

- On-demand provisioning of resources
- Full utilization of IT resources
- Pay per use model of provisioning
- IT infrastructure support as a service

Cloud computing and virtualization complement big data by enabling a global on-demand network access to a shared pool of configurable computing resources.

I.11.1 Virtualization:

The term virtualization refers to the use of software to divide a pool of physical infrastructure resources into several logical IT infrastructure resources.

With virtualization users can create many virtual systems within a single physical system rather than assigning a dedicated set of physical resources to a set of tasks, a pooled set of virtual resources are allocated as needed across all workloads, virtualization also provide a level of automation and standardization to optimize a computing environment, it supports the scalability and operating efficiency required for big data and this is achieved by its three key characterizations which are for instance partitioning, isolation and encapsulation.

1. **Portioning:** allows multiple applications and operating systems to exist in a single physical system and share available resources.

2. **Isolation:** ensures that each virtual machine runs as a separate instance and is isolated from the physical system and other virtual machines, thereby minimizing the chances of crash or breach of data.

3. **Encapsulation:** enables the virtual machine to be presented to an application as a complete entity, thereby protecting it from interference by other applications.

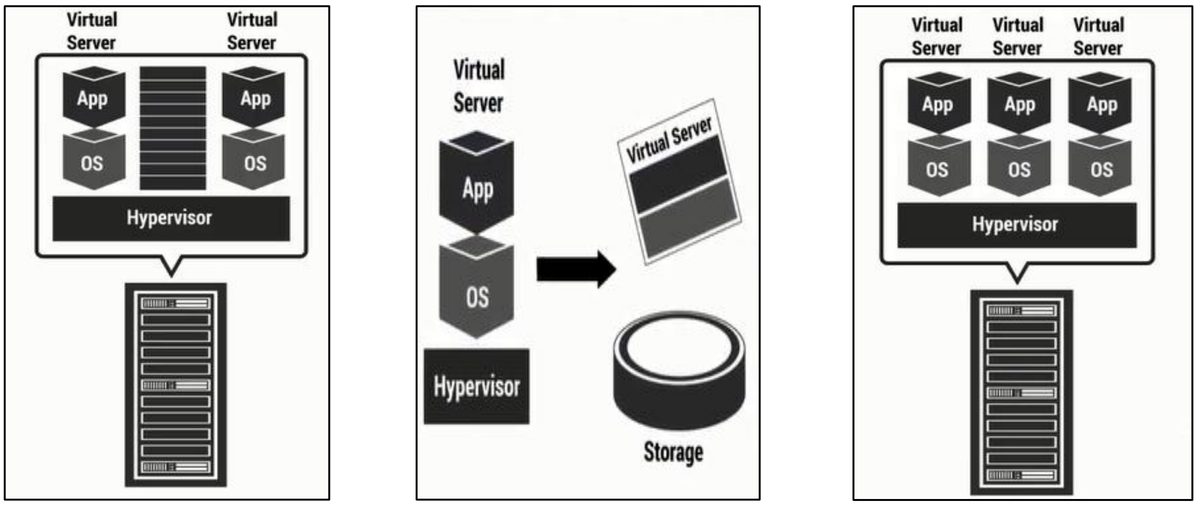


Figure I-21 : Partitioning – Isolation – Encapsulation.

Some of the important benefits of virtualization includes:

- ✓ Cost Saving.
- ✓ Security.
- ✓ Efficiency.
- ✓ Enhanced speed.
- ✓ Flexibility.

In order for the big data environments to scale almost without bounds, the elements of it should be virtualized, this includes:

I.11.1.1 Server virtualization:

This involves the use of a software application that divides one physical server into multiple isolated virtual environments. this ensures the scaling of the big data environment to perform analysis of very large data sets.

I.11.1.2 Application virtualization:

Big data analysis may require independent deployment of different applications, application virtualization encapsulates individual applications for big data and removes their dependencies from the underlying physical computer system. This in turn improves the overall manageability and portability of these applications on different computers.

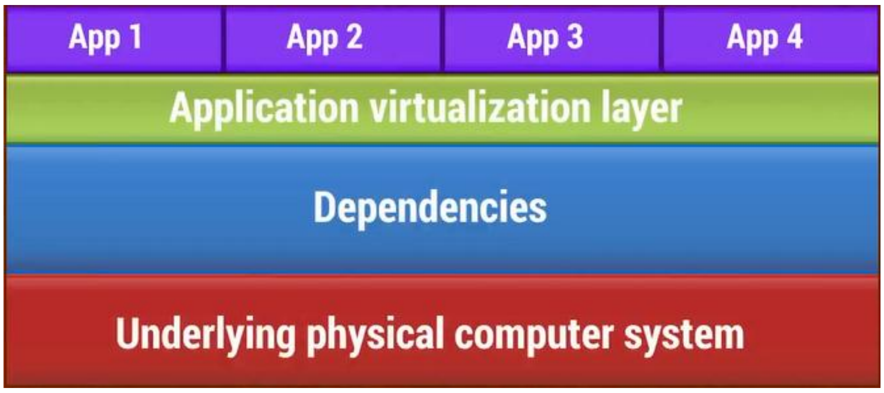
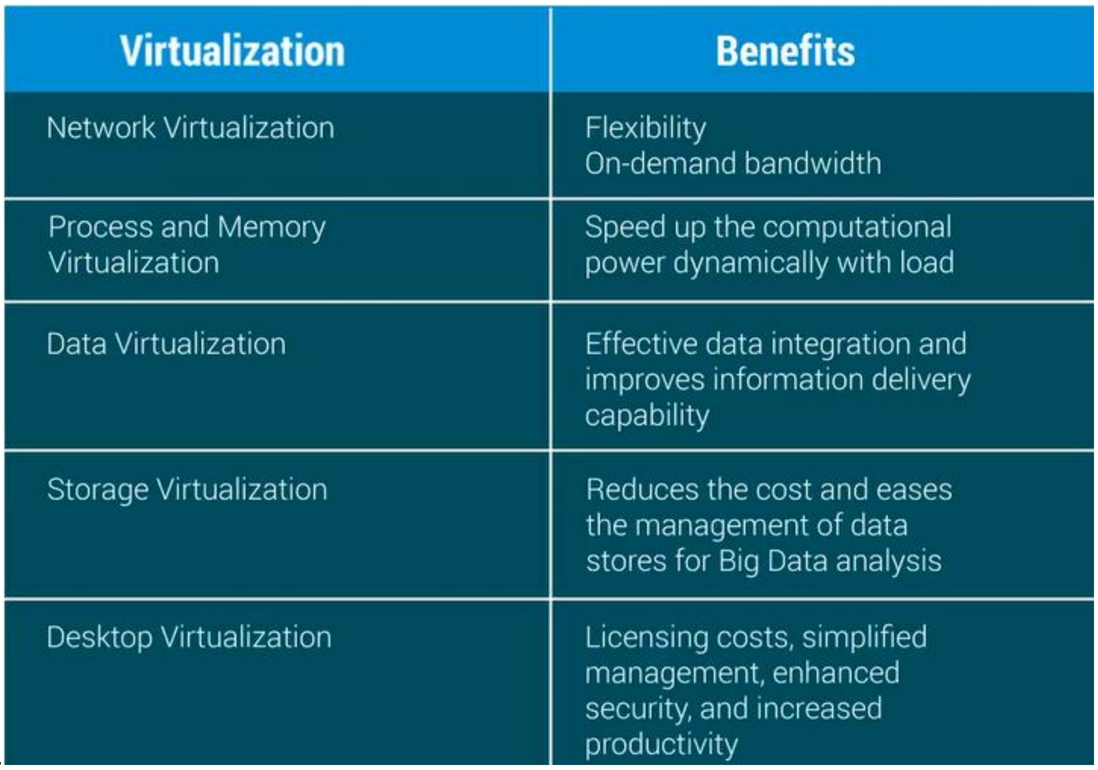

App 1
App 2
App 3
App 4
Application virtualization layer
Dependencies
Underlying physical computer system

Figure I-22 : Application Virtualization.

Other than consolidation of servers and application virtualization, elements than can be virtualized and which also have a positive impact on big data include network, processors, memory, data, storage and desktop.

The table below lists this these elements along with their benefits:

Table I-2 : Virtualization of different elements.



Virtualization	Benefits
Network Virtualization	Flexibility On-demand bandwidth
Process and Memory Virtualization	Speed up the computational power dynamically with load
Data Virtualization	Effective data integration and improves information delivery capability
Storage Virtualization	Reduces the cost and eases the management of data stores for Big Data analysis
Desktop Virtualization	Licensing costs, simplified management, enhanced security, and increased productivity

I.11.2 Cloud Computing:

The generally accepted definition of cloud computing comes from the National Institute of Standards and Technology NIST, it defines cloud computing as fellow:

"Cloud computing is a model for enabling convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction."

What this means in plain terms is the ability to utilize parts of bulk resources and that it enables rapid scaling of resources quickly and easily, often the term cloud computing is wrongly used synonymously for virtualization and data center however both are different technologies, let's now look at the difference between a data center and a cloud.(12)

I.11.2.1 Data Center vs. Cloud Computing:

A data center refers to on-premise or off-premise networked computer servers used within an entreprise for the storage, processing and distribution of vast amounts of data.

A cloud on the other hand is an off-premise internet computing that is used by other external enterprises for storage, processing and distribution of vast amounts of data.

Figure I-23 highlights some of their differences:

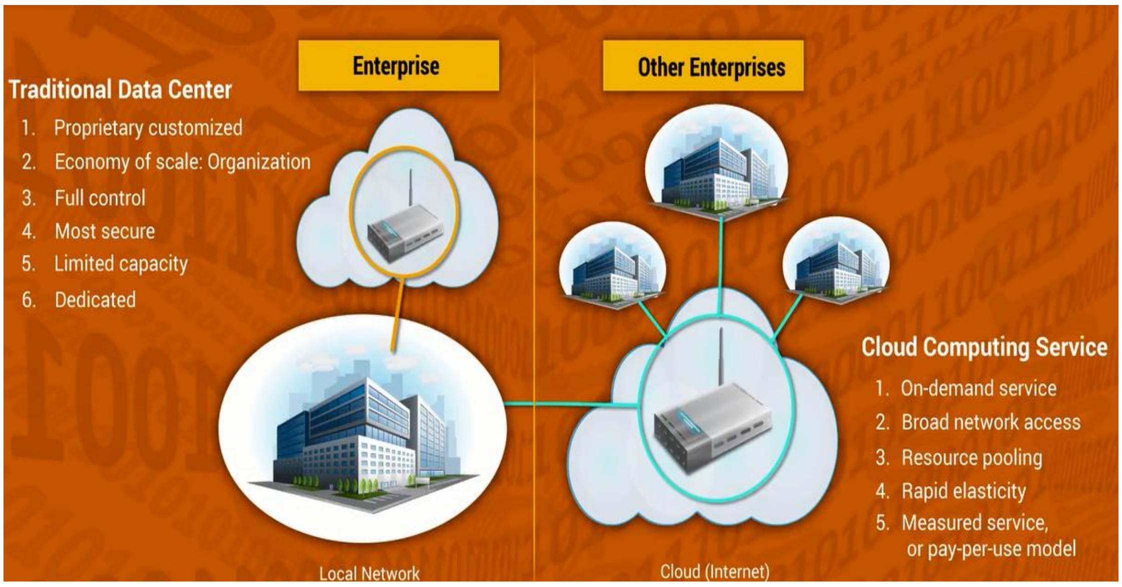


Figure I-23 : Data Center vs. Cloud Computing.

I.11.2.2 Cloud as a solution to big data requirements:

The benefits of cloud computing can be easily understood and appreciated based on the requirements of big data analysis, for any big data implementation availability of various components and a plan for their seamless integration and ongoing maintenance is a must, cloud allows for self-provision cloud services this automates and centralizes maintenance, software updates, configuration and other management tasks, cloud computing provides high power servers for analyzing big data in minutes, this rapid provisioning, scalability and elasticity is a cost effective way to support big data technologies clear benefit of clouds for handling big data analysis.

Finally, for reliability requirement of big data the cloud needs to provide fault tolerance, by the mean of virtualization that help shared applications and resources to coexist as independent virtual machines.

I.11.2.3 Cloud Computing Stack:

The broad collection of services that are made available to end users on a pay-as-you-use model by the cloud is commonly referred to as cloud computing stack.

The stack shows three different categories within cloud computing, Software as a service (***SaaS***), Platform as a service (***PaaS***), Infrastructure as a service (***IaaS***).

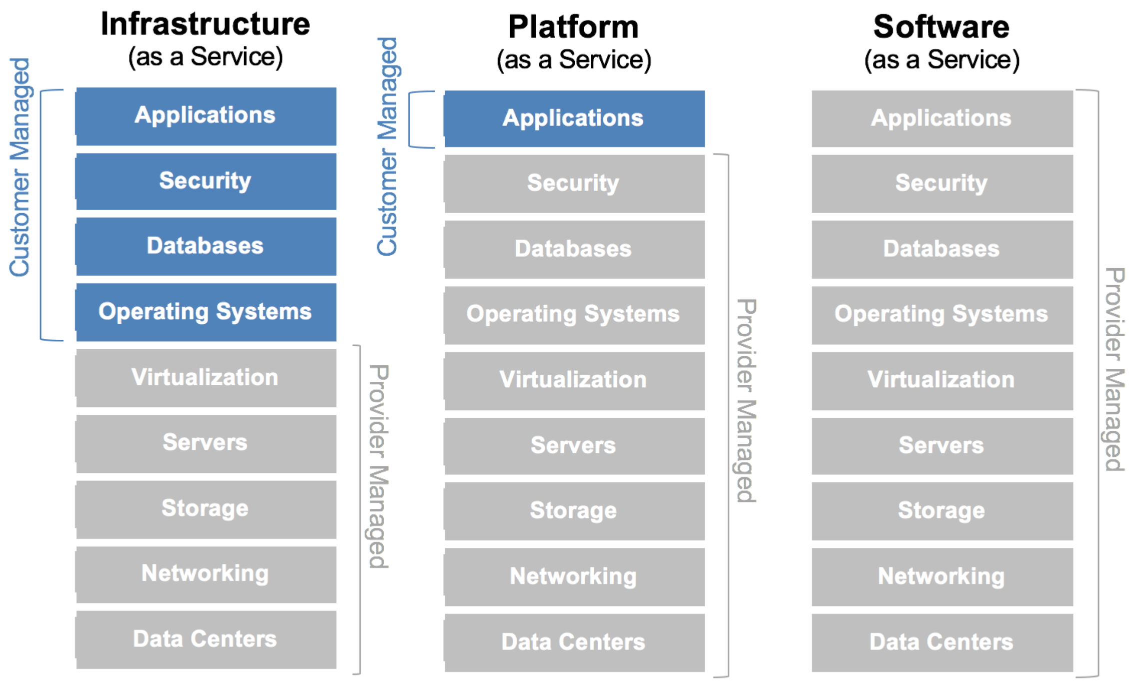


Figure I-24 : Cloud Computing Stack.

1. Infrastructure as a Service (IaaS):

IaaS provides hardware, storage and network as a service examples include virtual machines, load balancers and network attached storage a business for example can save a lot on physical infrastructure by using a public cloud IaaS.

2. Platform as a Service (PaaS):

PaaS on the other hand provides a platform to write and run user's applications examples include *Windows Azure* and *Google App Engine* (GAE), note that a platform here refers to the OS which is a collection of middleware services and software development and deployment tools if an organization uses a private cloud PaaS its programmers can create and deploy applications for its needs.

3. **Software as a Service (SaaS):**

Lastly SaaS provides software that can be accessed from anywhere for SaaS to work however the infrastructure IaaS and the platform PaaS must be in place.

Organizations can choose where, when and how they use these services however most organizations use all three services as infrastructure by itself isn't useful and idle till the platform and the necessary information or application is made available for solving a particular problem.

I.11.2.4 Cloud Deployment models:

different deployment models exist in cloud computing which answer questions of ownership, operations and usage.

1. **Public Cloud:**

One model is a public cloud which is owned and operated by an organization for use by other organizations and individuals, a public cloud can customize hardware and software to optimize performance however problems of security and latency are an inherent part of public clouds.

2. **Private Cloud:**

A second cloud deployment model is a private cloud which is owned and operated by an organization for its own purposes all stakeholders of an organization have access to this cloud, a private cloud incorporates the systems and processes of that organization and is highly automated and protected by firewall, as a result latency is reduced and security is improved.

3. **Hybrid Cloud:**

Some organizations combine the two last mentioned models in what is called a hybrid cloud, a number of connections are formed between the two clouds and operations are automated to improve efficiency.

Key Points – Chapter 01 :

- We presented the field of big data, gave a brief history of it and the different definitions attributed by the practitioners in the field.
- We defined the characteristics of big data for instance: Volume, Velocity and Veracity.
- We discussed big data types, structured / unstructured, at rest / in motion.
- We presented the big data technology stack, which is comprehensive environment that includes hardware infrastructure and software that provide a fully functional model for managing the Big Data requirements.
- We highlighted some databases technologies associated with big data as well as some of the analytical methods traditional and advanced that help derive insight and value from big data.
- We Concluded the chapter by mentioning some of the benefits brought by cloud computing and virtualization relative to big data.

Chapter II :

Graph Theory and Frequent Subgraph Mining

II. Chapter 02 :

Graph Theory and Frequent Subgraph Mining

Context:

This Chapter defines in details the concept of graph mining and focus primarily on frequent subgraph mining (FSM), it is organized in two parts:

Part 01 mainly dedicated to present, in a simplified way, the basic notions related to graphs and graph theory.

Part 02, focus on presenting "the state of the art" of Frequent Subgraph mining (FSM) algorithms and techniques. A survey of current research in the field, and solutions to address the main research issues are also presented.

II.1 Data mining:

Data mining is a particular step in the process of Knowledge Discovery in databases (KDD), which has a to extract statistically significant and useful knowledge from a huge volume of raw data sets, extracting such important knowledge can be crucial, sometimes essential, for the next phase in the analysis: the modeling.(13) The KDD process is outlined in figure II-1.

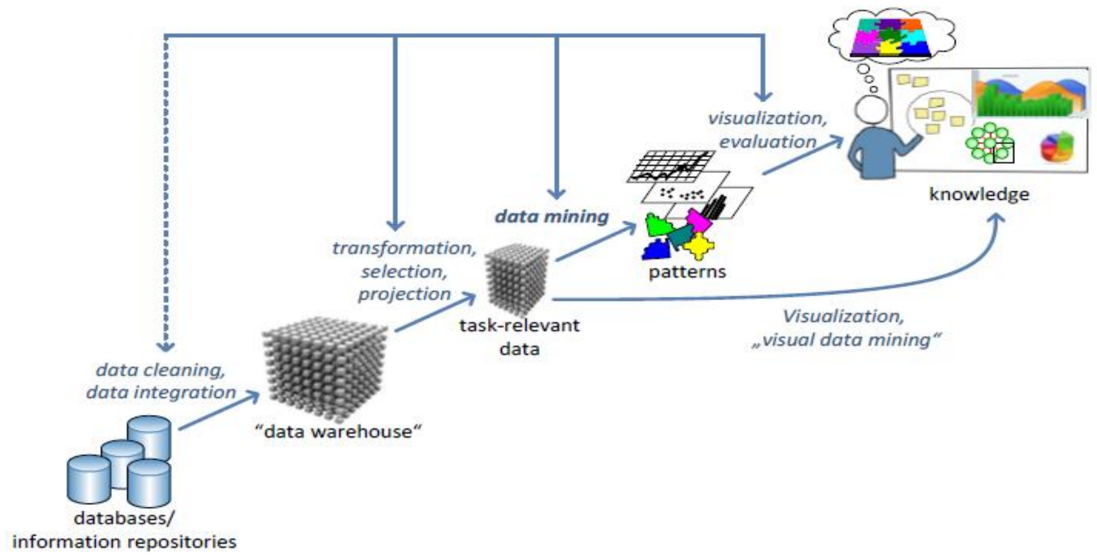

visualization, evaluation
knowledge
data mining
patterns
transformation, selection, projection
task-relevant data
Visualization, „visual data mining"
data cleaning, data integration
"data warehouse"
databases/ information repositories

Figure II-1: The steps of the KDD process.(14)

The additional steps in the KDD process include the data selection and projection, and the visualization, and evaluation steps.

During the past decade, the field of data mining has emerged as a novel field of research, investigating interesting research issues and developing challenging real-life applications. The objective data formats in the beginning of data mining, were limited to relational tables and transactions where each instance is represented by one row in a table or one transaction represented as a set.

However, the studies within the last several years began to extend the classes of considered data to semi-structured data such as HTML and XML texts, symbolic sequences, and relations represented by advanced logics.

Frequent pattern mining for instance has been a focused theme in data mining research for over a decade. Abundant literature has been dedicated to this research and tremendous progress has been made, ranging from efficient and scalable algorithms for frequent item set mining in transaction databases, mining association rules, to numerous research frontiers, such as sequential pattern mining. However, the arising and variety of the above-mentioned complex semi structured data and the need of discovering structural patterns in large datasets, which go beyond sets, sequences, and trees, toward complicated structure, makes the frequent item sets and frequent sequence mining approaches inefficient and unsuitable for such requirements, thus the emergence of graphs and frequent structural mining as a solution to these concerns.

Certainly graphs as a data structure can meet the demands of modeling complicated substructure patterns and relations among data, and they are suitable representation for complex objects so from this perspective, there has been much interest in the mining of graph data, (often referred to as graph based data mining or shortly graph mining).

II.2 Graph mining:

Generally speaking, Graph mining is the process of discovering, retrieving and analyzing non trivial patterns in graph shaped data. Graph based data mining or graph mining has a strong relation with Multi-relational data mining. However, the main objective of graph mining is to provide new principles and efficient algorithms to mine topological substructures embedded in graph data, while the main objective of multi-relational data mining is to provide principles to mine and/or learn the relational patterns, represented by the expressive logical languages, the former is more geometry oriented and the latter more logic and relation oriented.(15)

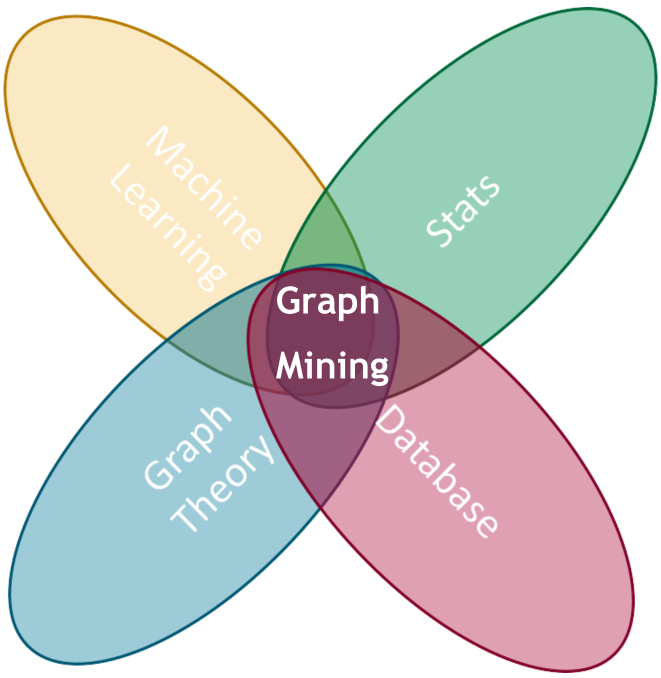


Figure II-2 : Graph mining Related Concept

A number of popular research sub-domains of graph mining are listed in Table

Table II-1 : Graph mining research subdomains

Frequent subgraph mining(16–18)
Correlated graph pattern mining(19)
Optimal graph pattern mining(20)
Approximate graph pattern mining(21)
Graph pattern summarization(22)
Graph classification(23)
Graph clustering(24,25)
Graph indexing(26)
Graph searching(27,28)
Graph kernels(29–31)
Link mining(32–34)
Web structure mining(35)(36)
Work-flow mining(37)
Biological network mining(38)

II.3 Graphs applications:

Due to its capability of modeling complicated structures, graph representation of data is well adopted and prevalent in a variety of domains including wired/wireless interconnections (networks), 2D/3D objects (vision and pattern recognition), chemical compounds/biological networks (chem/bio-informatics), circuits (computer-aided design), loosely schemed data (XML), RDF data (semantic web), program traces (software engineering), social media, etc.(39)

In chemistry for example chemical data, Chemical data (molecules, compounds) is often represented as graphs in which the nodes correspond to atoms, and the links correspond to bonds between the atoms.

Figure II-3 present a graph representation of a chemical compound:

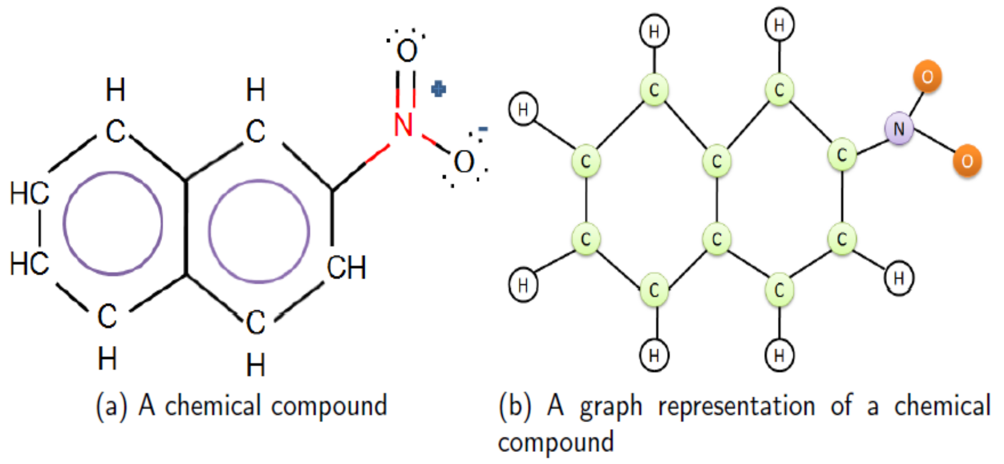


Figure II-3 : Graph representation of a chemical compound.(13)

Benefiting from systems for searching and mining frequent pattern in chemical compounds, researchers can do screening, designing, and knowledge discovery in large-scale compound and molecular data sets.

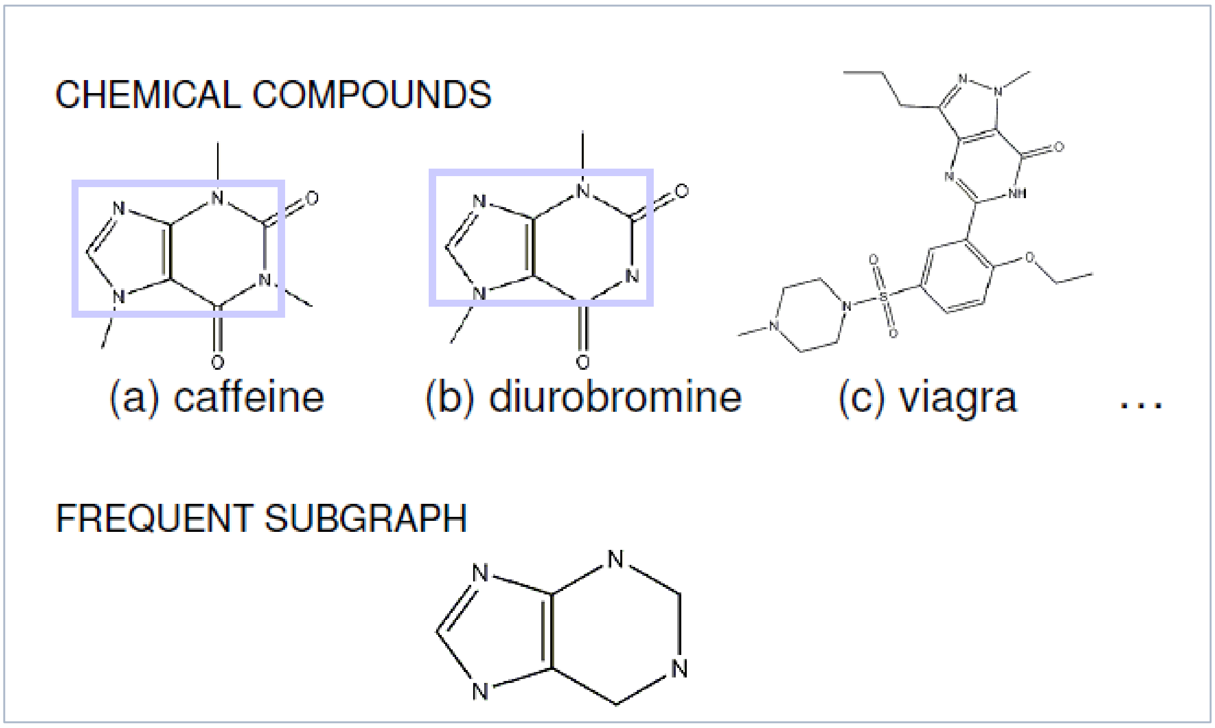


Figure II-4 : Frequent subgraph mined from a variety of chemical compounds

In software engineering a program can be modeled by control flow graph where basic blocks are represented as nodes and edges between nodes indicate the possible flow of the program. Analysis of control flow graphs can shed light on the static and dynamic behaviors of programs and aid in detecting malware and viruses.

Additionally, advanced frequent patterns mining techniques can help us understand different advanced functions and relations. For example, in a protein-protein interaction network (PPI), a frequent pattern could uncover unknown functions of a protein. Similarly, in a social network, a frequent pattern could show a friend clique.

Figure II-5 shows a protein–protein interaction network, represented as a graph where vertexes denote different proteins and the edges denote the physical interactions between them, additionally Figure II-6 shows an example of a social network graph representation.

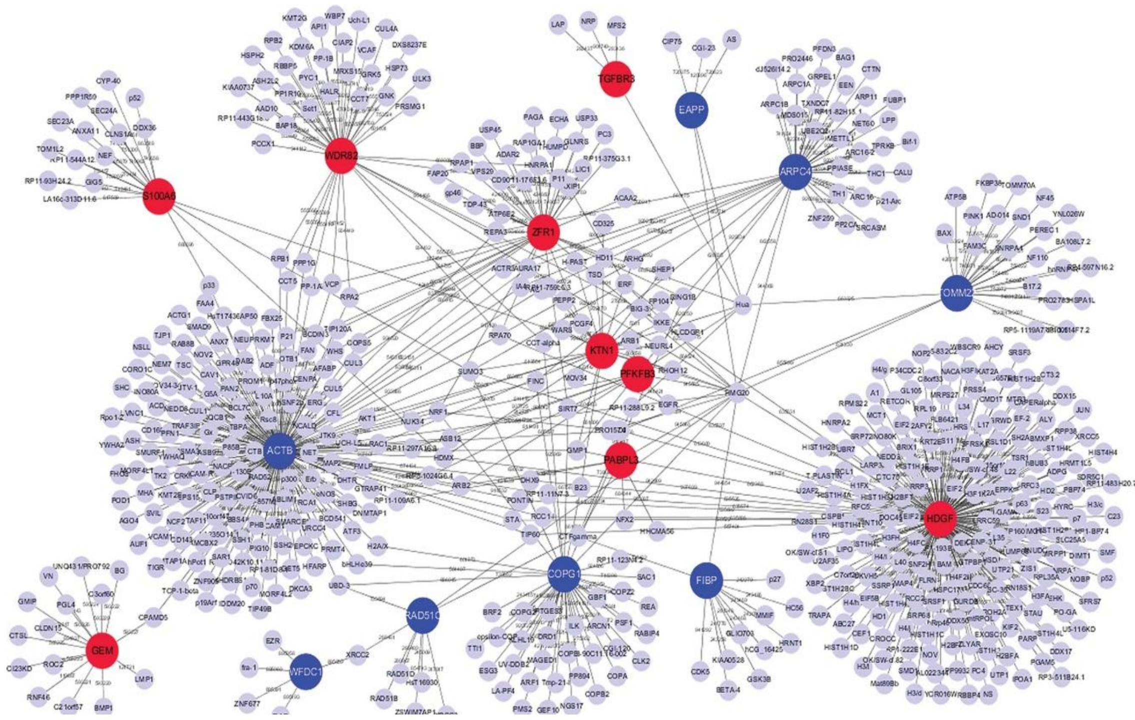


Figure II-5 : Protein – Protein interaction network.

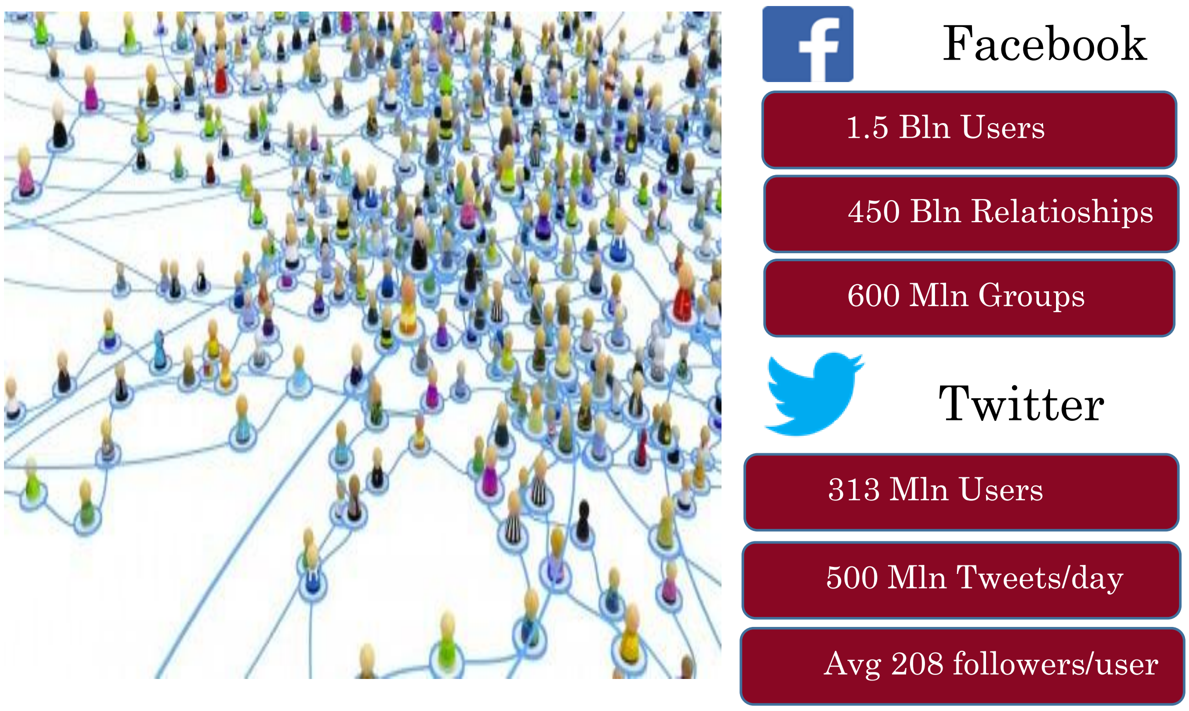


Figure II-6 : Social media graphs : there are complex Groups, links, preferences and attributes.

Social media networks (graphs), along with other example of recommendation and knowledge graphs has the feature of being complex, ubiquitous and valuable, therefore applying advanced mining techniques for finding frequent patterns that specify a given minimum frequency constraint, could help reveal the rules that derives their evolution.

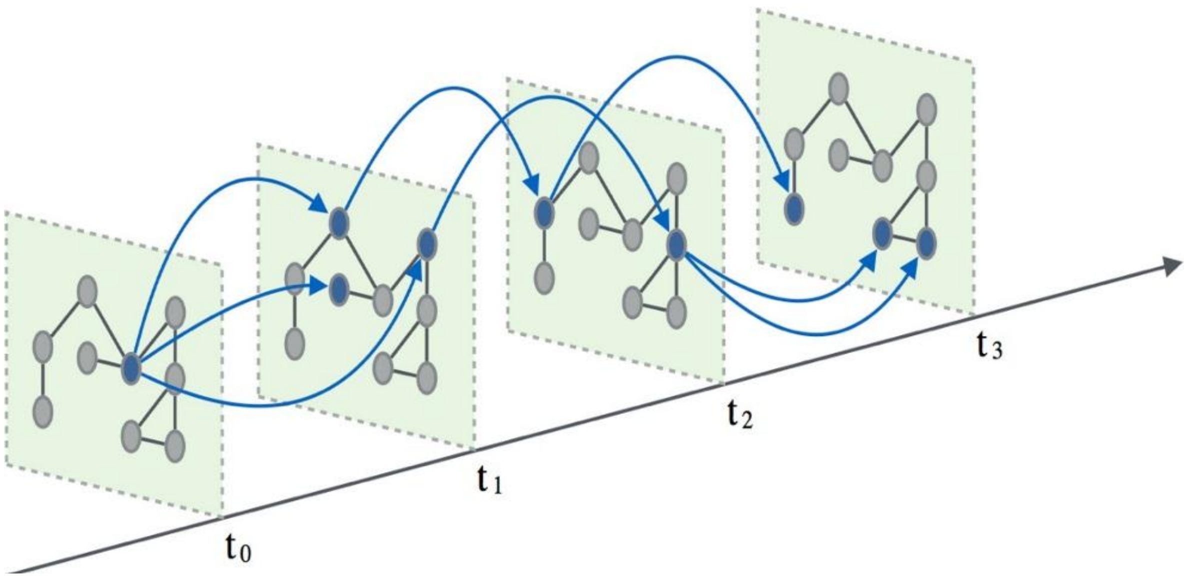


Figure II-7 : Mining graph evolution rules.

II.4 What is Involved in graph mining:

- Basic graph algorithms (shortest paths, BFS, DFS, isomorphisms, traversals, random walks …)
- Storage and indexing
- Smart representations for compactness
- Modeling of problems as graphs
- Distance metrics and similarity measures
- Exact, Approximate, and heuristic algorithms
- Evolving structures
- Interactivity and online updates
- Complexity (most of the problems are not polynomially solvable)

II.5 Frequent subgraph mining (FSM):

Among the various kinds of graph pattern, frequent subgraphs are very basic ones that can be discovered in a set of graphs (graph database) or a single large graph, they are useful at characterizing graphs sets, discriminating different groups of graphs, classifying and clustering graphs and building graphs indices, frequent subgraph mining encompass all the techniques and methodologies used to discover such patterns.(40)

Before diving into the details of the variant frequent subgraph mining approaches and algorithms, let’s review first some of graph theory basic concepts and terminologies.

II.6 Graph theory:

Graph theory is a branch of discrete mathematics that deals with the way objects are connected. Thus, the connectivity in a system is a fundamental quality of graph theory. The principal concept in graph theory is that of a *graph.* For a mathematician, a graph is the application of a set on itself, i.e., a collection of elements of the set and the binary relations between these elements. Graphs are one-dimensional objects, but they can be embedded or realized in spaces of higher dimensions.(41)

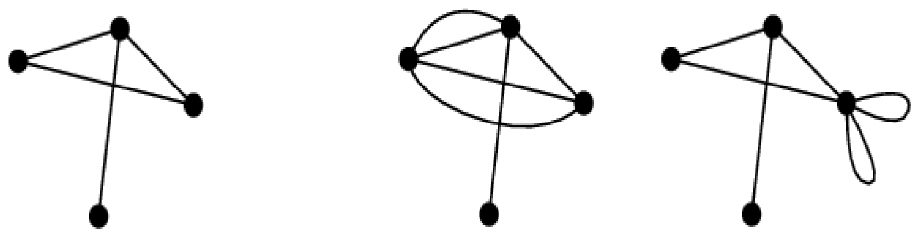
II.7 Preliminary definitions:

In the following paragraphs a number of widely used definitions, used later in this chapter are introduced:

II.7.1 Types of graphs:

Generally speaking, a ***graph G (V, E)*** is defined to be a set V of ***vertexes*** (nodes) which are interconnected by a set E of ***edges*** (links). The number of elements N in V is called the ***order*** of G and it is noted $|V| = N$ and the number of elements M in E is the ***size*** of G and it is noted $|E| = M$.

Simple and multigraphs : In a graph G, when any two vertices of V are joined by more than one edge, the graph is called a ***multigraph***. A graph without loops and with at most one edge between any two vertices is called a ***simple graph*** The graphs used in FSM are assumed to be *labelled simple graphs*.



(a) (b)

Figure II-8 : (a) Simple Graph, (b) nom simple graph having multiple edge (left) nom simple graph having loops(right).

In a graph G (V, E) for an edge $e = \{u, v\}$, we say:

- e **connects** u and v.
- u and v are **end points** of e.
- u and e are **incident** (v and e are incident).
- u and v are **adjacent** or **neighbors**.

The **degree deg(v)** of a vertex v is the number of edges incident to it. A vertex of degree 0 is called **isolated**.(42)

Regular Graphs : a graph G in which all vertices are of equal degree is called a **regular graph**, A regular graph of degree k is also called $\boldsymbol{k-Regular}$.

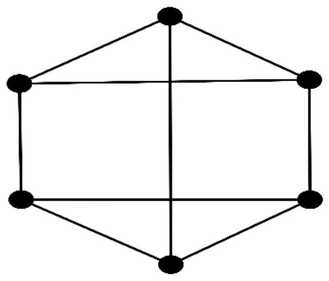


Figure II-9 : 3-Regular graph k=3.

Labeled Graphs : A labelled graph can be represented as $G(V, E, L_V, L_E, \varphi)$,where V is a set of vertexes, $E \subseteq V \ x \ V$ is a set of edges; L_V and L_E are sets of vertex and edge labels. respectively; and φ is a label function that defines the mappings $V \rightarrow L_V$ and $E \rightarrow L_E$, When the edge labels are members of an ordered set (e.g., the real numbers), a labeled graph may be called a ***weighted graph***.(43)

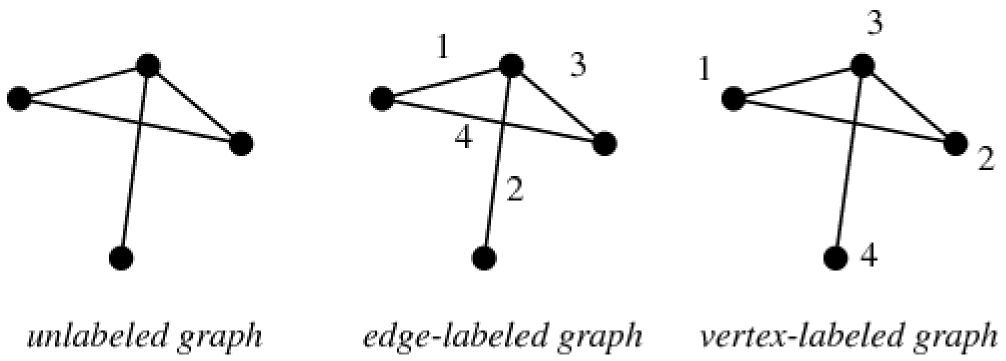


Figure II-10 : Unlabeled and Labeled graphs.

Directed and undirected graphs : a graph G is ***un- directed*** if $\forall \ e \in E$, e is an un-ordered pair of vertexes, and directed otherwise.

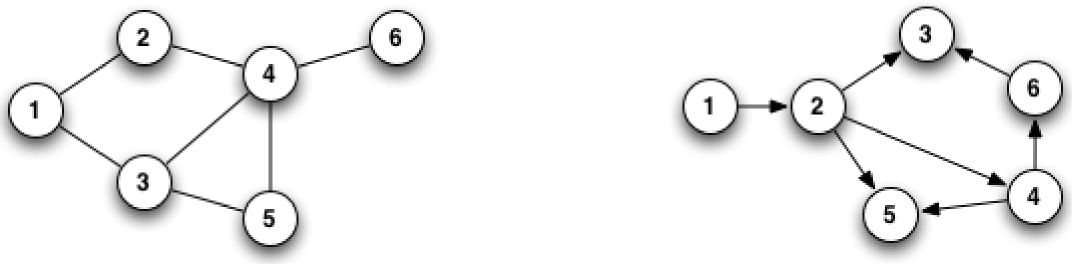
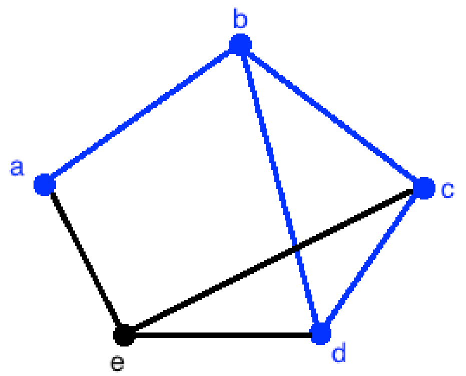


Figure II-11 : Undirected graph (left), Directed graph (right).

Walk, Trails , Paths and Cycles : A ***walk*** of a graph G is an alternating sequence of vertices and edges $v_0, e_1, v_1, \dots \dots .., v_{i-1}, e_i, v_i$ beginning and ending with vertices, in which each edge is incident with two vertices immediately preceding and following it. This walk joins the vertices v_0 and v_i, and may also be denoted by $v_1, v_2, \dots \dots .., v_i$ (the edges being evident by context). The length l of a walk is the number of occurrences of edges in it; v_0 is called the ***ini1ial vertex*** of the walk, while v_i, is called the ***terminal vertex*** of the walk.

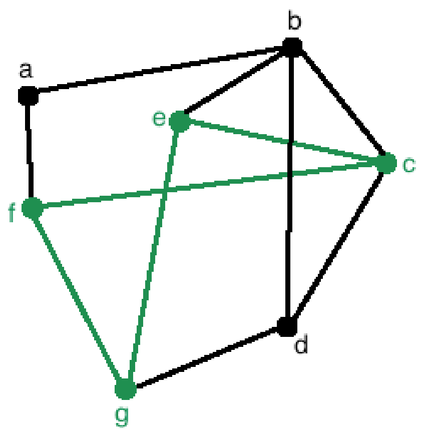
For example, the graph below outlines a possibly walk (in blue). The walk is denoted as $abcdb$. Note that walks can have repeated edges. For example, if we had the walk $abcdcbce$, then that would be perfectly fine even though some edges are repeated.



In the graph above, the length of the walk is $abcdb$ is 4 because it passes through 4 edges.

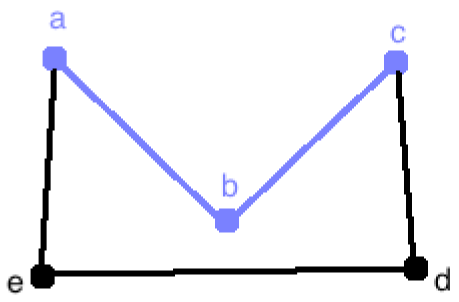
A ***closed walk*** is a $v_i - v_i$ walk, i.e., a walk which starts and ends at the same vertex v_i, Otherwise, a walk is said to be open.

For example, the follow graph shows a closed walk in green:



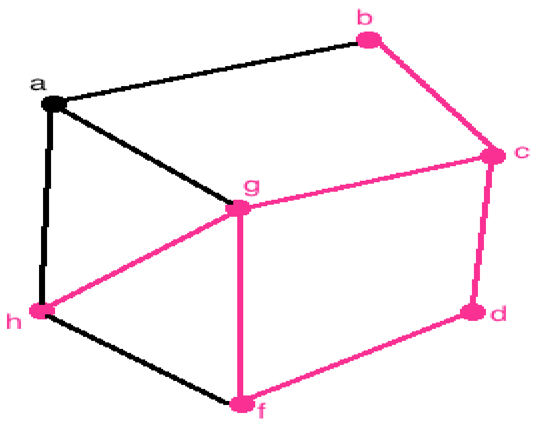
Notice that the walk can be defined by $cegfc$, and the start and end vertices of the walk is c. Hence this walk is closed.

A walk is a ***trail*** if all the edges are distinct. So far, both of the earlier examples can be considered trails because there are no repeated edges. Here is another example of a trail:



Notice that the walk can be defined as abc. There are no repeated edges so this walk is also a trail.

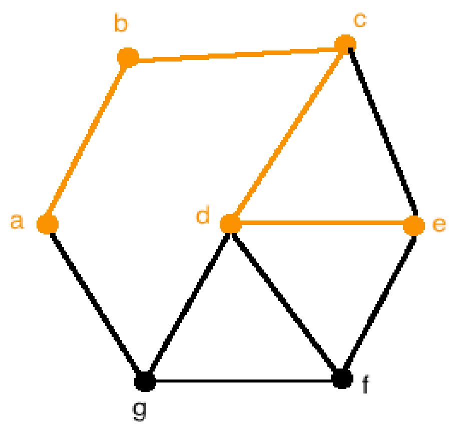
Now let's look at the next graph:



Notice that this walk must repeat at least one edge.

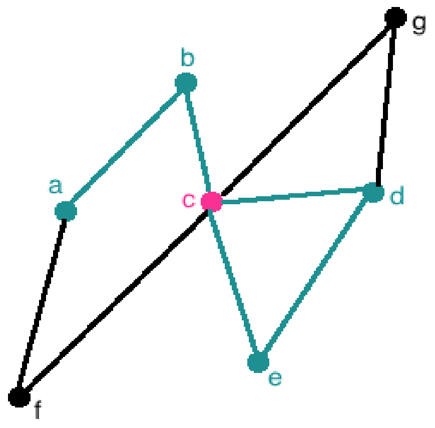
A walk is a ***path*** if all vertices (and thus necessarily all edges) are distinct, in other means a path is defined as an open trail with no repeated vertices.

Notice that all paths must therefore be open walks, as a path cannot both start and terminate at the same vertex. For example, the following orange colored walk is a path:



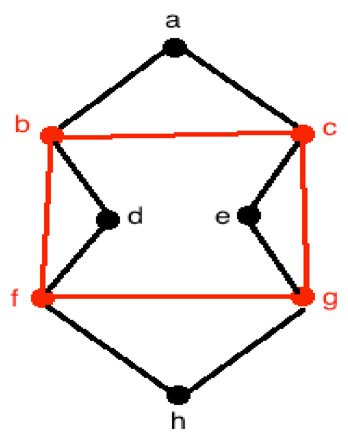
because the walk $abcde$ does not repeat any edges.

Now let's look at the next graph with the teal walk. This walk is NOT a path since it repeats a vertex, namely the pink vertex c:



Moreover, a ***cycle*** in G is defined as a closed trail where no other vertices are repeated apart from the start/end vertex. And additionally an acyclic graph G is defined as a graph having no cycle.

Below is an example of a cycle. Notice how no edges are repeated in the walk $bcgfb$, which makes it definitely a trail, and that the start and end vertex b is the same which makes it closed.



Connected and complete graphs : G is ***connected***, if it contains a path for every pair of vertexes in it and ***disconnected*** otherwise. G is ***complete (clique)*** *if* each pair of vertexes is joined by an edge.(44)

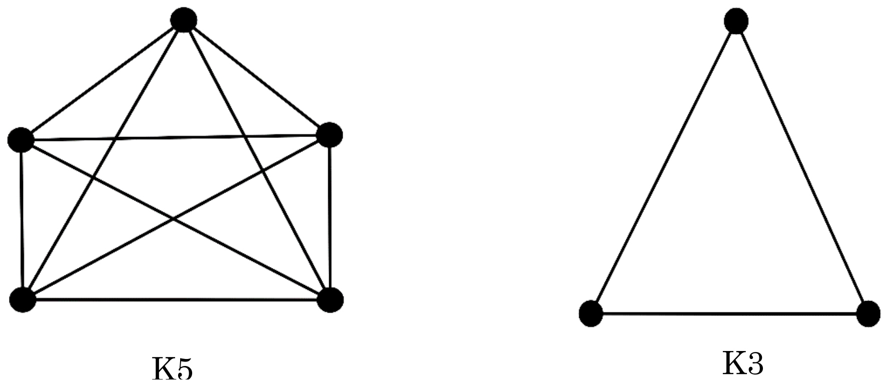


Figure II-12 : Two complete and connected graphs with 5 and 3 vertices respectively when considered together they form a disconnected graph.

II.7.2 Subgraph:

Given two graphs $G_1(V_1, E_1, L_{V_1}, L_{E_1}, \varphi_1)$ and $G_2(V_2, E_2, L_{V_2}, L_{E_2}, \varphi_2)$ G_1 is a called a ***general subgraph*** of G_2, if G_1satisfies: (i) $V_1 \subseteq V_2$, and $\forall v \in V_1$,$\varphi_1(v) = \varphi_2(v)$, (ii) $E_1 \subseteq E_2$, and $\forall (u, v) \in E1$, $\varphi_1(u, v) = \varphi_2(u, v)$. Figure II-13 (a) is an example of the general subgraph in which a vertex v_5 and edges e_4; e_6; e_7; e_8; e_9 are missed G_1 is an ***induced subgraph*** of G_2, if G_1 further satisfies: $\forall u, v \in V_1$, $(u, v) \in E_1 \Leftrightarrow (u, v) \in E_2$,simply put, an induced subgraph G_1 of a graph G_2 has a subset of the vertices of G_2 and the same edges between pairs of vertices as in G_2. in addition to the above conditions. G_2 is also a ***supergraph*** of G_1 . Figure II-13 (c) is an example of the induced subgraph in which a vertex v_5 is missed. In this case, only the edges

e_8 and e_9 are also missed, and e_4; e_6; e_7 are retained since they exist among v_1; v_3 and v_4 in the original G.(43)

The third important and generic class of the substructure is a ***connected subgraph*** where $V_1 \subseteq V_2$, $E_1 \subseteq E$, and all vertices in V_1 are mutually reachable through some edges in E_1. Figure II-13 (d) Is an example where v_6 is further missed from (c).

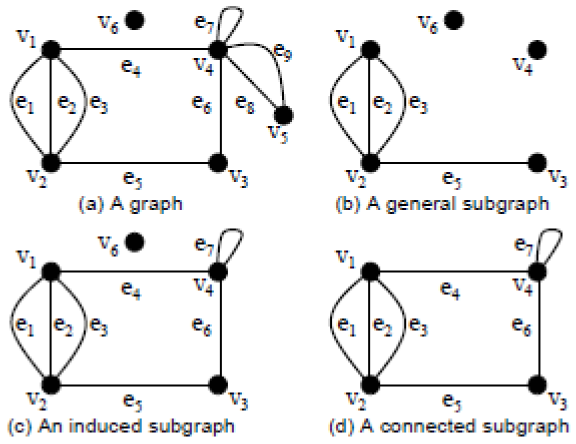


Figure II-13 : (a) a graph G , (b), (c) , (d) represent a general, induced, and connected subgraphs respectively.(15)

II.7.3 Graph isomorphism:

A graph $G_1(V_1, E_1, L_{V_1}, L_{E_1}, \varphi_1)$ is isomorphic to another graph $G_2(V_2, E_2, L_{V_2}, L_{E_2}, \varphi_2)$ and is noted : $G_1 \simeq G_2$ if and only if a bijection f : $V_1 \rightarrow V_2$ exists such that: $(i)\, \forall\, u \in V_1,\ \ \phi_1(u) = \phi_2(f(u)),\ \ (ii) \forall (u,v) \in E_1 \Leftrightarrow \big(f(u), f(v)\big) \in E_2$, $(iii)\ \forall (u,v) \in E_1,\ \phi_1(u,v) = \phi_2(f(u), f(v))$. The bijection f is an isomorphism between $G_1$and G_2. A graph G_1 is ***subgraph isomorphic*** to a graph G_2, if and only if there exists a subgraph $g \subseteq G_2$ such that G_1 is isomorphic to g. In this case g is called an embedding of G_1 in G_2.(43)

Figure II-15, and Figure II-16 present respectively graph and subgraph isomorphism:

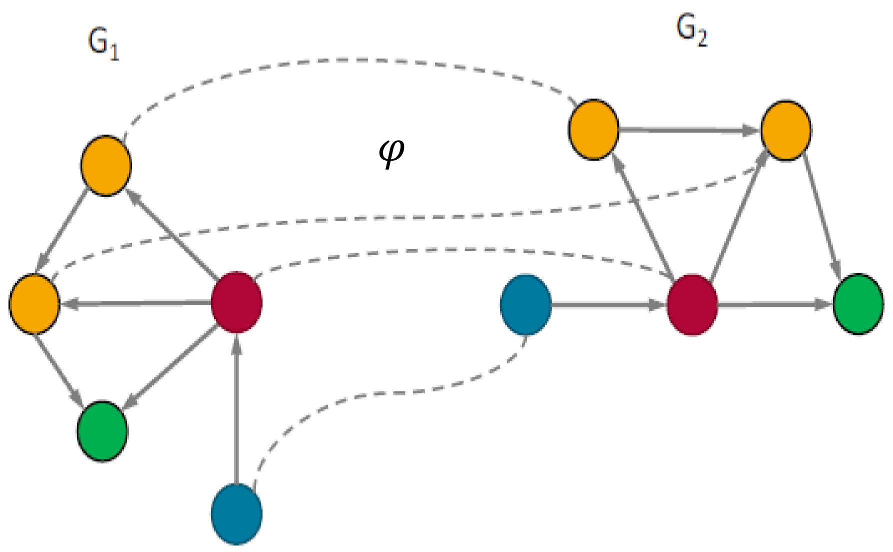


Figure II-14 : Graph isomorphism.

The two graphs shown above are isomorphic, despite their different looking drawings.

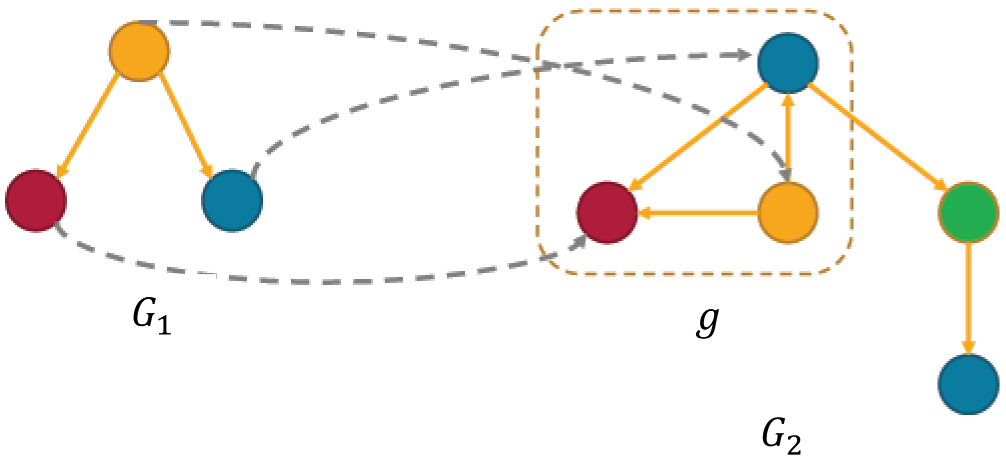


Figure II-15 : Subgraph Isomorphism.

Think of a graph isomorphism as of being a structure preserving bijection, and it follows from the definition that the isomorphic graphs are identical, but differently drawn, graphs.

Generally, the problem of recognizing isomorphic graphs is one of the grand unsolved problems of graph theory. Construction of all N! possible mappings from one graph to another (where N is the number of vertices), although obviously impractical, remains as the only secure check for isomorphism of graphs.

An invariant of a graph G is a quantity associated with G which has the same value for any graph isomorphic to G. Consequently, ***graph invariants*** are quantities independent of the labeling of the vertices of a graph. Hence, the number of vertices and the number of edges are invariants. A complete set of invariants determines a graph up to isomorphism.

II.7.4 Automorphism:

An isomorphic mapping of the vertices of a graph G onto themselves (which also preserves the adjacency relationship) is called an ***automorphism*** of a graph G. Evidently, each graph possesses a trivial automorphism which is called the ***identity automorphism***. For some graphs, it is the only automorphism; these are called identity graphs. The set of all automorphisms of a graph G forms a group which is called the automorphism group of G.(45)

II.7.5 Lattice:

Given a database G, a lattice is a structural form used to model the search space for finding frequent subgraphs, where each vertex represents a connected subgraph of the graph in G. The lowest vertex depicts the empty subgraph and the vertexes at the highest level depict the graphs in G. A vertex p is a parent of the vertex q in the lattice, if q is a subgraph of p, and q is different from p by exactly one edge. The vertex q is a child of p. All the subgraphs of each graph $G_i \in G$ which occur in the database are present in the lattice and every subgraph occurs only once in it.(43)

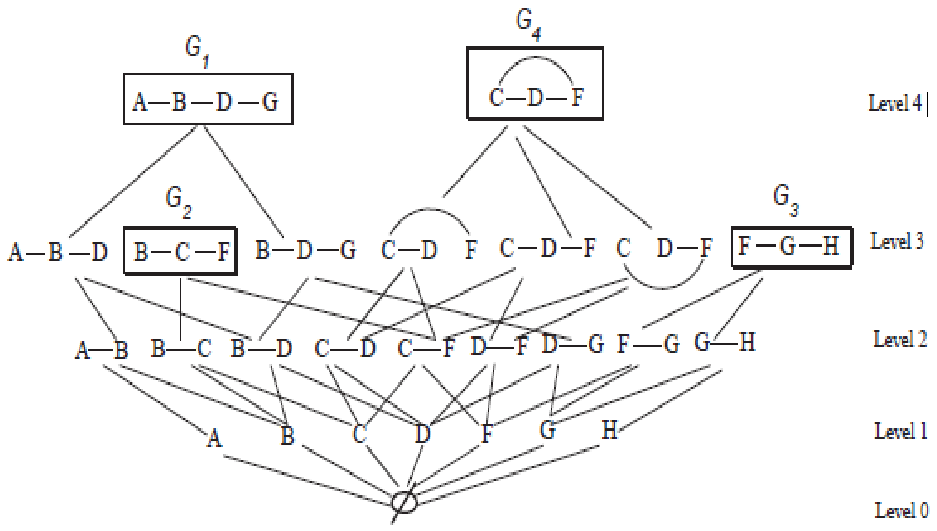


Figure II-16 : Lattice(G).

Example: given a graph data set $G = \{G_1, G_2, G_3, G_4\}$, the corresponding Lattice(G), is given in Figure II-16. In the figure, the lowest vertex ∅ represents the empty subgraph, and the vertexes at the highest level correspond to G_1, G_2, G_3, and G_4. The parents of the subgraph $B - D$ are subgraphs $A - B - D$ (joining the edge $A - B$) and $B - D - G$ (joining the edge $D - G$). Similarly, subgraphs $B - C$ and $C - F$ are the children of the subgraph $B - C - F$.

II.7.6 Density:

The density of a graph $\boldsymbol{G} = (\boldsymbol{V}; \boldsymbol{E})$ is calculated by:

$$desnsity(G) = 2 \,.\, \frac{|E|}{\big(|V|\,.\,(|V| - 1)\big)}.$$

The graph density measures the ratio of the number of edges compared to the maximal number of edges in a complete graph. A graph is said to be ***dense*** if the ratio is close to 1, and is considered as ***sparse*** if the ratio is close to 0.(13)

II.7.7 Trees:

Free Tree: a free tree is defined as an undirected graph that is connected and acyclic.

Labelled Unordered Tree: A labeled unordered tree (an unordered tree, for short) is directed acyclic graph denoted as $T(V, \varphi, E, v_r)$, where V is a set of vertexes of T; φ is a labeling function, such that $\forall v_i \in V$, $\varphi(v_i) \rightarrow v_i$; $E \subseteq V \times V$ is a set of edges of T; and v_r is a distinguished vertex called root of T. For $\forall v_i \in V$, there is a unique path $(v_r, v_1, v_2, \dots \dots \dots, v_i)$ from the root v_r to v_i. If a vertex v_i is on the path from the root to the vertex v_j , then v_i is an *ancestor* of v_j , and v_j is a *descendant* of v_i. For each edge $(v_{i\,,}v_j) \in E$, v_i is the *parent* of v_j, and v_j is a *child* of v_i. Vertexes that share the same parent are *siblings*. The *size* of T is defined to be the number of vertexes in T. A vertex without any child is a *leaf* vertex; otherwise it is an *intermediate* vertex. The *right most path* of T is the path from the root vertex to the *rightmost leaf*. The *depth(level)* of a vertex is the *length of the path* from the root to that vertex.

Labelled Ordered Tree: A labelled ordered tree (an ordered tree, for short) is a labelled unordered tree but with a left-to-right ordering imposed among the children of each vertex.

Other form of subtrees includes: Bottom-up subtree, Induced Subtree and embedded Subtree.

II.8 Overview of FSM:

Frequent Subgraph Mining (FSM) is the essence of graph mining, The field of study concentrates on the identification of frequent subgraphs within graph data sets. The research goals are directed at: (i) effective mechanisms for generating candidate subgraphs (without generating duplicates) and (ii) how best to process the generated candidate subgraphs so as to identify the desired frequent subgraphs in a way that is computationally efficient and procedurally effective. frequent subgraphs are considered so, if their counts are above a minimum support threshold. Figure II-8 (a) presents an overview of the domain of FSM in terms of the number of significant FSM algorithms that have been proposed over the period 1994 to the present. From the figure we can see periods of activity in the early 90s (coinciding with the introduction of the concept of data mining) followed by another period of activity from 2002 to 2007. No “new” algorithms have been introduced over the past few years, indicating that the field is reaching maturity, although there has been much work focused on variations of existing algorithms.

Other than the research activity associated with FSM the importance of FSM is also reflected in its many areas of its application. Figure II-8 (b) presents an overview of the application domain of FSM in terms of the number of FSM algorithms reported in the literature and the specific application domain at which they have been directed. From the figure it can be seen that three application domains (chemistry, web, and biology) dominated the usage of FSM algorithms.

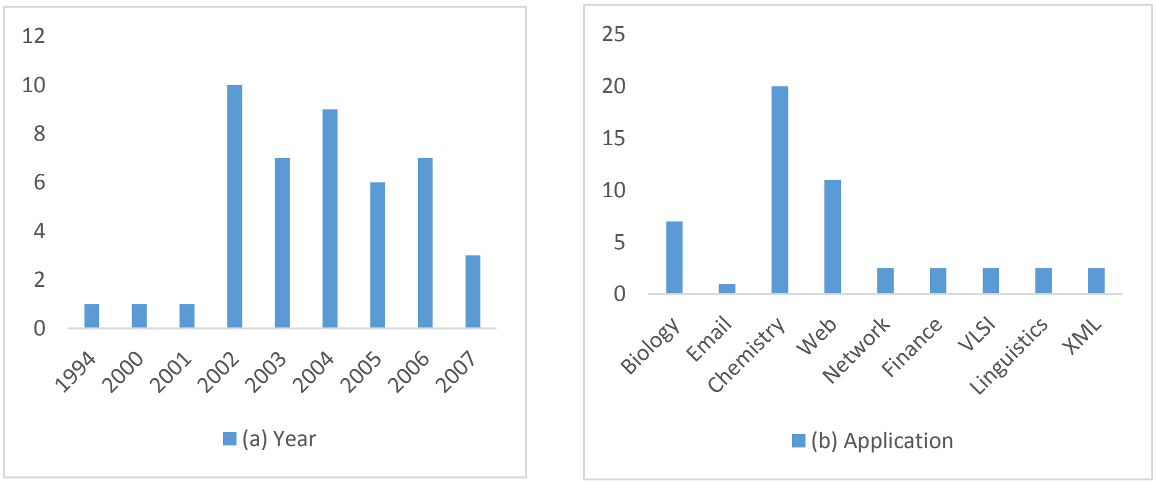


Figure II-17 : The distribution of the most significant FSM algorithms with respect to year of introduction and application domain.

The straightforward idea behind FSM is to “grow” candidate subgraphs, in either a breadth first (BFS) or depth first (DFS) manner (candidate generation), and then determine if the identified candidate subgraphs occur frequently enough in the graph data set for them to be considered interesting (support counting). The two main research issues in FSM are thus how to efficiently and effectively:

(i) Generate the candidate frequent subgraphs.

(ii) Determine the frequency of occurrence of the generated subgraphs.(43)

Effective candidate subgraph generation requires that the generation of duplicate or superfluous candidates is avoided. Occurrence counting requires repeated comparison of candidate subgraphs with subgraphs in the input data, a process known as *isomorphism checking*. FSM, in many respects, can be viewed as an extension of Frequent Itemset Mining (FIM) popularized in the context of association rule mining (see for example (46)). Consequently, many of the proposed solutions to addressing the main research issues effecting FSM are based on similar techniques found in the domain of FIM. For example, the downward closure property (DCP) associated with itemsets has been widely adopted with respect to candidate subgraph generation, we will define it later in the chapter.

II.9 Formalism:

There are two separate problem formulations for FSM: (i) *graph transaction based FSM* and (ii) *single graph based FSM*. In graph transaction based FSM, the input data comprises a collection of medium-size graphs called *transactions*. Note that the term “transaction” is borrowed from the field of Association Rule Mining.(47)

In single graph based FSM the input data, as the name implies, comprises one very large graph.

A subgraph g is considered to be frequent if its *occurrence count* is greater than some predefined threshold value. The occurrence count for a subgraph is usually referred to as its *support*, and the consequently the threshold is referred to as the *support threshold*. The support of g may be computed using either *transaction-based counting* or *occurrence-based counting*. Transaction based counting is only applicable to graph transaction based FSM, while occurrence-based counting may be applied to either transaction based FSM or single graph based FSM. However, occurrence-based counting is typically used with single graph based FSM.

In transaction-based counting the support is defined by the number of graph transactions that g occurs in, one count per transaction regardless of whether g occurs once or more than once in a particular graph transaction. Thus, given a database $G = \{G_1, G_2, G_3 \ldots\ldots, G_T\}$ consisting of a collection of graph transactions, and a support threshold $\sigma \epsilon [0,1]$ then the set of graph transactions where a subgraph g occurs is defined by $\delta_G(g) = \{G_i | g \subseteq G_i\}$. Thus, the *support* of g is defined as:

$$sup_G(g) = |\delta_G(g)|/T$$

where $|\delta_G(g)|$ denotes the cardinality of $\delta_G(g)$ and T the number of graphs (transactions) in G. Therefore, g is *frequent* if and only if $sup_G(g) \geq \sigma$. In occurrence-based counting we simply count up the number of occurrences of g in the input set, (note that we are interested only on the transaction based FSM in this report.)

Transaction-based counting offers the advantage that the well-known *Downward closure property* can be employed to significantly reduce the computation overhead associated with candidate generation in FSM. In the case of occurrence-based counting, either an alternative frequency measure, which maintains the DC property, must be established; or some heuristics adopted to keep the computation as inexpensive as possible.(43)

II.10 Graph isomorphism detection:

The kernel of FSM is *(sub)graph isomorphism detection*. Graph isomorphism is neither known to be solvable in polynomial time nor *NP-complete*, while subgraph isomorphism, where we wish to establish whether a subgraph is wholly contained within a super graph, is known to be NP-complete (48). When restricting the graphs to trees, (sub)graph isomorphism detection becomes (sub)tree isomorphism detection. Tree isomorphism detection can be solved in a linear time.

Subgraph isomorphism detection is fundamental to FSM. A significant number of "efficient" techniques have been proposed, all directed at reducing, as far as possible, the computational overhead associated with it. Subgraph isomorphism detection techniques can be roughly categorized as being either: exact matching (49–53) or error tolerant matching (54–57). Most FSM algorithms adopt exact matching. A categorization of the main exact matching subgraph isomorphism detection algorithms is presented in Table 2.

Table II-2 : Categorization of exact matching (sub) graph isomorphism testing algorithms.

Algorithms	*Main Techniques*	*Matching Types*
Ullman	*Backtracking + look ahead*	*Graph & subgraph isomorphism*
SD	*Distance matrix + backtracking*	*Graph isomorphism*
Nauty	*Group theory + canonical labeling*	*Graph isomorphism*

VF	*DFS strategy + feasibility rules*	*Graph & subgraph isomorphism*
VF2	*VF's rationate + advanced data structures*	*Graph & subgraph isomorphism*

With reference to Table 2, *Ullmann*'s algorithm employs a backtracking procedure with a look-ahead function to reduce the size of the search space (49). The ***SD*** algorithm, in turn, utilizes a distance matrix representation of a graph with a backtracking procedure to reduce the search (50). The ***Nauty*** algorithm (51) uses group theory to transform graphs to be matched into a canonical form so as to provide for more efficient and effective graph isomorphism checking. However, it has been noted (58) that the construction of the canonical forms can lead to exponential complexity in the worst case. Although Nauty was regarded as the fastest graph isomorphism algorithm by *Conte* (58), *Miyazaki* in (59) demonstrated that there exist some categories of graphs which required exponential time to generate the canonical labelling. The ***VF*** (52) and ***VF2*** (53) use a Depth First Search (DFS) strategy, assisted by a set of feasibility rules to prune the search tree. VF2 is an improved version of VF, that explores the search space more effectively so that the matching time and the memory consumption are significantly reduced.

II.11 Search strategy:

There are two basic search strategies employed for mining frequent subgraphs, the depth first search (DFS) strategy and the breadth first search (BFS) strategy.

The Depth First Search (DFS) strategy is a method for traversing or searching tree or graph data structures. It starts at the root (selecting a node as the root in the graph case) and explores as far as possible along each branch before backtracking.

the Breadth First Search (BFS) uses the opposite strategy that is performed by DFS. It starts at the tree root (or some arbitrary node of a graph, sometimes referred to as a 'search key'), and explores all of the neighbor nodes at the present depth prior to moving on to the nodes at the next depth level. Figure II-9 Illustrate the process of DFS and BFS.

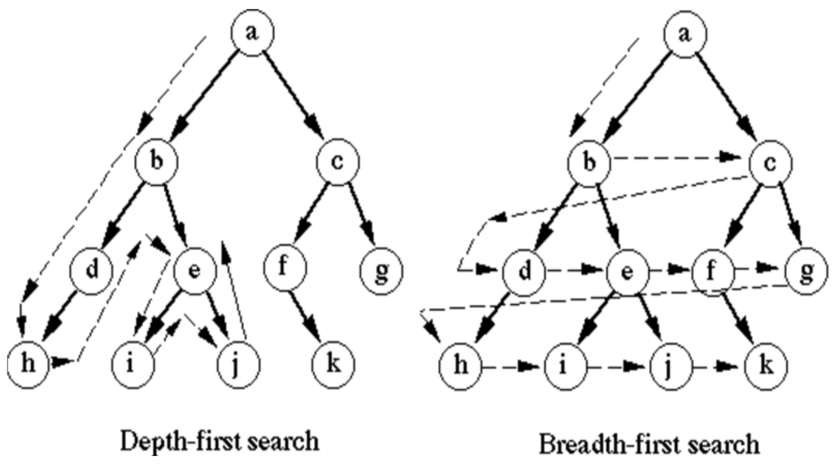


Figure II-18 : DFS and BFS search strategies.

II.12 FSM algorithmic approaches:

This section provides a generic overview of the process of FSM, it is widely accepted that FSM techniques can be divided into two categories:

(i) Apriori-based approaches.

(ii) Pattern growth-based approaches.

These two categories are similar in spirit to counterparts found in Association Rule Mining (ARM), namely the Apriori algorithm (46) and FP-growth algorithm (60) respectively. Before defining each of them let's review first the apriority property.

II.12.1 Apriori Property:

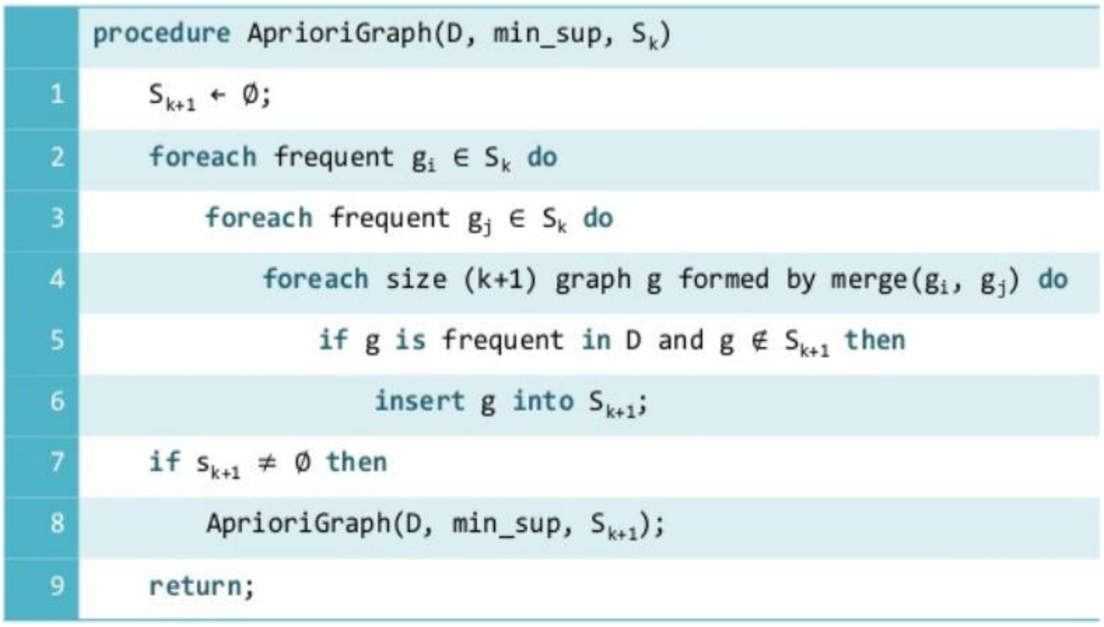
The Apriori property also known as the downward closure property (DCP), expresses a monotonic decrease of an evaluation criterion accompanying with the progress of a sequential pattern mining. It is activated in order to efficiently discover all frequent sequential patterns, in simple terms this property impose that if a graph is frequent, then all of its subgraphs will also be frequent, thus the frequency or the support of a sequential graph is always decreasing or remaining constant, and never increases to overpass the support of its parent subgraphs.

This property must be hold for both the Apriori and the Pattern growth based algorithms to safely prune the candidates that are not frequent.

II.12.2 Apriori based approach:

The Apriori-based approach proceeds in a generate-and-test manner using a Breadth First Search (BFS) strategy to explore the subgraph lattice of the given database. Therefore, before considering $(k + 1)$ subgraphs, this approach has to first consider all k subgraphs.(43)

The general framework of Apriori-based algorithms is outlined in the Algorithm AprioriGraph below:



```
procedure AprioriGraph(D, min_sup, $S_k$)
    $S_{k+1} \leftarrow \emptyset$;
    foreach frequent $g_i \in S_k$ do
        foreach frequent $g_j \in S_k$ do
            foreach size (k+1) graph g formed by merge($g_i$, $g_j$) do
                if g is frequent in D and $g \notin S_{k+1}$ then
                    insert g into $S_{k+1}$;
    if $S_{k+1} \neq \emptyset$ then
        AprioriGraph(D, min_sup, $S_{k+1}$);
    return;
```

Figure II-19 : Apriori Algorithm.

Let Sk be the frequent subgraph set of size k, the Algorithm AprioriGraph adopts a level-wise mining methodology. At each iteration, the size of newly discovered frequent subgraphs is increased by one. These new subgraphs are first generated by joining two similar frequent subgraphs that are discovered in the last call of the Algorithm. The newly formed graphs are then checked for their frequency. The frequent ones are used to generate larger candidates in the next round. The main design complexity of Apriori-based algorithms comes from the candidate generation step. Although the candidate generation for frequent itemset mining is straightforward, the same problem in the context of graph mining is much harder, since there are many ways to merge two graphs. The diagram of figure II-10 highlight the Apriori subgraph generation method.

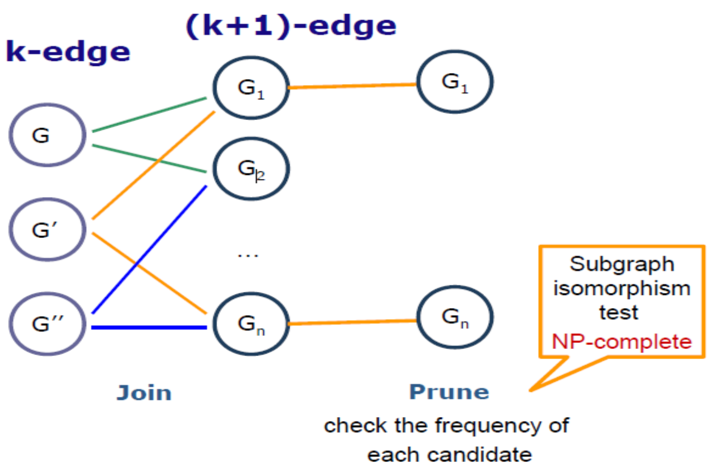
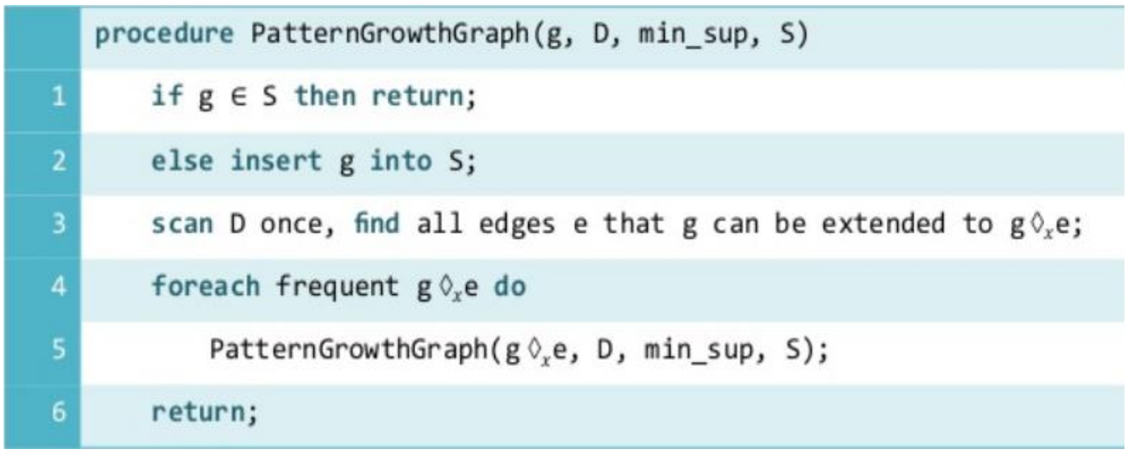

k-edge
(k+1)-edge
G
G′
G″
G1
G2
...
Gn
G1
Gn
Subgraph isomorphism test
NP-complete
Join
Prune
check the frequency of each candidate

Figure II-20 : Apriori-based Approach.

II.12.3 Pattern Growth Approach:

The pattern growth-based adopts a DFS or BFS strategies to explore the subgraph lattice, and for each discovered subgraph g, the subgraph is extended recursively until all frequent supergraphs of g are discovered.

Algorithm PatternGrowthGraph illustrates a framework of pattern growth-based frequent graph mining algorithms. A graph g can be extended by adding a new edge e. The newly formed graph is denoted by $g \lozenge_x e$. Edge e may or may not introduce a new vertex to g. For each discovered graph g, PatternGrowth performs extensions recursively until all the frequent graphs with g embedded are discovered. The recursion stops once no frequent graph can be generated any more.



```
  procedure PatternGrowthGraph(g, D, min_sup, S)
1     if g ∈ S then return;
2     else insert g into S;
3     scan D once, find all edges e that g can be extended to $g \diamond_x e$;
4     foreach frequent $g \diamond_x e$ do
5         PatternGrowthGraph($g \diamond_x e$, D, min_sup, S);
6     return;
```

Figure II-21 : PatternGrowth algorithm.

The Algorithm above is simple, but not efficient. The bottleneck is at the inefficiency of extending a graph. The same graph can be discovered many times. For example, there may exist n different $(n - 1)$ −edge graphs which can be extended to the same n −edge graph. The repeated discovery of the same graph is computationally inefficient. A graph that is discovered at the second time is called *duplicate graph*. Although Line 1 of the Algorithm gets rid of duplicate graphs, the generation and detection of duplicate graphs may cause additional workloads. In order to reduce the generation of duplicate graphs, each frequent graph should be extended as conservatively as possible in a sense that not every part of each graph should be extended.

The diagram of figure II-11 highlight the pattern growth subgraph generation method.

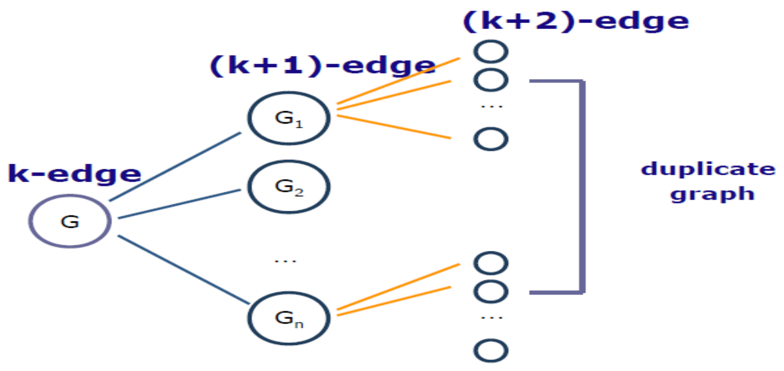


Figure II-22 : PatternGrowth-based approach.

II.13 Basic Framework of FSM algorithms:

Most existing FSM algorithms (both Apriori and Pattern growth) adopt an iterative pattern mining strategy where each iteration can be divided into two phases: (i) candidate generation, and (ii) support computation, Generally, research on FSM focuses on these two phases using a variety of techniques. Since it is harder to address subgraph isomorphism detection, more research effort is directed at how to efficiently generate subgraph candidates. Because subtree isomorphism detection can be solved in $O\left(\frac{k^{1.5}}{\log k}n\right)$ time, the computational complexity is reduced within the context of FSM.(43)

Figure II-23 highlight the basic framework adopted by the most FSM algorithms:

```
$Frequent\_Subgraph\_Mining\ (G, minsup)$
$//G\ is\ database\ containing\ graphs\ datasets.$
0 – $Mining\ starts\ with\ frequent\ pattern\ of\ size\ 1\ i.e.F_1\ (Populate\ F_1)$
1 – $while\ F_k\ \neq\ \emptyset$
2 –       $C_{k+1}Candidate\_generation(F_k\ ,G)$
2 –       $forall\ c\ in\ C_{k+1}$
3 –           $if\ isomorphism\_checking(c) = true$
4 –             $support\_counting(c, G)$
5 –           $if\ c.sup\ >=\ minsup$
```

```
6 –    $F_{k+1} = F_{k+1} \bigcup c$
7 –  $k = k + 1$
8 –  $return\ set\ of\ frequent\ pattrns \bigcup_{i=1,....k-1} F_i$
```

Figure II-23 : Baseline algorithm for FSM.

Before presenting a survey of the most FSM algorithms in literature, essential techniques used to support their operations are first presented, such techniques allow achieving:

01 – Efficient candidate generation.

02 – Isomorphism checking.

03 – Support computation.

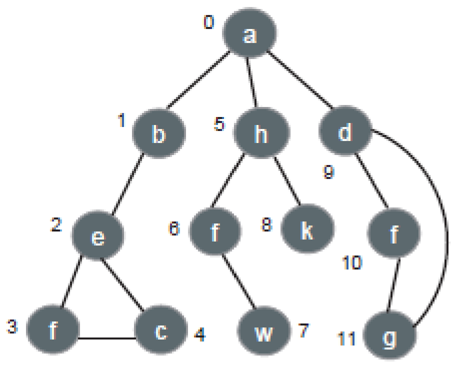
representation of graphs will first be considered. The aim here is to represent graphs in such a manner that subgraphs can be enumerated efficiently so as to facilitate the desired FSM and facilitate isomorphism checking on subgraphs.

II.13.1 Canonical Representations:

The simplest mechanism whereby a graph structure can be represented is by employing an *adjacency matrix* or *adjacency list*.

an *adjacency matrix* is a square matrix used to represent a finite graph. The elements of the matrix indicate whether pairs of vertices are adjacent or not in the graph. In the special case of a finite simple graph, the adjacency matrix is a *(0,1)-matrix* with zeros on its diagonal. If the graph is undirected, the adjacency matrix is symmetric.

an *adjacency list* is a collection of unordered lists used to represent a finite graph. Each list describes the set of neighbors of a vertex in the graph, There are many variations of this basic idea, differing in the details of how they implement the association between vertices and collections, in how they implement the collections, in whether they include both vertices and edges or only vertices as first class objects, and in what kinds of objects are used to represent the vertices and edges. Figure II-12 present a simple graph G along with its corresponding adjacency matrix.



$$\begin{pmatrix}
a & 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 \\
1 & b & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & c & 0 & 1 & 1 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & d & 0 & 1 & 1 & 0 & 0 & 0 \\
0 & 1 & 1 & 0 & e & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 1 & 1 & f & 1 & 1 & 0 & 1 \\
0 & 0 & 0 & 1 & 0 & 1 & g & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 1 & 0 & h & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & k & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & w
\end{pmatrix}$$

(a) Graph G with preorder subscript (b) G's adjacency matrix

Figure II-24 : A simple graph G with its corresponding adjacency matrix.

Throughout this section Graph G will be used to illustrate the canonical representations discussed, for ease of illustration, all edge labels are assumed to be the same and are represented by "1".

The use of the adjacency matrices and adjacency lists, although straightforward, it does not lend itself to isomorphism detection, because a graph can be represented in many different ways depending on how the vertexes (and edges) are enumerated. With respect to isomorphism testing it is therefore desirable to adopt a consistent labelling strategy that ensures that any two identical graphs are labelled in the same way regardless of the order in which vertexes and edges are presented (i.e. a *canonical labelling strategy*).

A canonical labelling strategy defines a unique code for a given graph, Canonical labelling facilitates isomorphism checking because it ensures that if a pair of graphs are isomorphic, then their canonical labellings will be identical. One simple way of generating a canonical labelling is to flatten the associated adjacency matrix by concatenating rows or columns to produce a code comprising a list of integers with a minimum (or maximum) lexicographical ordering imposed. To further reduce the computation resulting from the permutations of the matrix, canonical labellings are usually compressed, using what is known as a *vertex* *invariant scheme* (61), that allows the content of an adjacency matrix to be partitioned according to the vertex labels. Various canonical labelling schemes have been proposed, some of the more significant are described in this subsection.

- **Minimum DFS Code (M-DFS):**

There are a number of variants of DFS encodings, but essentially each vertex is given a unique identifier generated from a DFS traversal of a graph (DFS subscripting). Each constituent edge of the graph in the DFS code is then represented by a 5-tuple: (i, j, l_i, l_e, l_j) where i and j are the vertex identifiers,l_i and l_j are the labels for the corresponding vertexes, and l_e is the label for the edge connecting the vertexes. Based on the DFS lexicographic order, the M-DFSC of a graph g can be defined as the canonical labelling of g (17). The DFS codes for the left-most branch and the right-most branch of the example graph if figure II-24 (a) are : $\{(0,1,\mathrm{a},1,\mathrm{b}),(1,2,\mathrm{b},1,\mathrm{e}),(2,3,\mathrm{e},1,\mathrm{f}),(3,4,\mathrm{f},1,\mathrm{c}),(4,2,\mathrm{c},1,\mathrm{e})\}$ and $\{(0,9,\mathrm{a},1,\mathrm{d}),(9,10,\mathrm{d},1,\mathrm{f}),(10,11,\mathrm{f},1,\mathrm{g}),(11,9,\mathrm{g},1,\mathrm{d})\}$ respectively.

The algorithm FSM-H under study utilize M-DFS code as its coding scheme to issue isomorphism checking on candidate patterns.

- **Canonical Adjacency Matrix (CAM):**

Given an adjacency matrix M of a graph g, an encoding of M can be obtained by the sequence obtained from concatenating the lower (or upper) triangular entries of M, including entries on the diagonal. Since different permutations of the set of vertexes correspond to different adjacency matrices, the canonical (***CAM***) form of g is defined as the maximal (or minimal) encoding. The adjacency matrix from which the canonical form is generated defines the *Canonical Adjacency Matrix* or CAM (62–65). The encoding for the example graph given in Figure II-24 (a), represented by the matrix in Figure II-24 (b) is thus $\{a1b00c100d0110e00111f000101g1000010h00000001k000001000w\}$.

The above two schemes are applicable to any simple undirected graph. However, it is easier to define a canonical labelling for trees than graphs because trees have an inherent structure associated with them. There also exist more specific schemes that are uniquely focused on trees. Among these, ***DFS-LS*** and

DLS are directed at rooted ordered trees, ***DFS-LS*** for example adds all the labels of vertexes along the branch during a DFS traversal of the tree, to a string S, and whenever backtracking occurs a unique symbol, such as "−1" or "$" or "/", is added to S. others canonical coding schemes include BFCS and DFCS which are used for rooted unordered trees.(43)

II.13.2 Candidate Generation:

As noted earlier in this chapter, candidate generation is an essential phase in FSM. How to systematically generate candidate subgraphs without redundancy (i.e. each subgraph should be generated only once) is a key issue. Many FSM algorithms can be characterized by the strategy adopted for candidate generation.

The current methods for enumerating all the subgraphs might be classified into two categories: the join operation adopted by FSG and AGM and the extension operation. The major concerns for the join operation are that a single join might produce multiple candidates and that a candidate might be redundantly proposed by many join operations. The concern for the extension operation is to restrict the nodes that a newly introduced edge may attach to.

A number of the most significant are briefly described below. Since a significant proportion of strategies employed in FTM is interwoven with those employed in FGM, no clear distinction can be made between candidate generation strategies in terms of FTM (trees) and FGM (graphs), i.e. strategies initially proposed for (say) FGM are equally applicable to FTM, and vice versa.

- **Level-Wise Join:**

The level-wise join strategy was introduced by *Kuramochi & Karypis* (64). Basically, a $(k + 1)$ subgraph6 candidate is generated by combining two frequent k subgraphs which share the same $(k - 1)$ subgraph. This common $(k - 1)$ subgraph is referred to as a *core* for these two frequent k subgraphs. The main issue concerning this strategy is that one k subgraph can have at most k different $(k - 1)$ subgraphs and the joining operation may generate many redundant candidates. this issue was addressed by limiting the $(k - 1)$ subgraphs to the two $(k - 1)$ subgraphs with the smallest and the second smallest canonical labels. By carrying, out this adapted join operation, the number of duplicate candidates generated was significantly reduced. Other algorithms that adopted this strategy, and its variants, are ***AGM*** (18), ***DPMine*** (66,67), and ***HSISGRAM*** (68).

- **Rightmost path Extension:**

If a frequent graph is extended in every possible position, it may generate a large number of duplicate graphs, therefore a number of existing FSM algorithms impose restriction on the extension nodes of the parent pattern so that redundant generation paths can be reduced. One such restriction that is used in the popular gSpan algorithm (will be defined later) is called right most path generation or extension. The RMP extension method generates $(k+1)-subtrees$ from frequent $k-subtrees$ by adding vertexes only to the rightmost path of the tree Simply put, edge adjoining is done only with vertices on the right-most path.

In Figure II-25. (a) "RMB" denotes the rightmost branch, which is the path from the root to the rightmost leaf $(k-1)$, and a new vertex k is added by attaching it to any vertexes along the RMB.

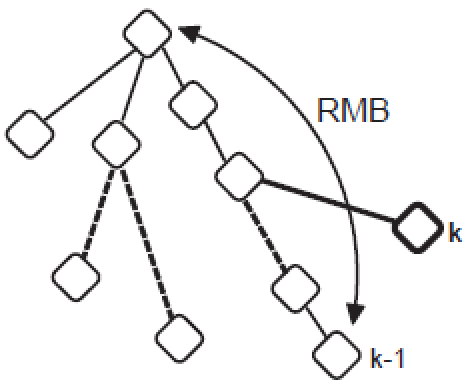


Figure II-25 : An illustration of the right most expansion.

- **Extension and join:**

The extension and join strategy was first proposed by *Huan* (69), and later used by *Chi* (70). It employed a BFCS representation; whereby a leaf at the bottom level of a BFCF tree is defined as a "leg". For a node V_n in an enumeration tree, if the height of the BFCF tree corresponding to V_n is assumed to be h, all children of V_n can be obtained by either of the following two operations:

(a) Extension Operation: Adding a new leg at the bottom level of the BFCF tree yields a new BFCF with height $h + 1$.

(b) Join Operation: joining V_n and one of its sibling yields a new BFCF with height h.

The above mentioned candidate generation strategies are directed at FGM problems, other strategies that are directed to FTM, may include Equivalence class based extension and right-and-left tree join.

Along with M-DFS code for canonical labeling of graphs and isomorphism checking, the algorithm FSM-H, subject of the study employ also the right most path (RMP) extension as its mechanism for reducing redundant generation paths in candidate generation step.

II.13.3 Support Computing:

Several methods are used for graph counting. Some frequent subgraph mining algorithms use transaction identifier (TID) lists for frequency counting. Each frequent subgraph has a list of transaction identifiers which support it. For computing frequency of a k subgraph, the intersection of the TID lists of $(k-1)$ subgraphs is computed. Embedding list also can be used for the purpose of frequency counting.(13)

II.14 Frequent subgraph mining algorithms:

As was indicated in Figure II-8, FGM algorithms find substantial application in chemical informatics and biological network analysis. There are a variety of FGM algorithms reported in the literature. As in the case of FTM, candidate generation and support counting are key issues. Since subgraph isomorphism detection is known to be $NP-complete$, a significant amount of research work has been directed at various approaches for effective candidate generation. The mechanism employed for candidate generation is the most significant distinguishing feature of such algorithms. An exploration of current well-known frequent subgraph mining algorithms is provided in this section.(43)

There exist many algorithms for solving the in memory version of frequent subgraph mining task, most notable among them are ***AGM***(18), ***FSG***(64),

gSpan(17), ***Gaston***(71) and ***DMTL***(72). These methods assume that the dataset is small and the mining task finishes in a reasonable amount of time using an in-memory method. To consider the large data scenario, a few traditional database based graph mining algorithms, such as, ***DB-Subdue***(73), ***DB-FSG***(74) and ***OO-FSG***(75) are also proposed. There also exist a couple of works that mine subgraphs that are frequent considering the induced occurrences of those subgraphs in a single large graph(76,77). *Wu et al.* developed a distributed subgraph mining algorithm(76) which requires the graph diameter and the number of vertices for pattern matching. *Liu et al.* proposed an algorithm ***MRPF***(77) that finds motifs in prescription compatibility network. Both of these latter two works, consider mining from a single large graph but FSM-H mines from a large set of moderate size graphs that can fit in a memory.

For large-scale graph mining tasks, researchers considered shared memory parallel algorithms for frequent subgraph mining. *Cook et al.* presented a parallel version of their frequent subgraph mining algorithm ***Subdue***(78). *Wang et al.* developed a parallel toolkit(79) for their ***MotifMiner***(80) algorithm. *Meinl et al.* created a software named ***Parmol***(81) which includes parallel implementation of *Mofa,* gSpan, *FFSG* and *Gaston.* ***ParSeMis***(82) is another such tool that provides parallel implementation of *gSpan* algorithm. To deal with the scalability problem caused by the size of input graphs, there are couple of notable works, ***PartMiner***(83) and ***PartGraphMining***(84) , which are based on the idea of partitioning the graph data.(85)

In addition to being classified as in memory, database-based, shared memory parallel algorithms, FSM algorithms could be further classified taking into account different considerations:

II.14.1 Classification based on algorithmic approaches:

It is widely accepted that FSM techniques can be divided into two categories: (i) Apriori-based approaches, and (ii) pattern growth-based approach.

Table II-1 and Table II-2 breaks FSM algorithms as being Apriori or pattern growth based algorithms respectively:

Table II-3 : Classification of FSM algorithms based on Apriori based approach.

No	Algorithm	Input type	Graph repre-sentation	Candidate generation	Frequency counting	Nature of output	Limitatio ns
1.	FARMER	Set of graphs	Trie structure	Level-wise search ILP	Trie data structure	Frequent subgraphs	Inefficient
2.	FSG	Set of graphs	Adjacency list	One edge extension	Transaction identifier (TID) lists	Frequent connected subgraphs	Np- complete
3.	HSIGRAM	Single large graph	Adjacency matrix	Iterative merging	Maximal indepen-dent set	Frequent subgraphs	Ineffecien t
4.	GREW	Single large graph	Sparse graph representati on.	Iterative merging	Maximal indepen-dent set	Maximal frequent subgraphs	Misses many interesting patterns
5.	FFSM	Set of graphs	Adjacency matrix	Merging and extension	Sub-optimal canonical adjacency matrix tree	Frequent subgraphs	Np- complete
6.	ISG	Set of graphs	Edge triplet	Edgetriplet extension	TID lists	Maximal Frequent subgraphs	Incomplet e set of Graphs
7.	SPIN	Set of graphs	Adjacency matrix	Join Operation	Canonical Spanning Tree	Maximal frequent subgraphs	Non maximal graphs can also be found but needs an entire database scan
8.	Dynamic GREW	Dynami c graphs	Sparse graph representati on.	Iterative merging	Suffix trees	Dynamic patterns in frequent subgraphs .	Extra overhead to identify dynamic patterns
9.	AGM	Graph databas e	Adjacency matrix	Vertex extension	Canonical labeling	Frequent subgraphs	
10.	MUSE	Uncerta in set of graphs	Adjaceny Matrix	Disjunctive normal forms	DFS coding scheme	Frequent subgraphs	Frequent subgraphs are not exact.

Table II-4 : Classification of FSM algorithms based of Pattern Growth approach.

SNo	Algorithm	Input type	Graph represen-tation	Subgraph generation	Frequency counting	Nature of output	Limita- tions
1.	SUBDUE	Single large graph	Adjacenc y matrix	Level-wise search	Minimum description code length	Complete set of frequent subgraphs	Extremely small no. of patterns

2.	GSpan	Set of graphs	Adjacency list	Rightmost extension	Depth first search (DFS) lexicographic order	frequent graphs	Not scalable
3.	Close Graph	Set of graphs	Adjacency list	Rightmost extension	DFS lexicographic order	Closed Connected frequent graphs	Failure detection takes lot of time overhead
4.	Gaston	Set of graphs	Hash table	Extension	Embedding lists	Maximal frequent sugraphs	Interesting patterns may be lost.
5.	TSP	Set of graphs	Adjacency list	Extension	TSP tree	Closed Temporal frequent sub graphs	Extra overhead to check whether temporal patterns are closed
6.	MOFA	Set of graphs	Adjacency list	Rightmost extension	DFS lexicographic order	All frequent subgraphs	Frequent graphs generated may not be exactly frequent.
7.	RP-FP	Set of graphs	Adjacency list	Rightmost extension	DFS lexicographic order	Represen-tative graphs	Time for summari-zing the patterns is more than that for mining
8.	RP-GD	Set of graphs	Adjacency list	Rightmost extension	DFS lexicographic order	Represen-tative graphs	Time for summari-zing the patterns is more than that for mining
9.	JPMiner	Set of graphs	Adjacency list	Rightmost extension	DFS lexicographic order	Frequent jump patterns	Sometimes much smaller set of jump patterns.
10.	MSPAN	Set of graphs	Adjacency list	Rightmost extension	DFS lexicographic order	Frequent subgraphs	

II.14.2 Classification based on Search strategy:

There are essentially two basic search strategies employed for finding out frequent subgraphs: the breadth first search (BFS) strategy and the depth first search (DFS) strategy.

II.14.3 Classification based on the nature of input:

The algorithms are of two types based on the exactness of the input they take. The first type takes in an exact graph sets as input, whereas the second type takes an uncertain set of graphs as input. Another possibility is based on the type of the graph. The first type takes in a single large graph as input, whereas the second type takes a set of small graphs as input. The third correctness of the graph data where it can be accurate or uncertain.

II.14.4 Classification based on the completeness of the output:

Based on the set of the frequent subgraphs discovered, the algorithms are of two types. The first type returns the complete set of frequent subgraphs, whereas the second type returns a partial set of frequent subgraphs.(86)

Figure gives a diagram of all FSM algorithms with respect to the classification mentioned above:

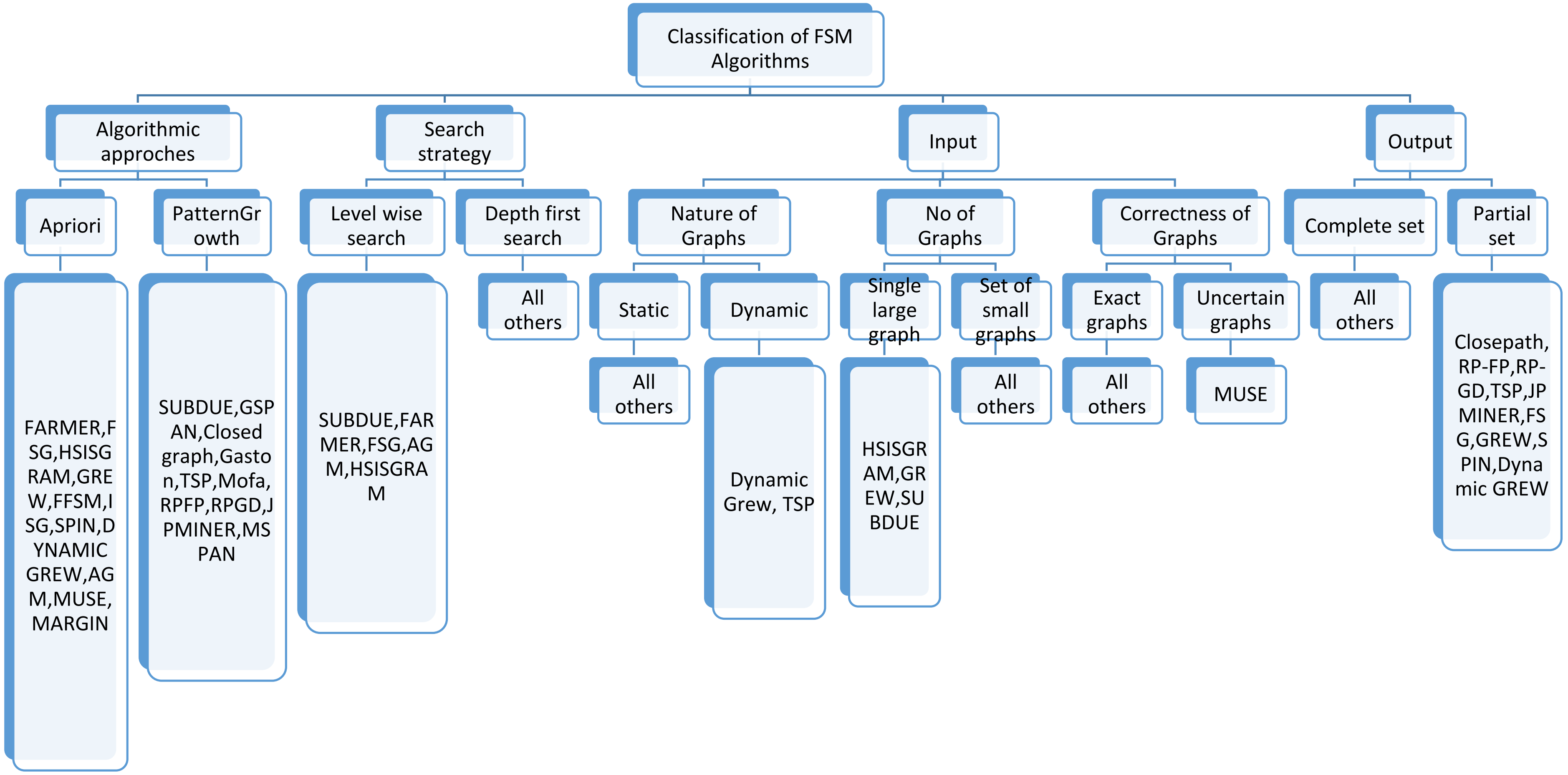


Figure II-26 : Classification of FSM Algorithms.(86)

In the subsequent paragraphs we will be discussing some of most important of the aforementioned algorithms, to aid the discussion, the algorithms are categorized according to three criteria: (i) the completeness of the search (exact search or inexact search), (ii) the type of input (transactions graphs or one single graph), and (iii) the search strategy (BFS or DFS).

II.15 Inexact FSM:

Inexact search based FSM algorithms use an approximate measure to compare the similarity of two graphs, i.e. any two subgraphs are not required to be entirely identical to contribute to the support count, instead a subgraph may contribute to the support count for a candidate subgraph if it is in some sense similar to the candidate. Inexact search is of course not guaranteed to find all frequent subgraphs, but the nature of the approximate graph comparison often leads to computational efficiency gains.

- ***SUBDUE***(87): There are only a few examples of inexact frequent subgraph mining algorithms in the literature. However, one frequently quoted example is the SUBDUE algorithm, SUBDUE uses the minimum description length principle to compress the graph data; and a heuristic beam search method, that makes use of background knowledge, to narrow down the search space. Although the application of SUBDUE shows some promising results in domains such as image analysis and CAD circuit analysis, the scalability of the algorithm is an issue, i.e. the run time does not increase linearly with the size of the input graph. Furthermore, SUBDUE tends to discover only a small number of patterns.

- ***GREW***(88): Another inexact search based FGM algorithm is GREW However, GREW is directed at finding connected subgraphs which have many vertex-disjoint embeddings (Two embeddings in a graph G are vertex-disjoint, if they do not share any vertexes in G.), in single large graphs. GREW uses a heuristic based approach that is claimed to be scalable, because it employs ideas of edge contraction and graph rewriting. GREW deliberately underestimates the frequency of each discovered subgraph in an attempt to reduce the search space. Experiments on synthetic data sets showed that GREW significantly outperformed SUBDUE with respect to: runtime, number of patterns found, and size of patterns found.

II.16 Exact FSM:

Exact FSM algorithms are much more common than inexact search based FSM algorithms. They can be applied in the context of graph transaction based mining or single graph based mining. A fundamental feature for exact search based algorithms is that the mining is complete, i.e. the mining algorithms are guaranteed to find all frequent subgraphs in the input data. However complete mining algorithms perform efficiently only on sparse graphs with a large amount of labels for vertexes and edges. Due to this completeness restriction, these algorithms undertake extensive subgraph isomorphism comparison, either explicitly or implicitly, resulting in a significant computational overhead.

We will be considering here only graph transaction based FSM.

With respect to graph transaction mining, the algorithms can be divided into two groups: BFS and DFS, according to the traversing strategy adopted. BFS tends to be more efficient in that it allows for the pruning of infrequent subgraphs (at the cost of high I/O and memory usage) at an early stage in the FSM process, whereas DFS requires less memory usage (in exchange for less efficient pruning). We will consider the BFS algorithms first.

As in the case of Association Rule Mining algorithms, BFS based FSM algorithms utilize the DCP, i.e. a $(k + 1)$ subgraph cannot be frequent if its immediate parent k subgraph is not frequent. Using BFS the complete set of k candidates is processed before moving on to the $(k + 1)$ candidates, where k refers to the expansion unit for growing the candidates, which can be expressed in terms of vertexes, edges, or disjoint paths.

Four well-established exact FSM algorithms are itemized below:

- ***AGM***(18) : AGM is a well-established algorithm used to identify frequent induced subgraphs. AGM uses an adjacency matrix to represent graphs and a level-wise search to discover frequent subgraphs. AGM assumes that all vertexes in a graph are distinct. AGM discovers not only connected subgraphs, but also unconnected subgraphs with several isolated graph components. A more efficient version of AGM, called ***AcGM***, has also been developed to mine only frequent connected subgraphs.

- ***FSG***(64): is directed at finding all frequent connected subgraphs. FSG uses the BFS strategy to grow candidates whereby pairs of identified frequent k subgraphs are joined to generate $(k + 1)$ subgraphs. FSG uses a canonical labelling method for graph comparison and computes the support of the patterns using a *vertical transactionlis*t data representation, which has been used extensively in Frequent tree mining algorithms (FTM). Experiments show that FSG does not perform well when graphs contain many vertexes and edges that have identical labels because the join operation used by FSG allows multiple automorphism of single or multiple cores (In the candidate generation phase, a *core* is a common $(k - 1)$ subgraph shared by two frequent k subgraphs. Two frequent k subgraphs are eligible for joining only if they contain the same core).

The FSG algorithm is directed at graph databases consisting of a two dimensional arrangement of vertexes and edges in each graph (sometimes referred to as topological graphs, same as what we are considering). However, in chemical compound analysis users are often interested in graphs that have coordinates associated with the vertexes in two-or three-dimensional space (sometimes referred to as geometric graphs). ***gFSG*** extends the FSG algorithm to discover frequent geometric subgraphs with some degree of tolerance among geometric graph transactions. The extracted geometric subgraphs are rotation, scaling and translation invariant. gFSG shares the approach of candidate generation with FSG.

FSM algorithms that adopt a DFS strategy tend to need less memory because they traverse the lattice of all possible frequent subgraphs in a DFS manner. the well-known among them algorithms are listed below:

- ***MoFa***(89): is directed at mining frequent connected subgraphs describing molecules. The algorithm stores the embedding list of previously found subgraphs and the extension operation is restricted only to these embeddings. MoFa also uses structural pruning and background knowledge to reduce support computation.

However, MoFa still generates many duplicates, resulting in unnecessary support computation.

- ***gSpan***(17): uses a canonical representation, M-DFSC, to uniquely represent each subgraph. The algorithm uses DFS lexicographic ordering to construct a tree-like lattice over all possible patterns, resulting in a hierarchical search space called a DFS code tree. Each node of this search tree represents a DFS code. The $(k + 1) - th$ level of the tree has nodes which contain DFS codes for k subgraphs. The k subgraphs are generated by one edge expansion from the $k - th$ level of the tree. This search tree is traversed in a DFS manner and all subgraphs with non-minimal DFS codes are pruned so that redundant candidate generations are avoided. Instead of keeping the embedding list, gSpan only preserves the transaction list for each discovered pattern; subgraph isomorphism detection only operates on the graphs within the list. In comparison with embedding list based algorithms, the gSpan algorithm saves on memory usage. Experiments show that gSpan outperforms FSG by an order of magnitude. gSpan is arguably the most frequently cited FSM algorithm.

- ***GASTON***(71): integrates frequent path, subtree, and subgraph mining into one algorithm, due to the observation that most frequent sub-structures in molecular databases are free trees. The algorithm provided a solution by splitting up the frequent subgraph mining process into path mining, then subtree mining, and finally subgraph mining. Consequently, the subgraph mining is only invoked when needed. Thus, GASTON operates best when the graphs are mainly paths or trees, because the more expensive subgraph isomorphism testing is only encountered in the subgraph mining phase. GASTON records the embedding list so as to grow only patterns that actually appear; thus saving on unnecessary isomorphism detection. Experiments show that GASTON is at a competitive level with a wide range of other FGM algorithms.(43)

II.17 Discussion:

A view of the “state of the art” of current FSM, referencing especially those algorithms most frequently referred to in the literature, has been presented. The most computationally expensive aspects of FSM algorithms are candidate generation and support computation; with the latter being the most computationally expensive.

It is trivial to mention that, because of the diversity of FSM algorithms, it is difficult to enumerate the strong and weak points of these various algorithms.

Although there are abundant research publications on FSM applications many important issues remain to be addressed:

Firstly, can we discover a compact and meaningful set of frequent subgraphs instead of a complete set of frequent subgraphs? Although not mentioned throughout the chapter, a lot of research effort has been directed at reducing the resultant set of frequent subgraphs; for example, the use of maximal frequent subgraphs, closed frequent subgraphs, approximate frequent subgraphs and discriminative frequent subgraphs. However, there is no clear understanding of what kind of frequent subgraphs are the most compact and representative for any given application.

Secondly, can we achieve better classification using frequent subgraph based classifiers than other approaches? Can we integrate *feature selection* techniques deeply into the frequent subgraph mining process and directly identify the most discriminative subgraphs which are effective for classification?

Thirdly, as many researchers have noted, exact frequent subgraphs are not very helpful with respect to many real applications. Can we therefore devise more efficient algorithms to generate *approximate frequent subgraphs*? Little work has been conducted in the context of approximate frequent subgraphs mining with the notable exception of the well-known SUBDUE algorithm.

Finally, in domains like: document image classification, work-flow mining, social network mining, single graph based mining, and so on; there is still a lot of work that can be done to improve the mining task. There is always a trade-off between the combinatorial complexity of FSM algorithms and the utility of the frequent subgraphs discovered by them.

Key Points – Chapter 02 :

- We introduced the chapter by defining graph mining.
- We gave some preliminary notions of graphs and graph theory.
- We focused in this chapter on Frequent Subgraph Mining (FSM).
- We gave the major operations that an FSM algorithm has to perform in order to find subgraphs, for instance candidate generation, isomorphism checking and support counting and presented the techniques associated to perform each of them.
- We presented the FSM algorithmic approaches, Apriori and Pattern Growth.
- We defined some FSM algorithms found in the literature and provided a classification for them with respect to various considerations.

Chapter III:

Hadoop and Map Reduce

III. Chapter 03 :

Hadoop and MapReduce

Context:

Apache Hadoop is a widely used open source distributed computing framework that is employed to efficiently process large volumes of data using large clusters of cheap or commodity hardware. In this chapter, we will present the Hadoop ecosystem, with a more focus on its core component being the MapReuce engine and the Hadoop distributed file system (HDFS), we will consider also some commercial distribution of Hadoop.

III.1 Presentation of Apache Hadoop:

Hadoop is a popular open source platform that is based on distributed computing environment, was originally built by a Yahoo! engineer named Doug Cutting and is now an open source project managed by the Apache Software Foundation, Hadoop is a fundamental building block in our desire to capture and process big data. Hadoop is designed to parallelize data processing across computing nodes to speed computations and hide latency. At its core, Hadoop has two primary components:

✓ ***Hadoop Distributed File System***: A reliable, high-bandwidth, low-cost, data storage cluster that facilitates the management of related files across machines.

✓ ***MapReduce Engine***: A high-performance parallel/distributed data processing implementation of the MapReduce algorithm.

Hadoop is designed to process huge amounts of structured and unstructured data (terabytes to petabytes) and is implemented on racks of commodity servers as a Hadoop cluster. Servers can be added or removed from the cluster dynamically because Hadoop is designed to be "self-healing." In other words, Hadoop is able to detect changes, including failures, and adjust to those changes and continue to operate without interruption.(7)

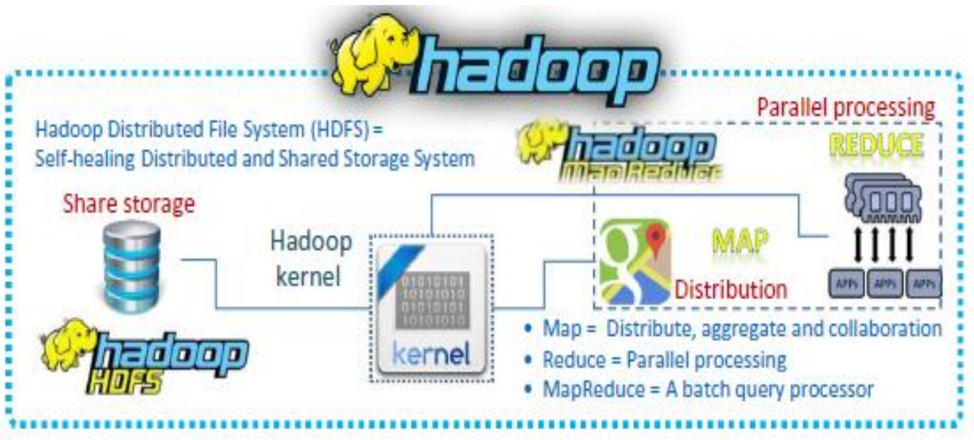

hadoop
Hadoop Distributed File System (HDFS) =
Self-healing Distributed and Shared Storage System
Share storage
Hadoop kernel
kernel
hadoop HDFS
hadoop MapReduce
Parallel processing
REDUCE
MAP
Distribution
• Map = Distribute, aggregate and collaboration
• Reduce = Parallel processing
• MapReduce = A batch query processor

Figure III-1 : The Hadoop Kernel.

III.2 The motivation for Hadoop:

Most of traditional technologies encountered difficulties while analyzing big data due to its volume velocity and variety as a result new technologies are created to address these difficulties among these technologies Hadoop is most popular name identified with big data Hadoop was developed as a practical solution to allow companies to manage and process huge volumes of data easily Hadoop manages different types of bi data whether structured or unstructured encoded or formatted this makes it useful for the decision making process new nodes or single commodity Hardware server computers can be easily added in system when required without altering the data formats how data is loaded how programs are written or modifying the existing applications Hadoop is an open source platform and runs on industry standard hardware it is also fault tolerant even if node gets lost or goes out of service the system automatically reallocates work to another location of the data and continues processing Hadoop s competencies are getting more and more real-time it generates cost benefits by reduction in the cost per terabyte of storage organizations are synchronizing Hadoop and cloud computing to manage big data thus Hadoop has become a fundamental technology to the success of big data .

III.3 History of Apache Hadoop:

big data is a word often used to promote the importance of the ever-growing data and the technologies applied to analyze this data. Big and small companies now understand the importance of data and are adding loggers to their operations with an intention to generate more data every day. This has given rise to a very important problem—storage and efficient retrieval of data for analysis. With the data growing at such a rapid rate, traditional tools for storage and analysis fall short. Though these days the cost per byte has reduced considerably and the ability to store more data has increased, the disk transfer rate has remained the same. This has been a bottleneck for processing large volumes of data. Data in many organizations have reached petabytes and is continuing to grow. Several companies have been working to solve this problem and have come out with a few commercial offerings that leverage the power of distributed computing. In this solution, multiple computers work together (a cluster) to store and process large volumes of data in parallel, thus making the analysis of large volumes of data possible. Google, the Internet search engine giant, ran into issues when their data, acquired by crawling the Web, started growing to such large volumes that it was getting increasingly impossible to process. They had to find a way to solve this problem and this led to the creation of Google File System (GFS) and MapReduce.

The GFS or GoogleFS is a file system created by Google that enables them to store their large amount of data easily across multiple nodes in a cluster. Once stored, they use MapReduce, a programming model developed by Google to process (or query) the data stored in GFS efficiently. The MapReduce programming model implements a parallel, distributed algorithm on the cluster, where the processing goes to the location where data resides, making it faster to generate results rather than wait for the data to be moved to the processing, which could be a very time consuming activity. Google found tremendous success using this architecture and released white papers for GFS in 2003 and MapReduce in 2004, Around 2002, Doug Cutting and Mike Cafarella were working on Nutch, an open source web search engine, and faced problems of scalability when trying to store billions of web pages that were crawled everyday by Nutch. In 2004, the Nutch team discovered that the GFS architecture was the solution to their problem and started working on an implementation based on the GFS white paper. They called them filesystem Nutch Distributed File System (NDFS).

In 2005, they also implemented MapReduce for NDFS based on Google's MapReduce white paper. In 2006, the Nutch team realized that their implementations, NDFS and MapReduce, could be applied to more areas and could solve the problems of large data volume processing. This led to the formation of a project called Hadoop. Under Hadoop, NDFS was renamed to Hadoop Distributed File System (HDFS). After Doug Cutting joined Yahoo! in 2006, Hadoop received lot of attention within Yahoo!, and Hadoop became a very important system running successfully on top of a very large cluster (around 1000 nodes). In 2008, Hadoop became one of Apache's top-level projects.(90)

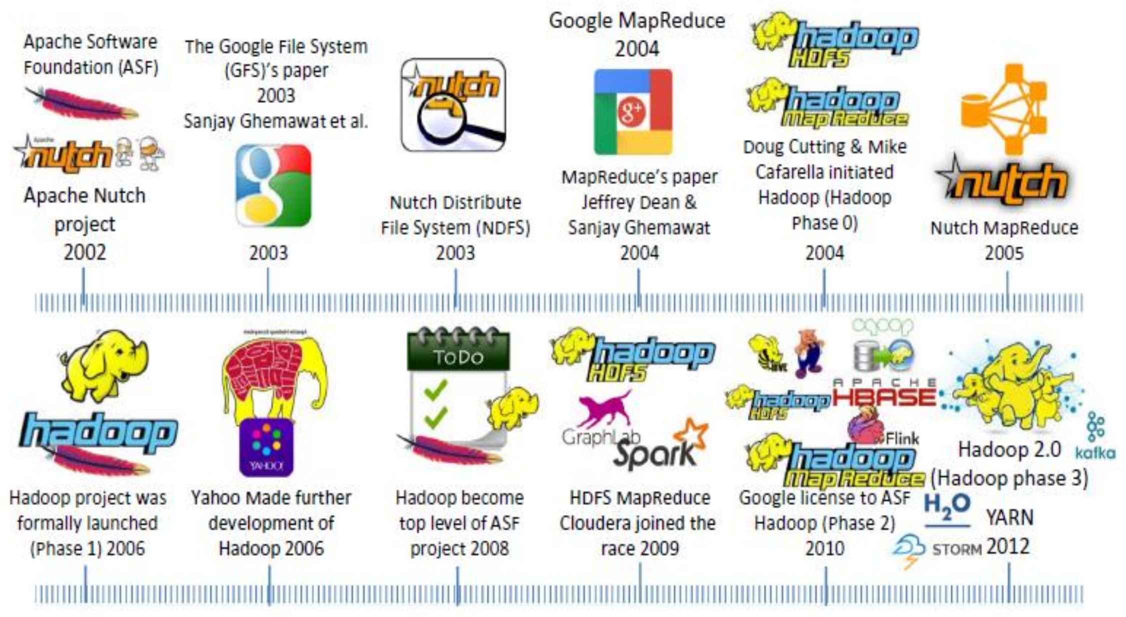

Apache Software Foundation (ASF)
Apache Nutch project 2002
The Google File System (GFS)'s paper 2003 Sanjay Ghemawat et al.
2003
Nutch Distribute File System (NDFS) 2003
Google MapReduce 2004
MapReduce's paper Jeffrey Dean & Sanjay Ghemawat 2004
Doug Cutting & Mike Cafarella initiated Hadoop (Hadoop Phase 0) 2004
Nutch MapReduce 2005
Hadoop project was formally launched (Phase 1) 2006
Yahoo Made further development of Hadoop 2006
Hadoop become top level of ASF project 2008
HDFS MapReduce Cloudera joined the race 2009
Google license to ASF Hadoop (Phase 2) 2010
Hadoop 2.0 (Hadoop phase 3) YARN 2012
HBASE
Flink
Spark
kafka
STORM

Figure III-2 : Brief History of Hadoop.

III.4 Hadoop Components and Ecosystem:

Hadoop is the most comprehensive collection of tools and technologies available today it is often compared to ecosystem just as in an ecosystem Hadoop is a cohesive system of various tools and techniques for handling big data challenges moreover a Hadoop develops and deploys Big data solutions with maximum use of available resources with minimum wastage so what are the different components of the Hadoop ecosystem the core components of the Hadoop ecosystem are Hadoop distributed file system HDFS and Hadoop Mapreduce these components provide the basic structure and services needed to support the key requirements of Big data solutions.

However just these two tools are not enough to manage Big data. The Hadoop ecosystem therefore provides a collection of tools and techniques for the complete development and deployment of Big data solutions, this ecosystem provides a common technological framework for the different stakeholders such as developers, database administrators and network managers who build Big data solutions. the additional tools and technologies included in the Hadoop ecosystem are HBase ,Hive, Pig,Sqcoop, Zookeekper ,Flume , Spark and Oozie,as we now understand Hadoop is not a single solution but a platform with a collection of applications and technique built on its foundation.

The tools and technologies of the Hadoop ecosystem provide the components needed to build and manage purpose-driven big data application for the real world let us take a look at these tools and technologies of the Hadoop ecosystem:

III.4.1 Apache HBase:

HBase is a low-latency, distributed (no relational) database built on top of HDFS. Modeled after Google's Bigtable, HBase presents a flexible data model with scale-out properties and a very simple API. Data in HBase is stored in a semi columnar format partitioned by rows into regions. It's not uncommon for a single table in HBase to be well into the hundreds of terabytes or in some cases petabytes. Over the past few years, HBase has gained a massive following based on some very public deployments such as Facebook's Messages platform. Today, HBase is used to serve huge amounts of data to real-time systems in major production deployments.

III.4.2 Apache Hive:

Hive creates a relational database−style abstraction that allows developers to write a dialect of SQL, which in turn is executed as one or more MapReduce jobs on the cluster. Developers, analysts, and existing third-party packages already know and speak SQL (Hive's dialect of SQL is called HiveQL and implements only a subset of any of the common standards). Hive takes advantage of this and provides a quick way to reduce the learning curve to adopting Hadoop and writing MapReduce jobs. For this reason, Hive is by far one of the most popular Hadoop ecosystem projects. Hive works by defining a table-like schema over an existing set of files in HDFS and handling the gory details of extracting records from those files when a query is run. The data on disk is never actually changed, just parsed at query time. HiveQL statements are interpreted and an execution plan of prebuilt map and reduce classes is assembled to perform the MapReduce equivalent of the SQL statement.

III.4.3 Apache Pig:

Like Hive, Apache Pig was created to simplify the authoring of MapReduce jobs, obviating the need to write Java code. Instead, users write data processing jobs in a high-level scripting language from which Pig builds an execution plan and executes a series of MapReduce jobs to do the heavy lifting. In cases where Pig doesn't support a necessary function, developers can extend its set of built-in operations by writing user-defined functions in Java (Hive supports similar functionality as well).

III.4.4 Apache Sqoop :

Not only does Hadoop not want to replace your database, it wants to be friends with it. Exchanging data with relational databases is one of the most popular integration points with Apache Hadoop. Sqoop, short for "SQL to Hadoop," performs bidirectional data transfer between Hadoop and almost any database with a JDBC driver. Using MapReduce, Sqoop performs these operations in parallel with no need to write code. For even greater performance, Sqoop supports database-specific plug-ins that use native features of the RDBMS rather than incurring the overhead of JDBC. Many of these connectors are open source, while others are free or available from commercial vendors at a cost. Today, Sqoop includes native connectors (called direct support) for MySQL and PostgreSQL. Free connectors exist for Teradata, Netezza, SQL Server, and Oracle (from Quest Software), and are available for download from their respective company websites.

III.4.5 Apache Flume :

Apache Flume is a streaming data collection and aggregation system designed to transport massive volumes of data into systems such as Hadoop. It supports native connectivity and support for writing directly to HDFS, and simplifies reliable, streaming data delivery from a variety of sources including RPC services, log4j appenders, syslog, and even the output from OS commands. Data can be routed, load-balanced, replicated to multiple destinations, and aggregated from thousands of hosts by a tier of agents.

III.4.6 Apache Oozie :

It's not uncommon for large production clusters to run many coordinated Map-Reduce jobs in a workflow. Apache Oozie is a workflow engine and scheduler built specifically, for large-scale job orchestration on a Hadoop cluster. Workflows can be triggered by time or events such as data arriving in a directory, and job failure handling logic can be implemented so that policies are adhered to. Oozie presents a REST service for programmatic management of workflows and status retrieval.

III.4.7 Apache ZooKeeper :

A true workhorse, Apache ZooKeeper is a distributed, consensus-based coordination system used to support distributed applications. Distributed applications that require leader election, locking, group membership, service location, and configuration services can use ZooKeeper rather than reimplement the complex coordination and error handling that comes with these functions. In fact, many projects within the Hadoop ecosystem use ZooKeeper for exactly this purpose (most notably, HBase).

III.4.8 Apache Spark:

Spark is both a programming and computing model and provides a gateway for in-memory computing. This has made Spark popular and the most widely adopted Apache project. Spark provides an alternative for MapReduce which enables workloads to execute in memory, instead of in disk, by implementing in-memory computing, Spark workloads run between 10 and 100 times faster compared to disk execution.

III.4.9 Apache Ambari:

Is web-based tool for provisioning managing and monitoring Apache Hadoop clusters, it also provides a dashboard for viewing cluster health.

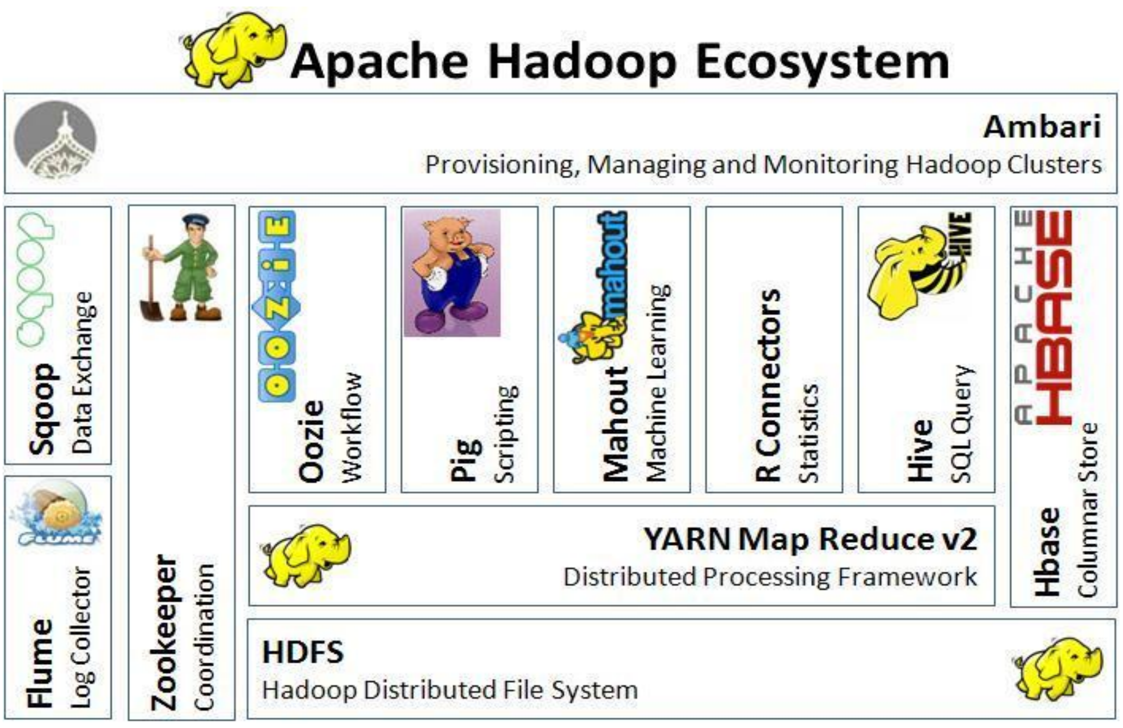


Figure III-3 : The Hadoop Ecosystem.

The aforementioned tools form the Hadoop ecosystem and provide some extension mechanism to it, but in this chapter will only concentrate on HDFS and MapReduce, which are the core technologies of Hadoop.(91)

III.5 Understanding the Hadoop Distributed File System (HDFS):

The data explosion was putting huge pressure on business to seek for innovative solutions to address the big data challenges the business needed more capable faster powerful and cost-effective computing resources including servers networking and storage infrastructure achieving proper balance of compute power data store and network was critical to optimal performance as a result the company decided on series of steps to address the challenges of handling with the volume and speed of big data the first step in this direction was to migrate from their traditional tower model servers and adopt a more robust and cost-effective rack model of servers the rack model of servers the servers offer increased computing power and improved reliability at reduced cost each server unit is referred to as a node several nodes depending on business requirement are connected with optic fibers to form cluster rack servers are ideal for virtualization and cloud computing the is they can be easily scaled up by adding more nodes to system as per business requirement there is also provision for replacing older slower node with new nodes with nodes with better performance next the business executive decided to adopt Hadoop distributed file system (HDFS) this approach will provide a fault-tolerant file system that can run on commodity hardware as well as one that allowed for the reliable storage and processing of large amounts of data.

The HDFS is a data storage cluster that facilitates the storage and management of related files across machines. It offers several unique capabilities and benefits, thus includes the following:

- Stores data reliably.
- Writes data only once.
- Allows data to be read from any cached copy of files replicated on different machines.
- Fault tolerant.
- Ensures portability of data and processes across heterogeneous commodity hardware and operating systems.
- Allows for reliable storage and processing of large amounts of data.

All these facilities together make HDFS the perfect solution to handle big data.

III.5.1 HDFS Architecture:

HDFS is comprises of interconnected clusters of nodes where files and directories reside it follows a master/slave architecture (see Figure III-4) the HDFS cluster includes single name node master server and multiple data nodes that run on the HDFS cluster the name node manages the file system namespace and regulates client access to files data nodes store data as blocks within files these blocks are distributed among the data nodes in the HDFS cluster and are managed by the name node that is the name node keeps track of where data is physically stored in a data node but how dose HDFS keep track of all these pieces the short answer is file system metadata or "data about data", HDFS metadata is a template for providing a detailed description of the following :

- When was the file created, accessed, modified, deleted, and so on?
- Where are the blocks of the file stored in the cluster?
- Who has the rights to view or modify the file?
- Where is the transaction log for the cluster located?

HDFS metadata is stored in the name node server, which is repository of all the HDFS metadata and data nodes data nodes refer to the place where the user data is stored as blocks within files the *NameNode* is therefore critical and is always stored in the memory and *DataNodes* are stored in racks. Racks are physical collections of nodes in a single location.(92)

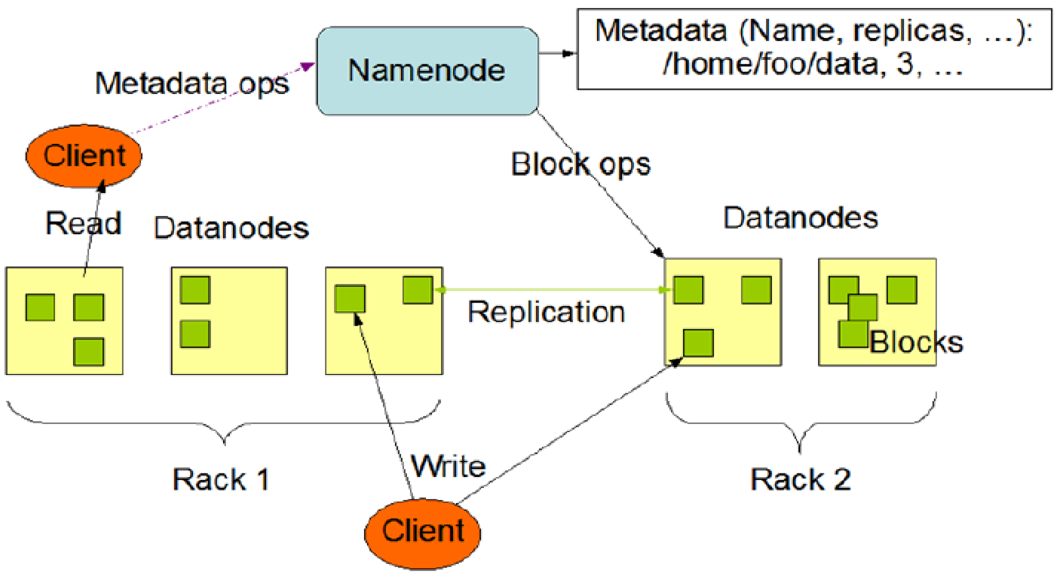


Figure III-4 : HDFS Architecture.

III.5.2 Role of Namenode and DataNode in HDFS Architecture:

Each cluster in HDFS has one master NameNode and many slave data nodes the existence of single NameNode in a cluster simplifies the architecture of the system because it acts a single arbitrator and repository for all HDFS metadata as a result of the relatively low amount of metadata per file.

A NameNode: stores all of the metadata in the main memory,enabling a fast random Manages all the file operations such as read/write create delete and replicate data locks on the data nodes it also Manages the file system Namespace.

III.5.3 How NameNodes works:

The NameNode is vital to correct operation of the cluster hence to ensure the availability of data, Secondary Name node is also available through a relationship exists between the NameNode and the DataNodes they are loosely this allows the cluster elements to add or subtract servers as the demand changes normally one NameNode and possibly a data node run on one physical server in the rack while other servers were data nodes only within the HDFS all the DataNode are collected into a the rack the NameNode uses a rack ID to keep track of all the DataNodes in the cluster the NameNode tracks the data on various DataNodes that make up a complete file.

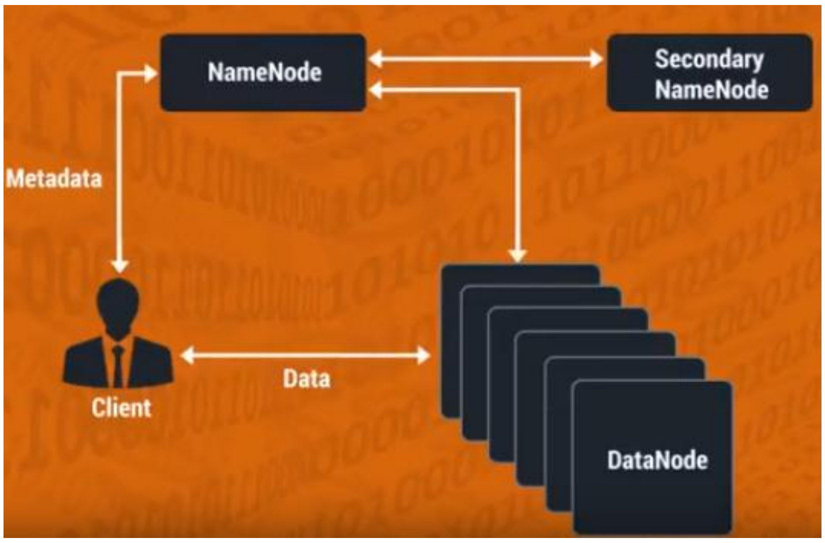


Figure III-5 : How NameNodes Works.

III.5.4 How DataNodes Works:

We know that in HDFS data is stored in multiple Data Node consequently access to a file will require access to multiple Data Nodes, its benefit throughput in two ways for one the Data Node, storing each HDFS data block in a separate file on a local file system Not creating all files in the same directory of the native operating system and instead determines the optimal number of files per directory and creates sub directories appropriately.

But how does Data Node and NameNode interact?

DataNodes constantly interact with the NameNode to check if there is anything for them to do which alerts the NameNode about the availability of DataNodes its also communicate among themselves to cooperate during normal file system operations which is important as blocks for one file are likely to be stored on multiple DataNodes.

DataNodes work by providing "heartbeat" messages to detect and ensure connectivity between the NameNode and themselves when a heartbeat is no longer detected the NameNode unmapped the DataNode from the cluster and keeps on operating as though nothing has happened then when the heartbeat returns or a new heartbeat appears it is added to the cluster.

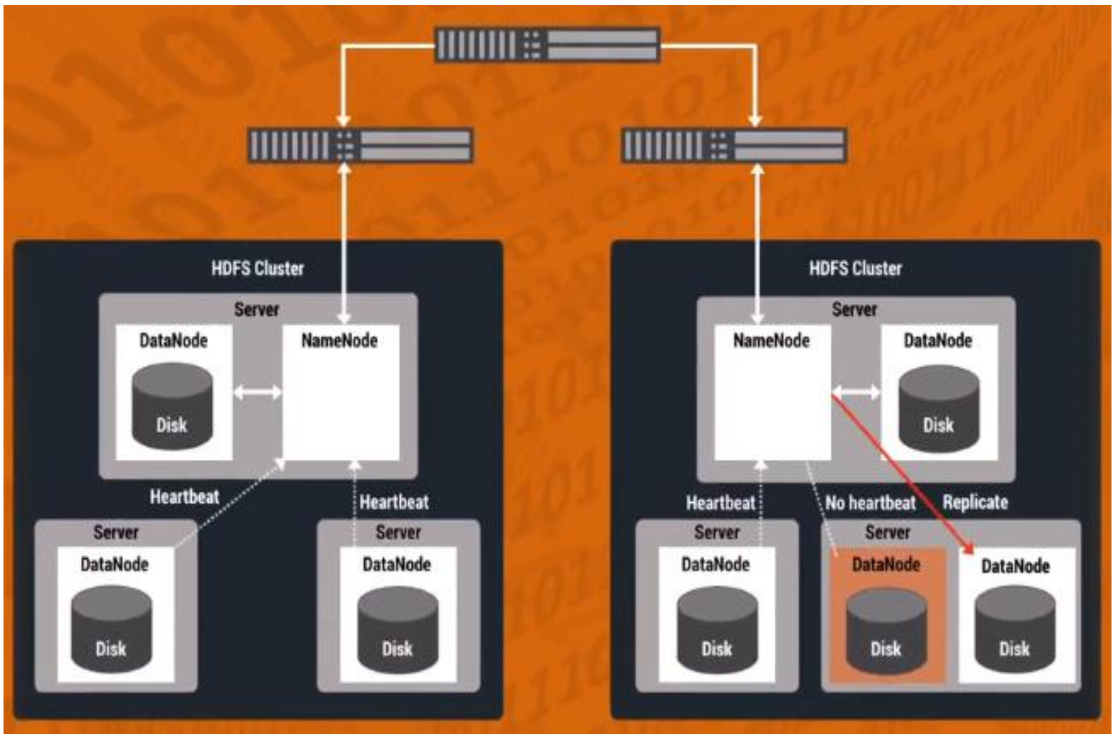


Figure III-6 : How DataNodes Works.

III.5.5 Rack Organization:

Data Notes that we have just discussed are organized within racks.

Racks are physical collections of machines in a single location using the Hadoop rack awareness process the NameNode determines the rack ID that each data node belongs to rack awareness also is an important characteristic of the data storage in HDFS large HDFS instances run on a cluster of computers that is usually spread across many racks network bandwidth and performance is usually better between machines in the same rack than between machines in different racks a simple policy is to place replicas on unique racks which not only prevents losing data when entire rack is lost but also evenly distributes replicas in the cluster in addition it also allows using bandwidth from multiple racks when reading data an optimization of a rack aware policy is to use a number of racks that is less than number of replicas to minimize global bandwidth consumption and read latency.

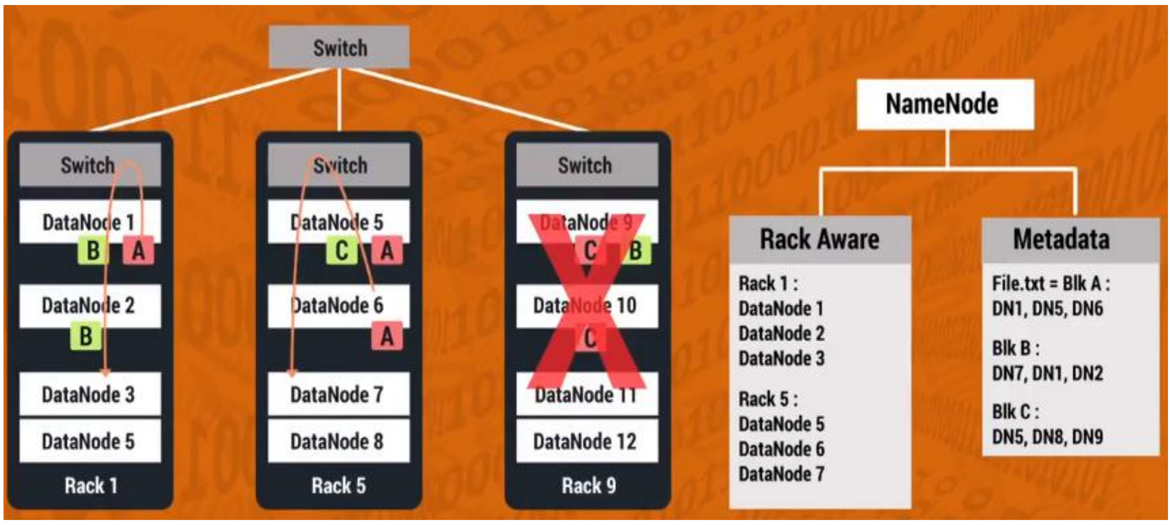


Figure III-7 : Rack Organization.

III.5.6 How Data is stored in HDFS :

To understand how data is stored in HDFS, think of a file that contains all the volumes of an encyclopedia with volume 1 being stored on server 1 volume 2 on server 2 and so on if we were to equate this with the Hadoop world pieces of this encyclopedia would be stored across the cluster which is a larger unit that is used to organize and identify files on the disk. to reconstruct the entire encyclopedia your program would need blocks from every server in the cluster to achieve availability if components fail HDFS replicates these smaller pieces on to additional servers by default this redundancy offers multiple benefits.

The most obvious being higher availability therefore HDFS is so resilient that these blocks are replicated throughout the cluster in case of a server failure.

Let us now see how this is translated to data storage in HDFS now we know that HDFS is implemented as a block structured file system in which individual files are broken into blocks of a fixed size and these are stored across clusters, each data file is broken into equal size blocks of 64 MB and each block is stored in three different DataNodes, this unique capability offers fault tolerant and faster processing capabilities but how is this done.

The process of storing each block in replicates of three, ensures data availability even if any one of the nodes becomes non-functional and thereby:

- ✓ Enhancing the fault tolerance capabilities, the splitting of the file and equal size blocks.
- ✓ Ensures that all nodes perform at the same speed and efficiency.

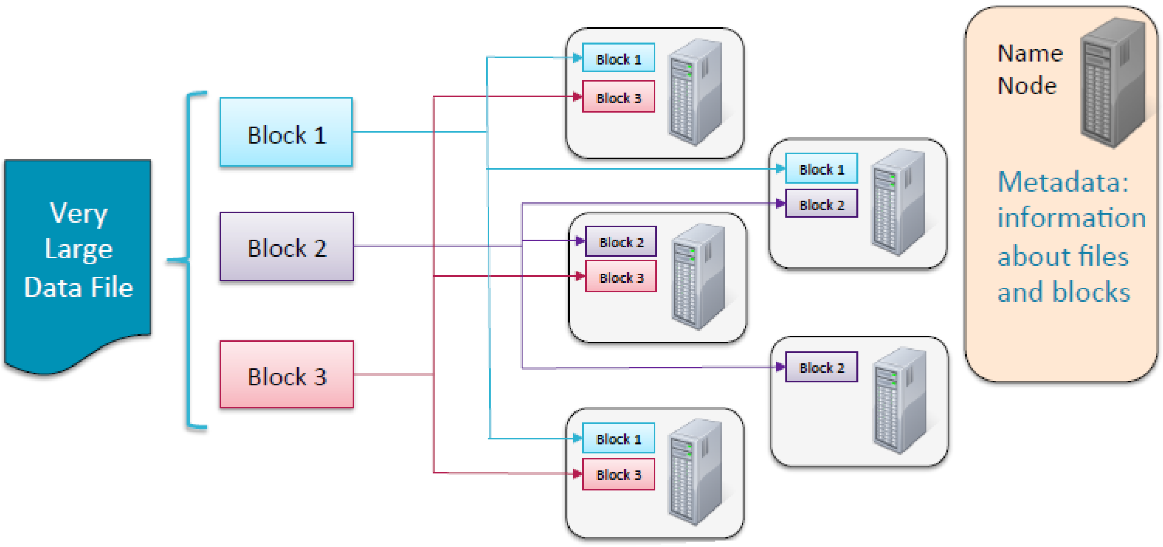


Figure III-8 : Data Storage in HDFS.

III.5.6.1 Replication and Recovery:

File can become unavailable if any one of the machines is lost to avoid the problem HDFS replicates each block across three machines by default, so the client is the HDFS user, it can read and write the data though calling the API provided by HDFS. While in the read and write process, the client first needs to obtain the metadata information from the NameNode, and then the client can perform the corresponding read and write operations.(92)

III.5.7 Data Reading Process in HDFS:

The data reading process in HDFS is not difficult. It is similar to the programming logic, which has created the object, i.e., calling the method and performing the execution. The following section will introduce the reading processing of the HDFS.(93)

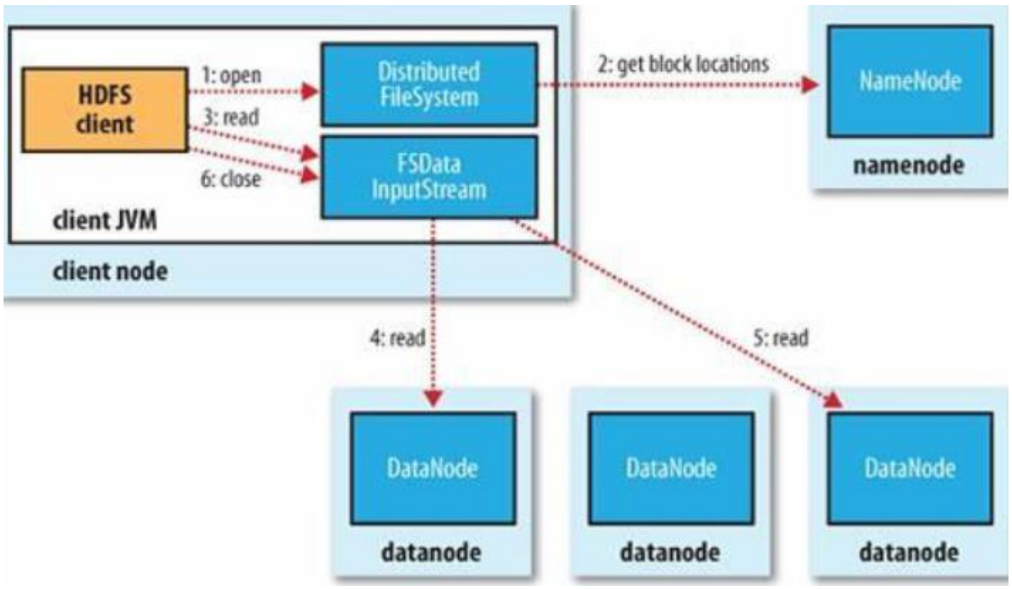


Figure III-9 : HDFS Reading Process.

According to Figure III-9, there are six steps when the HDFS has the reading process:

1. The client will generate a Distributed File System object of the HDFS class library and uses the open() interface to open a file.

2. Distributed File System sends the reading request to the Namenode by using the Remote Procedure Call Protocol to obtain the location address of the data block. After the calculating and sorting the distance between the client and the Datanode, the Namenode will return the location information of the data block to the Distributed File System.

3. After, the DistributedFileSystem has already received the distances and address of the data block; it will generate an FSDataInputStream object instance to the client. At the same time, the FSDataInputStream also encapsulates a DFSInputStream object, which is responsible for saving the storing data blocks and the address of the Datanode.

4. When everything gets ready, the client will call the read () method.

5. After receiving the calling method, the encapsulated DFSInputStream of FSDataInputStream will choose the nearest Datanode to read and return the data to the client.

6. When all the data has been read successfully, the DFSInputStream will be in charge of closing the link between the client and the Datanode. While the DFSInputStream is reading the data from the Datanode, it is hard to avoid the failure that may be caused by network disconnection or node errors. When this happens, DFSInputStream will give up the failure Datanode and select the nearest Datanode. In the later reading process, the disfunctioning Datanode will not be adopted anymore. It is observed that HDFS separates the index and data reading to the Namenode and Datanode. The Namenode is in charge of the light file index functions while the heavy data reading is accomplished by several distributed Datanodes. This kind of platform can be easily adapted to the multiple user access and huge data reading.

III.5.8 Data writing Process in HDFS:

The data writing process in HDFS is the opposite process of the reading but the writing process is more complex. The following section will introduce the writing process in HDFS briefly.

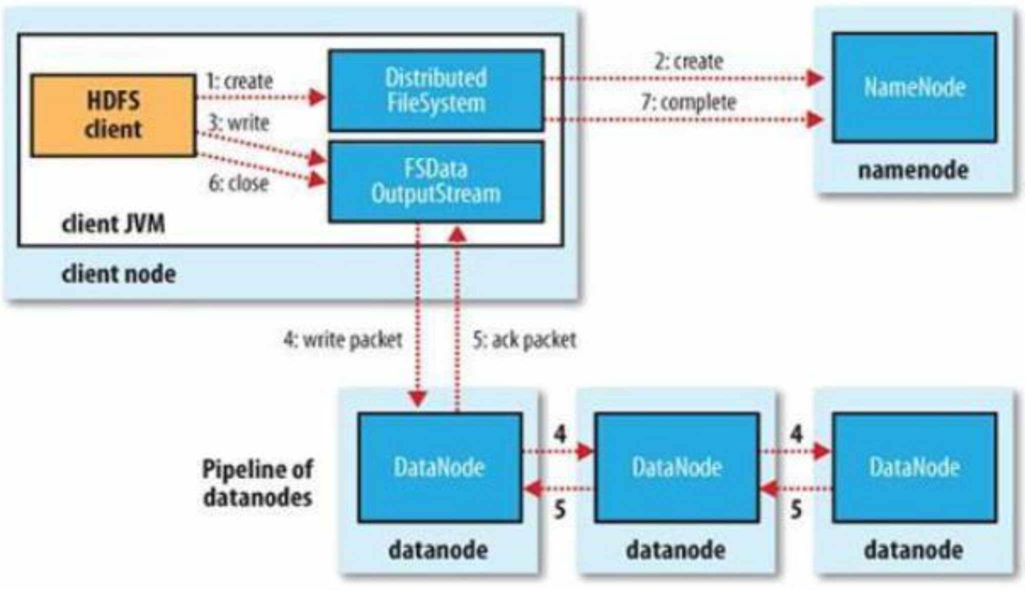


Figure III-10 : HDFS Writing Process.

The structure of HDFS reading process is similar to the writing process. These are the following seven steps:

1. The client generates a DistributedFileSystem object of the HDFS class library and uses the create() interface to open a file.

2. DistributedFileSystem sends the writing request to the Namenode by using the Remote Procedure Call Protocol (RPC). The Namenode will check if there is a duplicate file name in it. After that, the client with writing authority can create the corresponding records in the namespace. If an error occurrs, the Namenode will return the IOException to the client.

3. After the DistributedFileSystem has received the successful return message from the Namenode, it will generate a FSDataOutputStream object to the client. In the FSDataOutputStream, there is an encapsulated DFSOutputStream object which is responsible for the writing process. The client calls the write() method and sends the data to the FSDataInputStream. The DFSOutputStream will put the data into a data queue which is read by the DataStreamer. Before the real writing, the DataStreamer needs to ask for some blocks and the suitable address from the Datanode to store the data.

4. For each data block, the Namenode will assign several Datanodes to store the data block. For instance, if one block needs to be stored in three Datanodes. DataStreamer will write the data block at the first Datanode, then the first Datanode will pass the data block to the second Datanode, and the second one passes to the third one. Finally, it will complete the writing data in the Datanode chain.

5. After every Datanode has been written, Datanode will report to the DataStreamer. Step4 and Step5 will be repeated until all the data has been written successfully.

6. When all the data has been written, the client will call the close() method of FSDataInputStream to close the writing operation.

7. Finally, the Namenode will be informed by the DistributedFileSystem that all the written process has been completed. In the process of data writing, if one Datanode makes error and causes writing failure, all the links between the DataStreamer and the Datanode will be closed. At the same time, the failure node will be deleted from the Datanode chain. The Namenode will notice the failure by the returned packages and will assign a new Datanode to continue the processing. As long as one Datanode is written successfully, the writing operation will regard the process as completed.

III.5.9 Limitations of HDFS:

HDFS as the open source implementation of GFS is an excellent distributed file system and has many advantages. HDFS was designed to run on the cheap commodity hardware not on expensive machines. This means that the probabilities of node failure are slightly high. To give a full consideration to the design of HDFS, we may find that HDFS has not only advantages but also limits for dealing with some specific problems. These limitations are mainly displayed in the following aspects:

- High Access Latency : HDFS does not fit fort requests which should be applied in a short time. The HDFS was designed for the Big Data storage and it is mainly used for it high throughput abilities. This may cost the high latency instead.Because HDFS has only one single Master system, all the file requests need to be processed by the Master. When there is a huge number of requests, there is inevitably has the delay. Currently, there are some additional projects to address this limitation, such as using the Hbase uses the Upper Data Management project to manage the data.

- Poor small files performance : HDFS needs to use the Namenode to manage the metadata of the file system to respond to the client and return the locations so that the limitation of a file size is determined by the Namenode. In general, each file, folder, and block need to occupy the 150 bytes' space. In other words, if there are one million files and each file occupies one block, it will take 300MB space. Based on the current technology, it is possible to manage millions of files. However, when the files extend to billions, the work pressures on the Namenode is heavier and the time of retrieving data is unacceptable.
- Unsupported multiple users write permissions : in HDFS, one file just has one writer because multiple users' writer permissions are not supported yet. The write operations can only be added at the end of the file not at the any positions of the file by using the Append method.

We believe that, with the efforts of the developers of HDFS, HDFS will become more powerful and can meet more requirements of the users.

III.6 MapReduce:

MapReduce is a programming model designed for processing large volumes of data in parallel by dividing the work into a set of independent tasks. MapReduce programs are written in a particular style influenced by functional programming constructs, specifically idioms for processing lists of data. This module explains the nature of this programming model and how it can be used to write programs, which run in the Hadoop environment, MapReduce engine is a high-performance parallel or distributed data processing implementation of the MapReduce algorithm this means that it can be used to write programs that can process the large amounts of unstructured data by using a number of distributed processors simultaneously.

III.6.1 MapReduce Functional Concept:

The MapReduce model is a combination of two capabilities in existing functional computer languages Map and reduce the map function of MapReduce distributes jobs tasks across a large number of systems it also handles the placement of these tasks in a way that it balances the load manages recovery from failures. The reducer function aggregates all the elements back together to provide a result the map and reduce functions are a good choice for Big Data as they do not modify the original data but create new data structures as their output.

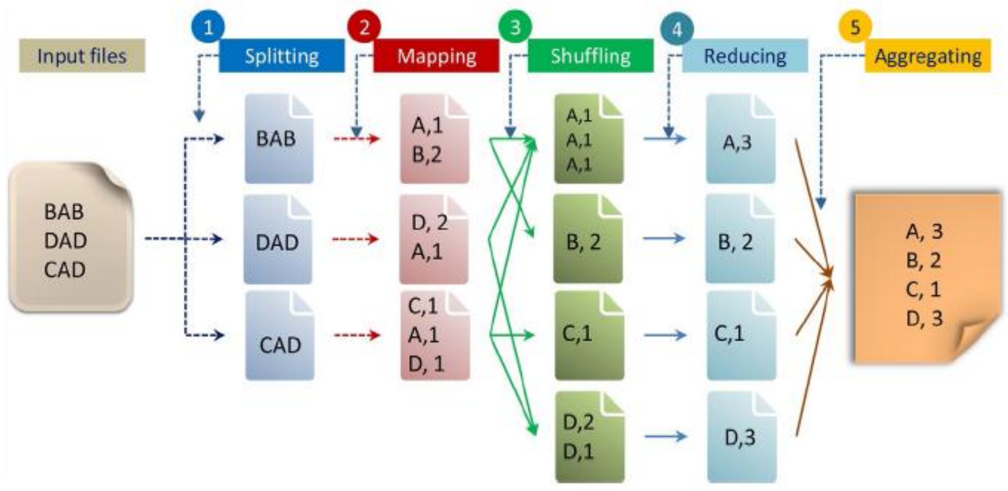


Figure III-11 : How MapReduce Works.

III.6.2 Characteristics of MapReduce:

There are four main characteristics of the MapReduce:

- Scheduling: In Map Reduce jobs are broken down into individual tasks for the map and the reduce functions of the application the mapping is completed before reducing can begin and the entire process is complete only when all the reduced tasks have run successfully.

- Synchronization: since more than one process is concurrently executed in the cluster synchronization mechanisms must be in place this includes a function called shuffle and sort, which collects and prepares all the mapped data for reduction.

- Code /Data co-location: where code refers to the mapping functions the code and data must be co-located or located on the same machine or node to ensure effective processing.

- Fault and error handling: most MapReduce engines have error handling, fault tolerance mechanisms in place that recognize when something wrong, and make the necessary correction.

III.6.3 The working process of MapReduce:

When to use big data efficiently it is necessary to access large amounts of input data select relevant parts from it and to then compute something of value for businesses from these parts all the while ensuring that the original data does not get changed to ensure that this is done without human error an application needs to perform these tasks, the MapReduce framework consists of a single master which is called the job tracker and three slaves(see Figure III-12) , referred to as task trackers the client application provide jobs to job tracker which in turn submits or schedules the jobs to different task trackers these task trackers then process the data the processed data also Known as map outputs is then is forwarded to reduce tasks which integrates the data from different task trackers and generates the final output MapReduce performs its tasks in a series of steps:

1. The input is split into multiple pieces of data.

2. The master and workers are created and the worker processes is executed remotely.

3. The map worker uses the map function to extract relevant data, and then generates a key-value pair for the extracted data.

4. The map worker uses the partitioning function to partition the data into R regions.

5. The master now instructs the reduce workers to contact the map workers to get the key/value data for their partition. The data received is sorted as per keys, a process termed as the shuffle process.

6. After storing of the data the reduce function is called for every unique key, and is used to write the output sent to file.

7. When the reduce workers complete their work, the master transfers the control to the user program.

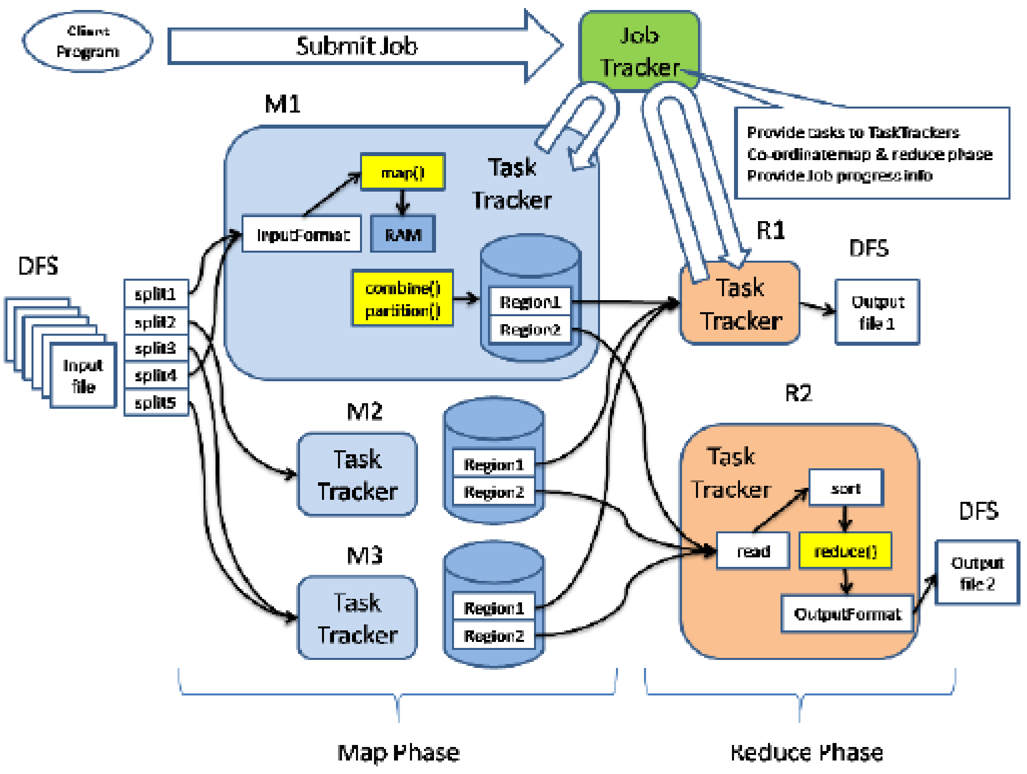


Figure III-12 : MapReduce Procedure.

III.6.4 Limitations of MapReduce:

Although MapReduce is popular all over the world, most people still have realized the limits of the MapReduce. The following are the four main limitations of the MapReduce:

- ***The bottleneck of Job Tracker***:

The JobTracker should be responsible for jobs allocation, management, and scheduling. In addition, it should also communicate with all the nodes to know the processing status. It is obvious that the JobTracker which is unique in the MapReduce, takes too many tasks. If the number of clusters and the submission jobs increase rapidly, it will cause network bandwidth consumption. As a result, the JobTracker will reach bottleneck and this is the core risk of MapReduce.

- ***TaskTracker***:

Because the jobs allocation information is too simple, the TaskTracker might assign a few tasks that need more sources or need a long execution time to the same node. In this situation, it will cause node failure or slow down the processing speed.

- ***Jobs Delay***:

Before the MapReduce starts to work, the TaskTracker will report its own resources and operation situation. According to the report, the JobTracker will assign the jobs and then the TaskTracker starts to run. Consequently, the communication delay may make the JobTracker to wait too long so that the jobs cannot be completed in time.

- ***Inflexible Framework***:

Although the MapReduce currently allows the users to define its own functions for different processing stages, the MapReduce framework still limits the programming model and the resources allocation.

III.7 YARN (Yet Another Resource Negotiator) :

In order to solve above limitations, the designers have put forward the next generation of MapReduce: YARN (Yet Another Resource Negotiator) is Hadoop's cluster resource management System.

YARN was introduced in Hadoop 2 to improve the MapReduce implementation, but it is general enough to support other distributed computing paradigms as well. YARN provides APIs for requesting and working with cluster resources, but these APIs are not typically used directly by user code. Instead, users write to higher-level APIs provided by distributed computing frameworks, which themselves are built on YARN and hide the resource management details from the user. The situation is illustrated in Figure III-13, which shows some distributed computing frameworks (MapReduce, Spark, and so on) running as YARN applications on the cluster compute layer (YARN) and the cluster storage layer (HDFS and HBase).(94)

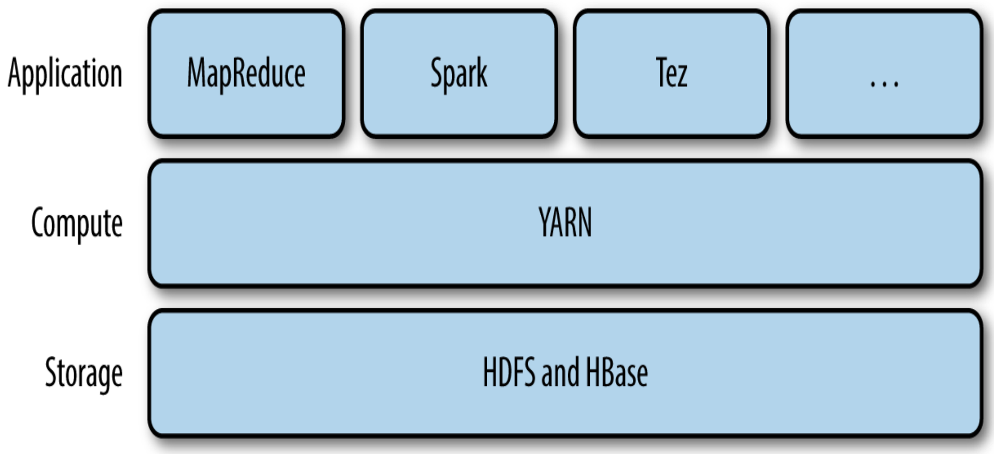


Figure III-13 : YARN Applications.

Given the limitations of MapReduce, the main purpose of YARN is to divide the tasks for the JobTracker.

In YARN resources are managed by the ResourceManager and the jobs are traced by the ApplicationMaster. The TaskTracker has become the NodeManager. Hence, the global ResourceManager and the local NodeManager compose the data computing framework. In YARN, the ResourceManager will be the resources distributor while the ApplicationMaster is responsible for the communication with the ResourceManager and cooperate with the NodeManager to complete the tasks.

III.7.1 YARN architecture:

Compared with the old MapReduce Architecture, it is easy to find out that YARN is more structured and simple. Then, the following section will introduce the YARN architecture:

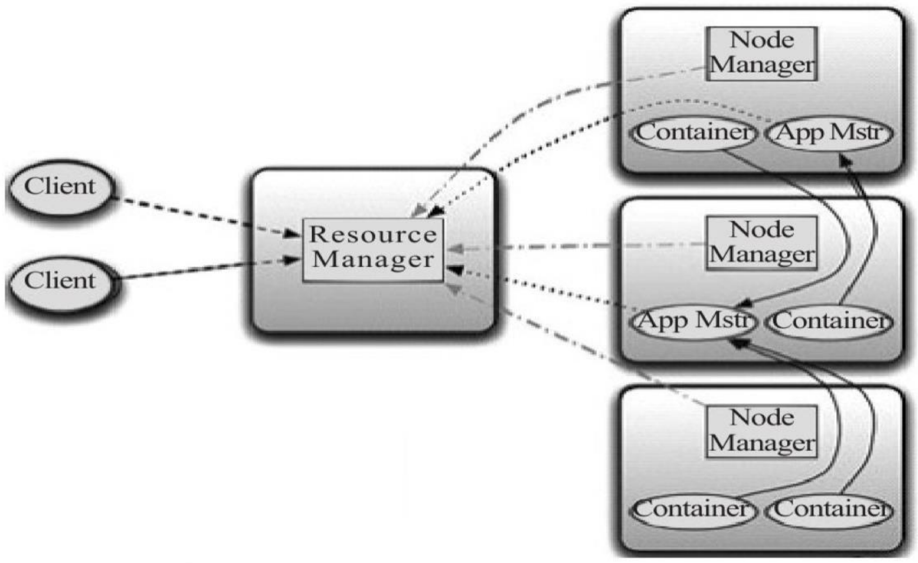


Figure III-14 : Yarn Architecture.

According to Figure III-14 , there are following four core components of the YARN Architecture:

1. ***Resource Manager***:

According to the different functions of the ResourceManager, it designers has divided it into two lower level components: The Scheduler and the ApplicationManager. On the one hand, the Scheduler assigns the resource to the different running applications based on the cluster size, queues, and resource constraints. The Scheduler is only responsible for the resources allocation but is not responsible for the monitoring the application implementation and task failure. On the other hand, the ApplicationManager is in charge of receiving jobs and redistributing the containers for the failure objects.

2. ***NodeManager :***

The NodeManager is the frame proxy for each node. It is responsible for launching the application container, monitoring the usage of the resource, and reporting all the information to the Scheduler.

3. ***ApplicationMaster :***

The ApplicationMaster is cooperating with the NodeManager to put tasks in the suitable containers to run the tasks and monitor the tasks. When the container has errors, the ApplicationMaster will apply for another resource from the Scheduler to continue the process.

4. ***Container :***

In YARN, the Container is the source unit which is the available node splitting the organization resources. Instead of the Map and Reduce source pools in MapReduce, the ApplicationMaster can apply for any numbers of the Container. Due to the same property Containers, all the Containers can be exchanged in the task execution to improve efficiency.

III.7.2 Advantages of YARN:

Compared to the MapReduce, there are many advantages of the YARN framework. There are four main advantages of YARN compared to the MapReudce:

- YARN greatly enhances the scalability and availability of the cluster by distributing the tasks to the JobTracker. The ResourceManager and the ApplicationMaster greatly relieves the bottleneck of the JobTracker and the safety problems in the MapReduce.

- In YARN, the ApplicationMaster is a customized component. That means that the users can write their own program based on the programming model. This makes the YARN more flexible and suitable for wide use.

- YARN, on the one hand, supports the program to have a specific checkpoint. It can ensure that the ApplicationMaster can reboot immediately based on the status which was stored on HDFS. On the other hand, it uses the ZooKeeper on the ResourceManager to implement the failover. When the ResourceManager receives errors, the backup ResourceManager will reboot quickly. These two measures improve the availability of YARN.

The cluster has the same Containers are the Reduce and Map pools in Map Reduce. Once there is a request for resources, the Scheduler will assign the available resources in the cluster to the tasks and regard the resource type. It will increase the utilization of the cluster resources.

III.8 Commercial distribution of Hadoop:

Apart from the aforementioned open source distribution of Hadoop which is maintained by Apache, several other commercial distribution versions exist too, each of them offers unique features to address big data challenges. Together these distributions complete the ecosystem of Hadoop, ***Cloudera***, ***Hortoworks***, ***intel***, ***Greenplum***,***MapR***,and ***AWS EMR*** are example of such distributions:

- ✓ ***Hortonworks***: Hortonworks data platform is a complete solution offering not just data processing and management, but the enterprise spanning security and governance.

✓ ***MapR***: this Apache Hadoop distribution claims to provide full data protection, no single points of failure, improved performance, and dramatic ease of use advantages.

✓ ***Cloudera*** : Cloudera is seen by many people as the market leader in the Hadoop space because it released the first commercial Hadoop distribution and it is a highly active contributor of code to the Hadoop ecosystem, in addition to its commercial distribution cloudera also maintain a free and open source version which integrate the Hadoop core component , called CDH (Cloudera Distribution with Hadoop), this will be discussed in detail in the next section as it is the platform used for building the cluster and running the application subject of the present thesis.

The Hadoop system can be extended with other technologies such as Dremel, HPCC in deploying big data solutions, the diagram (See Figure III-) shows the different tools and technologies that are based on Hadoop framework.

Together all the various elements mentioned above :(i) the Hadoop framework (ii) the core components (iii) the commercial distributions and (iv) the related technologies form a comprehensive toolset for targeting different big data challenges.

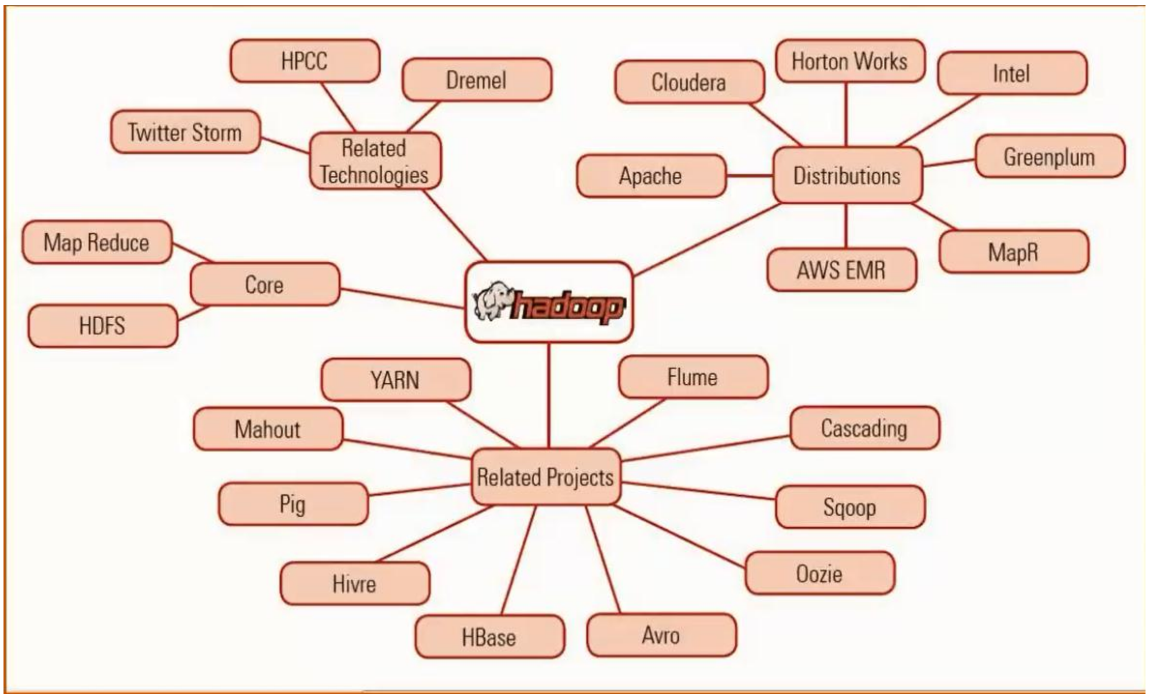


Figure III-15 : The Hadoop Ecosystem along with the Commercial Distributions.

III.8.1 Cloudera's Distribution with Hadoop (CDH):

Cloudera is an organization that has been working with Hadoop and its related technologies for a few years now. It is an expert in the field of handling large amounts of data using Hadoop and various other open source tools and projects. It is one of the major contributors to several of the Apache projects. Over the years, Cloudera has deployed several clusters for hundreds of its customers. It is equipped with practical knowledge of the issues and details of real production clusters. To solve these issues, Cloudera built CDH. In most distributed computing clusters, several tools need to work Together to provide the desired output. These tools are individually installed and are then configured to work well with each other. This approach often creates problems as the tools are never tested together. Also, the setup and configuration of these tools is tedious and prone to errors. CDH solves this problem as it is packaged with thoroughly tested tools that work well together in a single powerful distribution. Installation and configuration of the various tools and components is more organized with CDH. CDH has everything an enterprise needs for its big data projects. The components packaged into CDH provide tools for storage as well as the computation of large Volumes of data. By using CDH, an enterprise is guaranteed to have good support from the community for its Hadoop deployment.

Note that for this thesis we used CDH as our implementation platform.

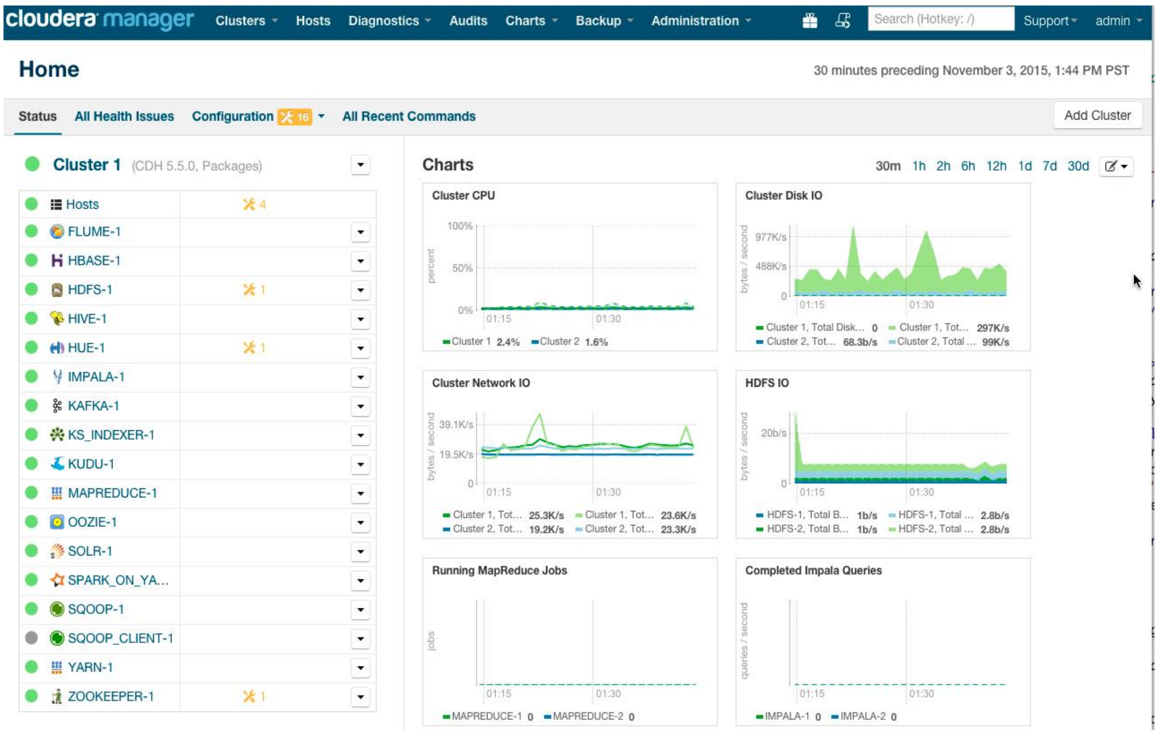


Figure III-16 : CDH Main Admin Console "Cloudera Manager".

III.8.1.1 Cloudera Manager:

Cloudera Manager is a web-browser-based administration tool to manage Apache Hadoop clusters. It is the centralized command center to operate the entire cluster from a single interface. Using Cloudera Manager, the administrator gets visibility for each and every component in the cluster. A few of the important features of Cloudera Manager are listed below:

✓ It provides an easy-to-use web interface to install and upgrade CDH across the cluster.

✓ It provides an easy-to-use web interface to install and upgrade CDH across the cluster.

✓ Each node in the cluster can be assigned roles and can be configured accordingly. It allows the starting and stopping of services across all nodes from a single web interface.

✓ It provides complete information for each node, for example, CPU, memory disk, and network statuses.

Cloudera Manager is available in the following two editions:

- Cloudera Manager Standard (free).
- Cloudera Manager Enterprise (licensed).

Cloudera Manager Standard Edition, though free, is a feature packed tool that ca be used to deploy and manage Apache Hadoop clusters with no limitation on the number of nodes. However, there are a few features that are not part of the standard edition. These are as follows:

- Lightweight Directory Access Protocol (LDAP) authentication.
- Alerts via SNMP (Simple Network Management Protocol).
- Operational reports and support integration.
- Enhanced cluster statistics.
- Disk quota management.

III.8.1.2 Understanding the Cloudera Manager Architecture:

The *Cloudera Manager Server* is the master service that manages the data model of the entire cluster in a database. The data model contains information regarding the services, roles, and configurations assigned for each node in the cluster.

The Cloudera Manager Server is responsible for performing the following functions:

- It communicates with Cloudera Manager Agents that are installed on each node of the cluster and assigns tasks as well as checking the health of each agent by monitoring its periodic heartbeats.
- It provides an administrator web interface for the end user to perform administrator operations.
- It calculates and displays dashboards of the health for the entire cluster.

- It monitors the important parameters such as disk usage, CPU, and RAM for each node in the cluster. It also allows full control on the Hadoop daemons running on the cluster.
- It manages the Kerberos credentials for the services running on the cluster. Kerberos is the tool used to manage the authentication and authorization requirements of the cluster.
- It exposes a set of easy-to-use APIs that helps developers write their own applications to interact with the Cloudera Manager Server.

The Cloudera Manager Agent is installed on each node of the cluster. It is responsible for accepting tasks from the Cloudera Manager Server and performs the starting and stopping of Hadoop daemons on its own node. It is also responsible for gathering all system-level information and statistics and is relayed back to the Cloudera Manager Server.

Figure III-17 depicts the cloudera manager architecture.

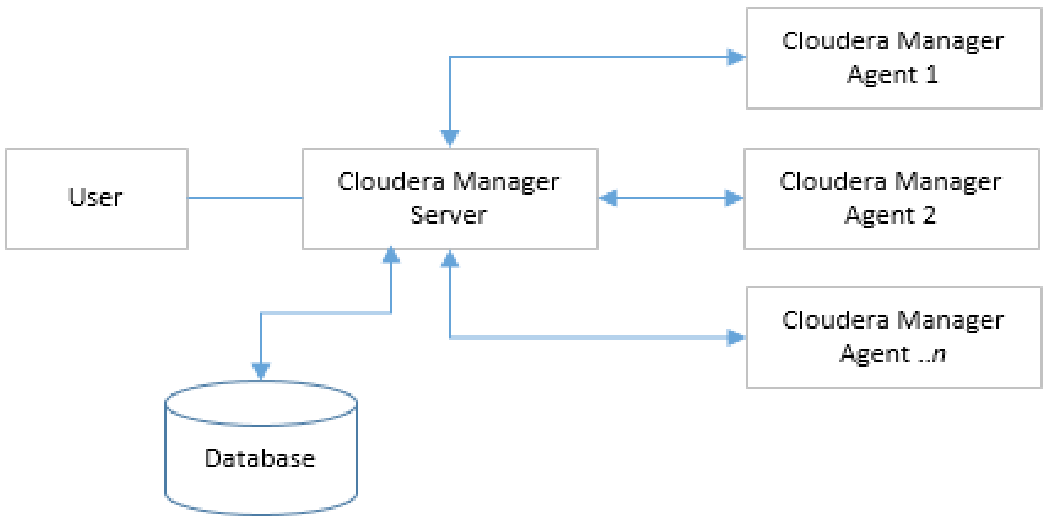


Figure III-17 : Cloudera Manager Architecture.(90)

Key Points – Chapter 03 :

- We Introduced the chapter by presenting the general History and a concepts of Hadoop platform.
- We described the main component that make up what is known by the Hadoop ecosystem such as Hbase, Hive,Flume,……etc
- We presented in detail the core component of Hadoop. HDFS its main fault tolerant storage system that provides the basic structure and service needed to support the core requirement of storage for Big Data and MapReuce its computational engine for distributed computing.
- We concluded the chapter by defining in brief the Cloudera Distribution with CDH and its main management console Cloudera Manager, which are used in conjunction as a platform for running the application.

Chapter IV:

Implementation

IV. Chapter 04

Implementation

Context:

As cited in previous chapters, frequent subgraph mining is one of the most challenging tasks, this task has been highly motivated by the tremendously increasing size of existing graph databases especially datasets in certain domains such as bioinformatics, chemoinformatics and social networks. Due to this fact, there is urgent need for efficient and scaling approaches for frequent subgraph discovery, in this chapter, we study a novel iterative map reduce based method for distributed large scale subgraph mining called FSM-H implemented with Hadoop. The algorithm allows for using a different filtering and partitioning schemes, and breaks the mining into different phases.

IV.1 Background:

In this work we are interested in frequent subgraph mining in a large graph database containing small-medium size graphs:

Let, $G = \{G_1, G_2, \dots \dots .., G_n\}$ be a graph database, where each $G_i \epsilon G, \forall i = \{1, \dots \dots, n\}$ represents a labeled, undirected, simple (no multiple edges between a pair of vertices), and connected graph. For a graph g, its size is defined as the number of edges it contains. Now, $t(g) = \{ Gi : g \subseteq Gi \epsilon G\}, \forall i = \{1 \dots n\}$, is the support-set of the graph g (here the subset symbol denotes a subgraph relation). Thus, $t(g)$ contains all the graphs in G that has a subgraph isomorphic to g. The cardinality of the support-set is called the support of g. g is called frequent if $support \geq \pi^{min}$, where π^{min} is predefined/user specified minimum $support$ (minsup) threshold. The set of frequent patterns are represented by F. Based on the size (number of edges) of a frequent pattern, we can partition F into several disjoint sets, F_i such that each of the F_i contains frequent patterns of size i only.

Example:

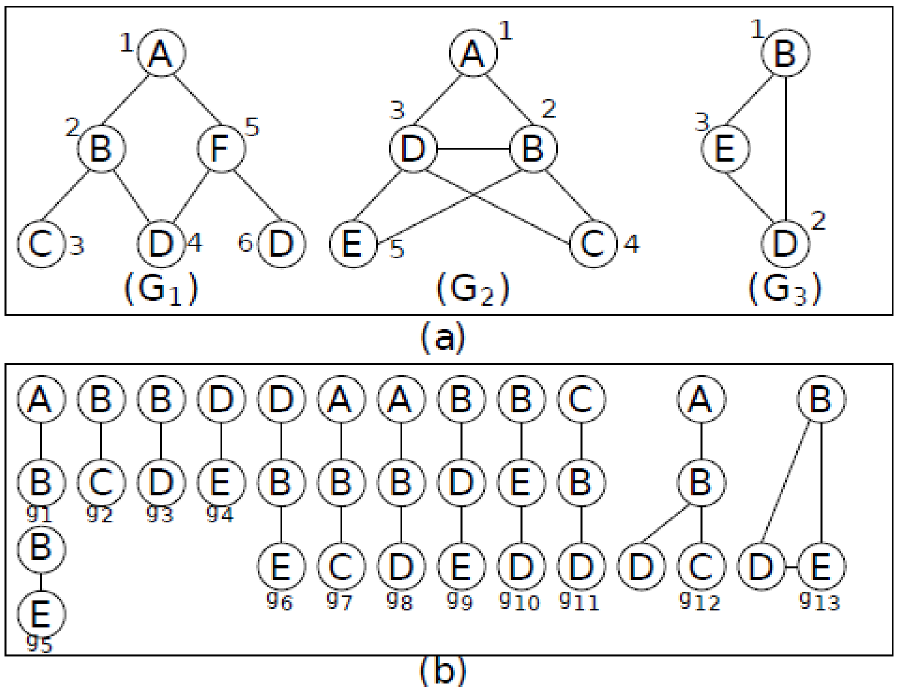


Figure IV-1 : (a) Graph database with 3 graphs with labeled vertices
(b) Frequent subgraph of (a) with minsup = 2

Figure IV-1 (a) shows a database with 3 vertex labeled graphs (G_1, G_2 and G_3) with $\pi^{min} = 2$, there are thirteen frequent subgraphs as shown in Figure IV-1 (b). Note that, For the sake of simplicity in this example we assume that the edges of the input graphs are unlabeled. But FSM-H is designed and developed to handle labels both on vertices and edges.

IV.2 Graph Partitions:

Let S_M $\{M_1, M_2, \dots\dots, M_N\}$ be a set of distributed machine, and let $Part_j\ (G) \subseteq G$ be a non-empty subset of G, we define partitioning of the graph database over S_M by the following:

$Part(G) = \{Part_1(G), Part_2(G), \dots\dots, Part_N(G)\}$ such that:

- $\cup_{i=1}^{N}\{Part_i(G)\} = G, and$

- $\forall\, i \neq j, Part_i(G) \cap Part_j(G) = \emptyset$.(13)

The above definition presents the general idea of partitioning graph datasets over a set of machines, later in the chapter we define the heuristic employed by FSM-H when doing so, for instance edge based of transaction based partitioning.

IV.3 Challenges:

Solving the task of frequent subgraph mining (FSM) on a distributed platform like Map Reduce is challenging for various reasons. First, an FSM method computes the support of a candidate subgraph pattern over the entire set of input graphs in a graph dataset.

In a distributed platform, if the input graphs are partitioned over various worker nodes like in our case. the local support of a subgraph in the respective partition at a worker node is not much useful for deciding whether the given subgraph is frequent or not. Also, local support of a subgraph in various nodes cannot be aggregated in a global data structure, because, MapReduce programming model does not provide any built-in mechanism for communicating with a global state. Also, the support computation cannot be delayed arbitrarily, as following Apriori principle, future candidate patterns can be generated only from a frequent pattern.

IV.4 Contribution and Goals:

We study here an FSM-H algorithm which implements a distributed frequent subgraph mining method over Map Reduce programming model. Given a graph database, and a minimum support threshold, FSM-H generates a complete set of frequent subgraphs. To ensure completeness, it constructs and retains all patterns in a partition that have a non-zero support in the map phase of the mining, and then in the reduce phase, it decides whether a pattern is frequent by aggregating its support computed in other partitions from different computing nodes. To overcome the dependency among the states of a mining process, FSM-H runs in an iterative fashion, where the output from the reducers of iteration $i - 1$ is used as an input for the mappers in the iteration i. The mappers of iteration i generate candidate subgraphs of size i (number of edge), and also compute the local support of the candidate pattern. The reducers of iteration i then find the true frequent subgraphs (of size i) by aggregating their local supports. They also write the data in disk that are processed in subsequent iterations.an external condition decides the termination of an iteration (job).

Pseudo code for iterative MapReduce algorithm is presented in Figure VI-2 :

```
Iterative_MapReduce():
1. While(Condition)
2.     Execute MapReduce Job
3.     Write result to DFS
4.     Update condition
```

Figure IV-2 : Iterative MapReduce Algorithm

In the subsequent sections to come:

- We introduce, FSM-H, a novel iterative MapReduce based frequent subgraph mining algorithm, which is complete.
- We describe the data structures that is used to save and consequently propagate the states of the mining process over different iterations.
- We empirically demonstrate the performance of FSM-H on synthetic as well as real world large datasets.

IV.5 Method:

As mentioned earlier FSM-H is designed as an iterative MapReduce process

At the beginning of iteration i, FSM-H has at its disposal all the frequent patterns of size $i-1$ (F_{i-1}) and at the end of iteration i, it returns all the frequen patterns of size i (F_i) Note that, in this work, the size of a graph is equal to the number of edges it contains.

For a mining task if F is the set of frequent patterns,FSM-H runs for a total of l iterations, where l is equal to the size of the largest graph in F.

To distribute a frequent subgraph mining (FSM) task, FSM-H partitions the graph dataset $G = \{G_i\}_{i=1,\dots,n}$ into k disjoint partitions, such that each partition contains roughly equal number of graphs; thus it mainly distributes the support counting (discussed in details later) subroutine of a frequent pattern mining algorithm. Conceptually, each node of FSM-H runs an independent FSM task over a graph dataset which is $1/k'$th of the size of $|G|$.Note that, k is an important parameter and details on how to choose it optimally is explained later In this chapter.(85)

FSM algorithms in general are an adaptation of the baseline algorithm shown in Figure II-23 far earlier in chapter 02, which actually runs in a sequential machine, although just mentioned in chapter 02 below we provide more details on this algorithm. Note that we do so with pattern growth approach as it is adopted by FSM-H:

The pseudo-code The pseudo-code shown in Figure II-23 implements an FSM algorithm that follows a typical candidate generation-and-test paradigm with breadth-first candidate enumeration. In this paradigm, the mining task starts with frequent patterns of size one (single edge patterns), denoted as F_1 (Line0). Then in each of the iterations of the while loop (Line 1-6), the method progressively finds F_2, F_3 and so on until the entire frequent pattern set F is obtained. If F_k is nonempty at the end of an iteration of the above while loop, from each of the frequent patterns in F_k the mining method creates possible candidate frequent patterns of size $k + 1$ (Line 2). These candidate patterns are represented as the set C. For each of the candidate patterns, the mining method computes the pattern's support against the dataset G (Line 5). If the support is higher than the minimum support threshold ($minsup$), the given pattern is frequent, and is stored in the set F_{k+1} (Line 6). Before support counting, the method also ensures that different isomorphic forms of a unique candidate patterns are unified and only one such copy is processed by the algorithm (Line 4). Once all the frequent patterns of size $k + 1$ are obtained, the while loop in Line 1 to 7 continues. Thus each iteration of the while loop obtains the set of frequent patterns of a fixed size, and the process continues until all the frequent patterns are obtained. In Line 8, the FSM algorithm returns the union of $F_i: 1 \leq i \leq k - 1$.

Below, we provide a short description of each of the subroutines that are called in the pseudo-code.

IV.5.1 Candidate Generation:

Given a frequent pattern (say, c) of size k, this step adjoins a frequent edge (which belongs to F_1) with c to obtain a candidate pattern d of size $k + 1$. If d contains an additional vertex then the added edge is called a *forward edge*, otherwise it is called a *back edge*; the latter simply connects two of the existing vertices of c. Additional vertex of a forward edge is given an integer id, which is the largest integer id following the ids of the existing vertices of c; thus the vertex-id stands for the order in which the forward edges are adjoined while building a candidate pattern. c is called the parent of d, and d is a child of c, and based on this parent-child relationship we can arrange the set of candidate patterns of a mining task in a candidate generation tree (see figure IV-3) :

Note however that, if d has $k + 1$ edges, based on the order how its edges have been adjoined, d could have many different generation paths in a candidate generation tree; FSM-H impose a restriction on the generation paths and only one of which is considered valid, so that multiple copies of a candidate pattern are not generated. Thus the candidate generation tree of an FSM-H can be unambiguously defined. FSM-H also impose restriction on the extension nodes of the parent pattern by allowing edge adjoining only with vertices on the right most path. Right most path is the mechanism used in the so popular gSpan algorithm, so simply put “right most vertex” (RMV) is the vertex with the largest id in a candidate subgraph and “right most path” (RMP) is the shortest path from the lowest id vertex to the RMV strictly following forward edges.(85)

Example: In the figure IV-3 below we define part of the candidate generation tree of the FSM-H task that we defined in figure IV-1.

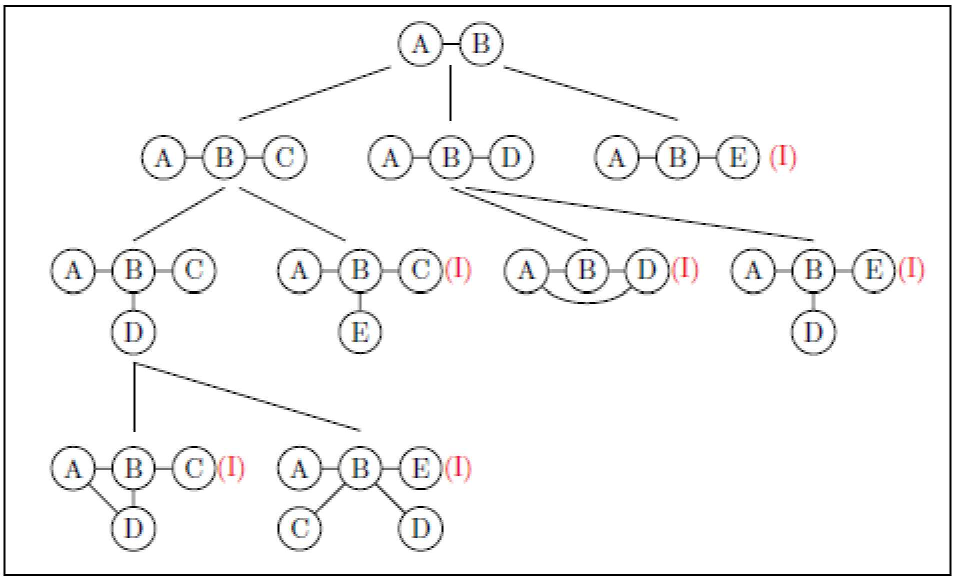


Figure IV-3 : Candidate generation subtree rooted under A-B.

Suppose we have explored all frequent level-1 patterns (g_1 to g_4 in figure IV-1 – (b)) and we want to generate candidates from one of those patterns, namely $A - B$. Figure IV-3 shows the part of the candidate generation subtree that is rooted at the pattern $A - B$. The nodes at the level 2 (root of the subtree is level 1) of this subtree shows all possible candidate patterns of size 2 that are built by adjoining the edge $B - C$, $B - D$, and $B - E$, respectively, with the pattern $A - B$. Note that, all these candidate patterns are created by introducing a forward edge. At this level, no candidate can be obtained by adding back edges because doing so will create a multi-graph, which we do not allow. Also note, we do not extend $A - B$ with another copy of $A - B$ to create the pattern $A - B - A$ because none of the database graphs in Figure IV-1 – (a) has multiple copies of the edge $A - B$. Among these three candidate patterns, the pattern $A - B - E$ is infrequent which is denoted with the mark (I) near the pattern. The remaining two patterns are frequent, and they are subsequently extended to generate level-3 candidates. For example, the pattern $A - B - D$ is extended with a back-edge to obtain the triangle pattern $A - B - D$ (all level-3 or level-4 candidates are not shown in this figure). There are other important observations in Figure IV-3. First, the extension of a pattern is only made on the rightmost path of that pattern. For visual clarification, for each pattern we draw its rightmost path along a horizontal line. The second observation is that, the duplicate generation paths are avoided; for example, the pattern $B - \{A, C, D\}$ (the first pattern from the left on level-3) is generated from the pattern $A - B - C$, but not from the pattern $A - B - D$.

IV.5.2 Isomorphism checking:

As we mentioned in the previous paragraph (candidate generation), a candidate pattern ca be generated from multiple generation paths, but only one such path is explored during the candidate generation step and the remaining paths are identified and subsequently ignored. To identify invalid candidate generation paths FSM-H needs to solve the graph isomorphism task as the duplicate copies of a candidate patterns are isomorphic to each other. well-known method for identifying graph isomorphism is to use canonical coding scheme, FSM-H uses min-dfs-code based canonical coding for isomorphism checking.

Example:

The Figure IV-4 below shows two isomorphic forms of the pattern $B - \{A, C, D\}$, however during candidate generation phase the first is generated from $A - B - C$ whereas the second would have been generated from $A - B - D$. According to the canonical coding scheme impose by min-dfs-code the pattern in Figure IV-4 (a) maps to a code string $(1, 2, A, B)(2, 3, B, C)(2, 4, B, D)$ in which each parenthesized part is an edge written in the format $(id_1, id_2, label_1, label_2)$. Using the same coding scheme, the pattern in Figure IV-4 (b) maps to the string $(1, 2, A, B)(2, 3, B, D)(2, 4, B, C)$. However, the min-dfs-code of the pattern $B - \{A, C, D\}$ is $(1, 2, A, B)(2, 3, B, C)(2, 4, B, D)$, which matches with the isomorphic form shown in Figure IV-4 (a) thus the pattern will only be generated by extending $A - B - C$. Other generation paths, including the one that extends $A - B - D$ are invalid and hence are ignored after performing isomorphism checking.

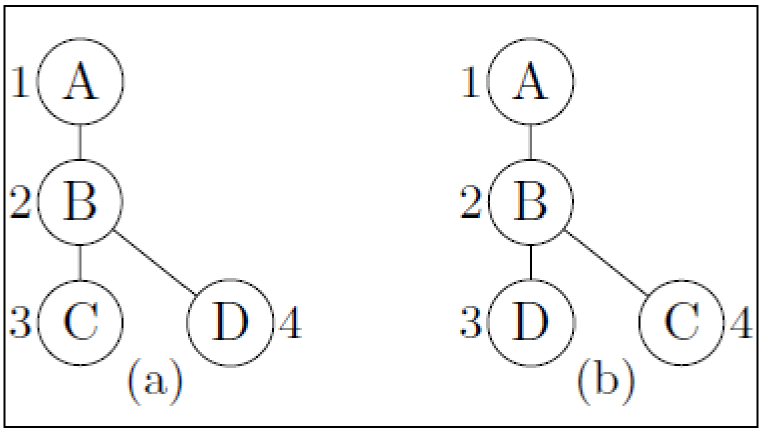


Figure IV-4 : Graph isomorphism.

IV.5.3 Support Counting:

Support counting of a graph pattern g is important to determine whether g is frequent or not. To count g's support we need to find the database graphs in which g is embedded. One possible way to compute the support of a pattern without explicitly performing the subgraph isomorphism test across all database graphs is to maintain the occurrence-list (OL) of a pattern; such a list stores the embedding of the pattern (in terms of vertex id) in each of the database graphs where the pattern exists. When a pattern is extended to obtain a child pattern in the candidate generation step, the embedding of the child pattern must include the embedding of the parent pattern, thus the occurrence-list of the child pattern can be generated efficiently from the occurrence list of its parent. Then the support of a child pattern can be obtained trivially from its occurrence-list.

Example:

In Figure IV-5 we illustrate a simple scenario of support counting based on occurrence list as it is performed by FSM-H. In the top three rows of Figure IV-5, we show the OL of the pattern $A - B, B - D$ and $B - E$. The Pattern $A - B$ occurs in Graph G_1 and G_2 in vertex pair $(1,2)$ and$(1,2)$, respectively; so its OL is: 1: [(1,2)]; 2: [(1,2)]. If we adjoin $B - D$ with the pattern $A - B$ and form the pattern $A - B - D$, then we can construct the OL of $A - B - D$ (shown in 4th row) by intersecting the OLs of $A - B$ and $B - D$. Note that, the intersection considers both the graph ids and the vertex ids in the OLs. By counting the graph ids present in an OL we can compute the support of that pattern. In Figure IV-5, the pattern $A - B - D$ is frequent given minimum support 2 but the pattern $A - B - E$ is not frequent.

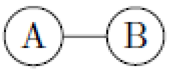
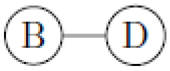
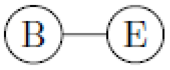
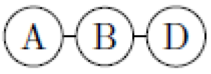
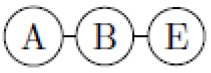
Pattern	Occerence List (OL)
	1 : [(1, 2)] ; 2 : [(1, 2)]
	1 : [(2, 4)] ; 2 : [(2, 3)] ; 3 : [(1, 2)]
	2 : [(2, 5)] ; 3 : [(1, 3)]
	1 : [(1, 2), (2, 4)] ; 2 : [(1, 2), (2, 3)]
	2 : [(1, 2), (2, 5)]

Figure IV-5 : Support Counting.

IV.6 Distributed paradigm of FSM-H:

An important observation regarding the baseline FSM algorithm (Figure II-14) is that it obtains all the frequent patterns of size k in one iteration of while loop from Line 1 to Line 6. The tasks in such an iteration comprise to one MapReduce iteration of FSM-H. Another observation is that, when the FSM-H algorithm generates the candidates of size $k + 1$, it requires the frequent patterns of size k (F_k) In an iterative MapReduce, there is no communication between subsequent iterations. So, $k + 1'th$ iteration of FSM-H obtains F_k from the disk which is written by the reducers at the end of the $k'th$ iteration. A final observation is that, deciding whether a given pattern is frequent or not requires counting it's support over all the graphs in the dataset (G). However, as we mentioned earlier each node of FSM-H works only on a disjoint partition of G. So, FSM-H requires to aggregate the local support from each node to perform the task in Line 5. From the above observations we identify the distribution of mining task of FSM-H among the mappers and the reducers.

IV.6.1 Pseudo code for the mapper:

Figure IV-6 shows the pseudo-code of a mapper. The argument F_k^p represents the set of $size - k$ frequent subgraph having non-zero support in a specific partition p. The mapper reads it from Hadoop Distributed FileSystems (HDFS). Each pattern ($say\ x$) in F_k^p is read as a key-value pair. The key is the min-dfs-code of the pattern ($x.min - dfs - code$) and the value is a pattern object ($x.obj$); here "object" stands for its usual meaning from the object oriented programming. This pattern object contains all the necessary information of pattern i.e., its support, neighborhood lists, and occurrence list within partition p. It also contains additional data structure that are used for facilitating candidate generation from this pattern in the same partition. We will discuss the pattern object in details in a later section.

```
Mapper_FSG($\mathcal{F}_k^p\langle x$.min-dfs-code, $x.obj\rangle$):
1. $\mathcal{C}_{k+1}$ = Candidate_generation($\mathcal{F}_k^p$)
2. forall $c \in \mathcal{C}_{k+1}$
3.   if isomorphism_checking($c$) = true
4.     populate_occurrence_List($c$)
5.     if $length(c.occurrence\_List) > 0$
6.       emit ($c$.min-dfs-code , $c.obj$)
```

Figure IV-6 : Mapper of distributed FSM-H Algorithm.

The mapper then generates all possible candidates of size $k + 1$ (Line 1) by extending each of the patterns in F_k^p . For each of the generated candidates (say, c), the mapper performs isomorphism checking to confirm whether c is generated from a valid generation path; in other words, it tests whether c passes the min-dfs-code based isomorphism test (Line 3). For successful candidates, the mapper populates their occurrence list (Line 4) over the database graphs in the partition p. If the occurrence list of a candidate pattern is non-empty, the mapper constructs a keyvalue pair, such as, ($c.min - dfs - code, c.obj$) and emits the constructed pair for the reducers to receive (Line6).

IV.6.2 Pseudo code for the reducer:

shows the pseudo code for a reducer in distributed frequent subgraph mining. The reducer receives a set of key-value pairs, where the key is the min-dfs-code of a pattern namely $c.min - dfs - code$ and the value is a list of $c.obj's$ constructed from all partitions where the pattern c has a non-zero support.

```
Reducer_FSG(c.min-dfs-code , ⟨ c.obj ⟩):
1. forall obj ∈ ⟨ c.obj ⟩
2.    support += length(obj.OL)
3. if support ≥ minsup
4.    forall obj ∈ ⟨ c.obj ⟩
5.       write (c.min-dfs-code , obj) to HDFS
```

Figure IV-7 : Reducer of distributed FSM-H Algorithm.

The Reducer then iterates (Line 1) over every $c.obj$ and from the length of the occurrence list of each $c.obj$ it computes the aggregated support of c. If the aggregated support is equal or higher than the minimum support threshold (Line 3), the reducer writes each element in the list paired with the $min - dfs - code$ of c in HDFS for the mappers of the next iteration.

IV.7 Execution flow of FSM-H:

The Figure IV-8 below illustrates the execution flow of FSM-H. The execution starts from the mappers as they read the key-value pair of size k patterns in partition p from the HDFS. As shown in the Figure IV-8, the mappers generate all possible $k + 1 - size$ candidate patterns and perform the isomorphism checking within partition p. For a pattern of size $k + 1$ that passes the isomorphism test and has a non-zero occurrence, the mapper builds its key-value pair and emits that for the reducers. These key-value pairs are shuffled and sorted by the key field and each reducer receives a list of values with the same key field. The reducers then compute the support of the candidate pattern by aggregating the support value computed in the partitions where the respective pattern is successfully extended. If a pattern is frequent, the reducer writes appropriate key-value pairs in the HDFS for the mappers of the next iteration. If the number of frequent $k + 1$ size pattern is zero, execution of FSM-H halts.

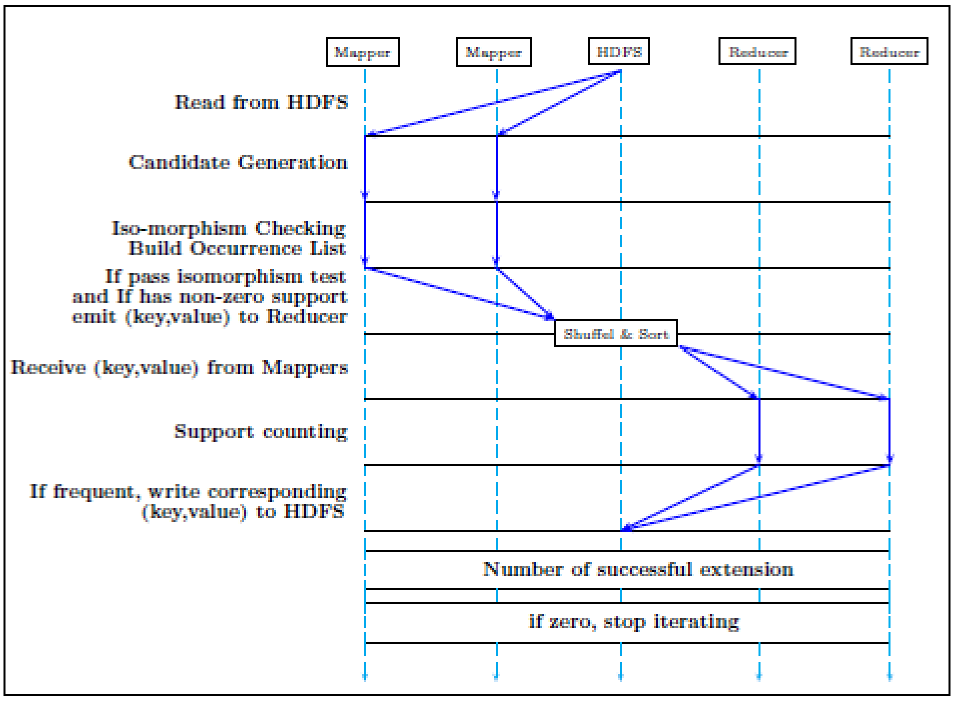


Figure IV-8 : Execution flow of FSM-H Algorithm.

IV.8 Framework of FSM-H:

FSM-H has three important phases: data partition preparation phase and mining phase. In data partition phase FSM-H creates the partitions of input data along with the omission of infrequent edges from the input graphs. Preparation and mining phase performs the actual mining task. Figure IV-9 shows a flow diagram of different phases for a frequent subgraph mining task using FSM-H.

Below, we present an in-depth discussion of each of the phases.

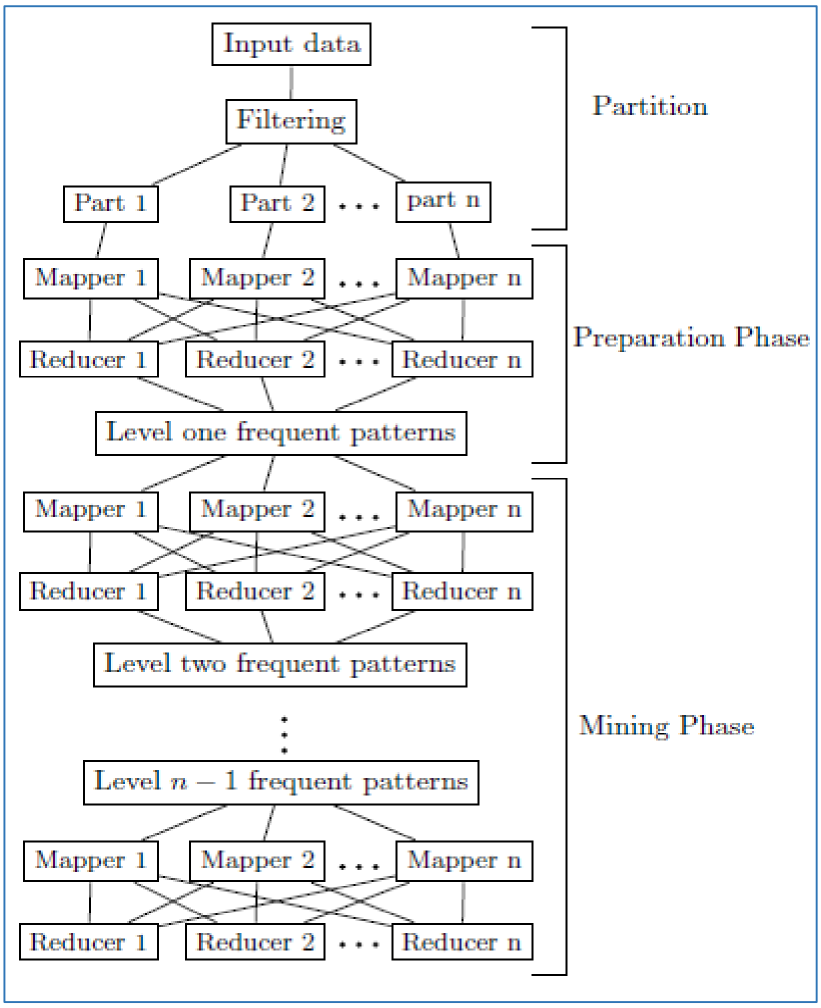


Figure IV-9 : Framework of FSM-H.

IV.8.1 Data partition Phase:

In data partition phase, FSM-H splits the input graph dataset (G) into many partitions. One straightforward partition scheme is to distribute the graphs so that each partition contains the same number of graphs from G. This works well for most of the datasets. However, for datasets where the size (edge count) of the graphs in a dataset vary substantially, FSM-H offers another splitting option in which the total number of edges aggregated over the graphs in a partition are close to each other. In experiment section, we show that the latter partition scheme has a better runtime performance as it improves the load balancing factor of a MapReduce job. For FSM-H, the number of partition is also an important tuning parameter. In experiment section, we show that for achieving optimal performance, the number of partitions for FSM-H should be substantially larger than the number of partitions in a typical MapReduce task. During the partition phase, input dataset also goes through a filtering procedure that removes the infrequent edges from all the input graphs. While reading the graph database for partitioning, FSM-H computes the support-list of each of the edges from which it identifies the edges that are infrequent for the given minimum support threshold.

Example:

For the graph dataset in Figure IV-1, for a minimum support threshold of 2, the edges $A - B, B - C, B - D, D - E$ and $B - E$ are frequent and the remaining edges are infrequent. Now suppose FSM-H makes two partitions for this dataset such that the first partition contains G_1, and the second partition contains G_2 and G_3.While making these partitions FSM-H filters the infrequent edges. Figure IV-10 shows the partitioning where the infrequent edges are stripped off from the database graphs.

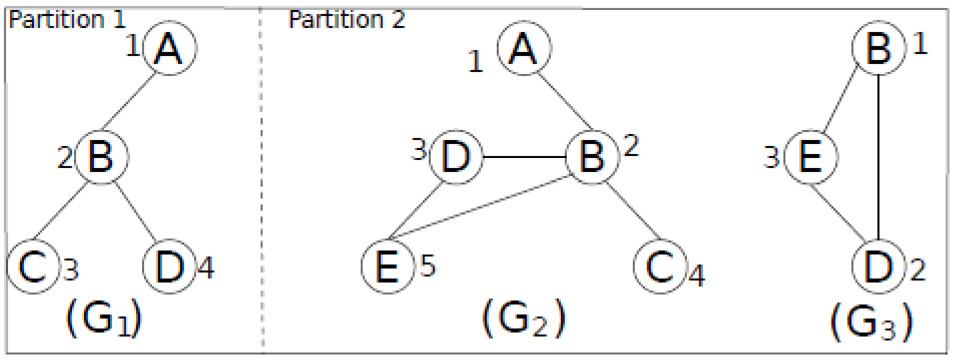


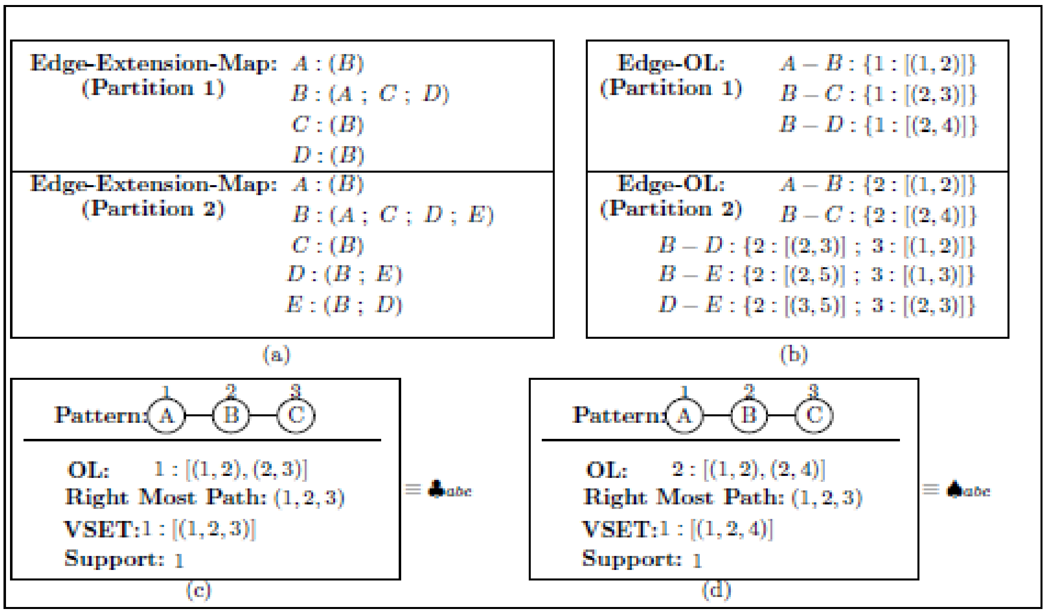
Figure IV-10 : Input dataset after partition and filtering phase.

IV.8.2 Preparation Phase:

The mappers in this phase prepare some partition specific data structures such that for each partition there is a distinct copy of these data structures. They are static for a partition in the sense that they are same for all patterns generated from a partition. The first of such data structure is called $edge - extension - map$, which is used for any candidate generation that happens over the entire mining session. It stores the possible extension from a vertex considering the edges that exists in the graphs of a partition. For example, the graphs in partition two have edges such as $B - D, B - C, B - A$, and $B - E$. So, while generating candidates, if B is an extension stub, the vertex A, C, D or E can be the possible vertex label of the vertex that is at the opposite end of an adjoined edge. This information is stored in the $edge-extension-map$ data structure for each of the vertex label that exist in a partition. The second data structure is called $edge-OL$, it stores the occurrence list of each of the edges that exist in a partition; FSM-H use it for counting the support of a candidate pattern which is done by intersecting the OL of a parent pattern with the OL of an adjoint edge.

Example:

Figure IV-11 (a) and Figure IV-11 (b) shows these data structures for the Partition 1 and 2 defined in Figure IV-10. In partition 1, the edge-extension choice from a vertex with label D is only B (shown as $D : (B)$), as in this partition $B - D$ is the only frequent edge with a B vertex. On the other hand, the corresponding choice for partition 2 is B and E (shown as, $D : (B; E)$), because in partition 2 we have two edges, namely $B - D$ and $D - E$ that involve the D vertex. In partition 1, the edge $B - D$ occurs in G_1 at vertex id $(2, 4)$; on the other hand in partition 2, the same edge occurs in G_2 and G_3at vertex id $(2, 3)$ and $(1, 2)$, respectively. This information is encoded in the $edge-OL$ data structures of these partitions as shown in this figure.



Edge-Extension-Map: (Partition 1)
$A : (B)$
$B : (A ; C ; D)$
$C : (B)$
$D : (B)$

Edge-Extension-Map: (Partition 2)
$A : (B)$
$B : (A ; C ; D ; E)$
$C : (B)$
$D : (B ; E)$
$E : (B ; D)$

(a)

Edge-OL: (Partition 1)
$A - B : \{1 : [(1, 2)]\}$
$B - C : \{1 : [(2, 3)]\}$
$B - D : \{1 : [(2, 4)]\}$

Edge-OL: (Partition 2)
$A - B : \{2 : [(1, 2)]\}$
$B - C : \{2 : [(2, 4)]\}$
$B - D : \{2 : [(2, 3)] ; 3 : [(1, 2)]\}$
$B - E : \{2 : [(2, 5)] ; 3 : [(1, 3)]\}$
$D - E : \{2 : [(3, 5)] ; 3 : [(2, 3)]\}$

(b)

Pattern:
OL: $1 : [(1, 2), (2, 3)]$
Right Most Path: $(1, 2, 3)$
VSET: $1 : [(1, 2, 3)]$
Support: 1

$\equiv \clubsuit_{abc}$

(c)

Pattern:
OL: $2 : [(1, 2), (2, 4)]$
Right Most Path: $(1, 2, 3)$
VSET: $1 : [(1, 2, 4)]$
Support: 1

$\equiv \spadesuit_{abc}$

(d)

Figure IV-11 : The static data structures and A-B-C pattern object in partition 1 and 2 (a) Edge-extension-map (b) Edge-OL (c) and (d) A-B-C Pattern object.

The mappers in the preparation phase also start the mining task by emitting the frequent single edge patterns as key-value pair. Note that, since the partition phase have filtered out all the infrequent edges, all single edges that exist in any graph of any partition is frequent. As we mentioned earlier the key of a pattern is its $min - dfs - code$ and the value is the pattern object.

Each pattern object has four essential attributes: (a) $Occurrence\ List$ (OL) that stores the embedding of the pattern in each graph in the partition, (b) $Right - Most - Path$ (c) $VSET$ that stores the embedding of the Right Most Path in each graph in the partition, and (d) $support$ value. Mappers in the preparation phase compute the $min - dfs - code$ and create the pattern object for each single-edge patterns. While emitting a key-value pair to a reducer, the mappers also bundle the static data structures, $edge - extension - map$ and $edge - OL$ with each of the pattern object. FSM-H uses Java serialization to convert these objects in to byte stream while sending them as value in a key-value pair. The reducers of this phase actually do nothing but writing the input key-value pairs in HDFS since all the single length patterns that the mappers send are frequent. In Figure IV-9, the second block portrays the preparation phase.

Example:

Figure IV-11 (c) and IV-11 (d) exhibits the $Pattern$ object along with their attributes for the pattern $A - B - C$ in partition 1 and 2, respectively. The attribute OL records the occurrence of this pattern in the corresponding database graphs; if a pattern has multiple embeddings in a database graph all such embeddings are stored. $Right - Most - Path$ records the id of the $right - most - path$ vertices in the pattern object and $VSET$ stores the corresponding ids in the database graphs. Like OL, $VSET$ is also a set and it stores information for multiple embedding if it applies. Finally, Support stores the support value of the pattern. In the following discussion, we use $\clubsuit$ and $\spadesuit$ to denote a pattern object from partition 1 (G_1) and 2 (G_2, G_3), respectively. For example, $\spadesuit_{abc}$identifies the pattern $A - B - C$ from partition 2 as shown in Figure IV-11 (d).

IV.8.3 Mining Phase:

In this phase, mining process discovers all possible frequent subgraphs through iteration. Preparation phase populates all frequent subgraphs of size one and writes it in the distributed file system. Iterative job starts by reading these from HDFS. Each of the mappers of an ongoing iteration is responsible for performing the mining task over a particular chunk of the data written in HDFS by the preparation phase. The map function of mining phase reconstructs all the static data structures that are required to generate candidate patterns from the current pattern. Using the static data structures and the pattern object, the mappers can independently execute the subroutine that is shown in Figure IV-6. The reducers in this phase simply execute the routine in Figure IV-7.

Example:

The figure IV-12 below provides a detail walk-through of a MapReduce job in iteration phase with respect to the partitioned toy dataset mentioned in Figure IV-10. Figure IV-12 (a) and (b) indicates the key-value pairs for pattern $A - B$ from partition 1 and 2. Suppose these key-value pairs are feed as input for Mapper 1 and Mapper 2 in Figure IV-12. The mappers first extract all data structures from the value field of key-value pair including the partition-specific static data structures (SDS in Figure IV-12) such as $edge - extension - map$ and $edge - OL$. Then they perform the steps mentioned in Figure IV-6. Figure IV-12 (c) and (d) show the key-value pairs of $A - B - C$ that are generated by Mapper 1 and Mapper 2 by extending the pattern $A - B$. The Reducers collect all the values for a key and compute the support of the pattern by adding the supports from individual partitions. In this example, the support of the pattern $A - B - C$ is 2; since $minsup = 2$, this pattern is frequent. Reducers then write the key-value pairs corresponding to the pattern $A - B - C$ in HDFS.

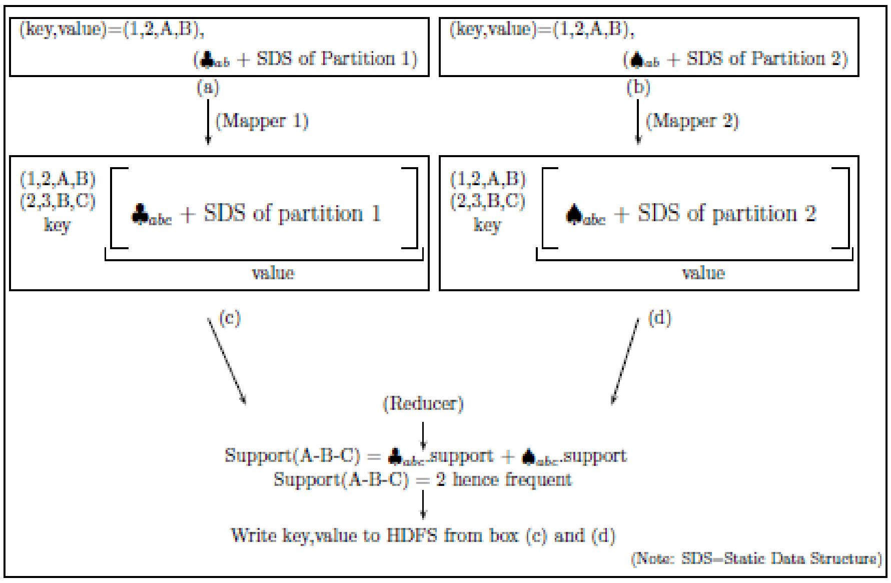
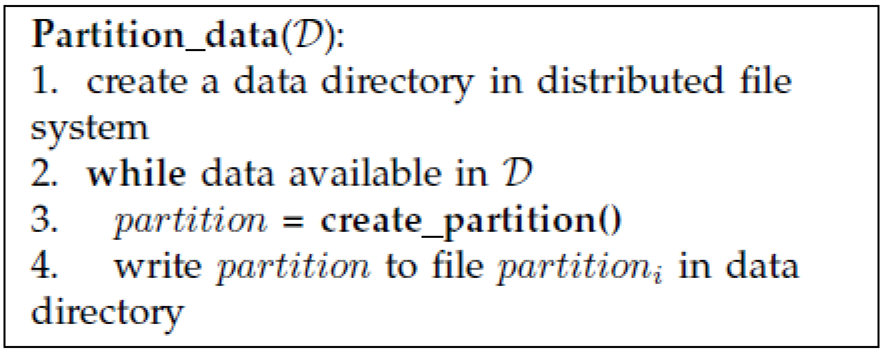

(key,value)=(1,2,A,B), ($\clubsuit_{ab}$ + SDS of Partition 1)
(key,value)=(1,2,A,B), ($\spadesuit_{ab}$ + SDS of Partition 2)
(a)
(b)
(Mapper 1)
(Mapper 2)
(1,2,A,B) (2,3,B,C) key
$\clubsuit_{abc}$ + SDS of partition 1
value
(1,2,A,B) (2,3,B,C) key
$\spadesuit_{abc}$ + SDS of partition 2
value
(c)
(d)
(Reducer)
Support(A-B-C) = $\clubsuit_{abc}$.support + $\spadesuit_{abc}$.support
Support(A-B-C) = 2 hence frequent
Write key,value to HDFS from box (c) and (d)
(Note: SDS=Static Data Structure)

Figure IV-12 : One iteration of the mining phase of FSM-H with respect to pattern A-B.

IV.9 Hadoop Pseudo Code:

In this section, we present the pseudo code of each phase using the syntax of Hadoop framework. Figure IV-13, IV-14 and IV-15 demonstrate data partitioning, preparation and mining phase, respectively. In Line 3 and 4 of Figure IV-13, FSM-H performs the filtering and partitioning of the input dataset and writes each partition and write in the HDFS.



```
Partition_data($\mathcal{D}$):
1.  create a data directory in distributed file
system
2.  while data available in $\mathcal{D}$
3.      $partition$ = create_partition()
4.      write $partition$ to file $partition_i$ in data
directory
```

Figure IV-13 : Data partitioning Phase.

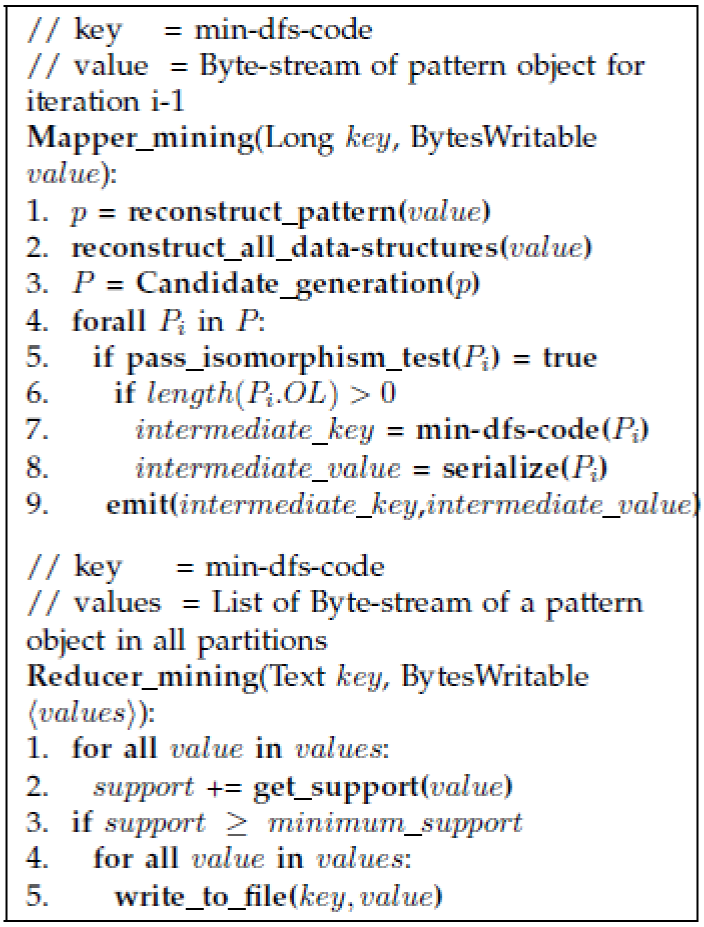
In line 1-7 of Figure IV-14 the mappers generate static data structure along with emit key-value pair of all single length pattern to reducer. Since all patterns are frequent, Reducers just relay the input key, value pair to the output file in HDFS.

```
// key    = offset
// value  = location of partition file in data
directory
Mapper_preparation(Long key, Text value):
1. Generate_Level_one_OL(value)
2. Generate_Level_one_MAP(value)
3. $P$ = get_single_length_patterns()
4. forall $P_i$ in $P$:
5.     intermediate_key = min-dfs-code($P_i$)
6.     intermediate_value = serialize($P_i$)
7.     emit(intermediate_key,intermediate_value)

// key     = min-dfs-code
// values  = List of Byte-stream of a pattern
object in all partitions
Reducer_preparation(Text key, BytesWritable ⟨
values ⟩):
1.     for all value in values:
2.         write_to_file(key,value)
```

Figure IV-14 : Preparation Phase.

In Line 1-3 of Mapper mining function in Figure IV-15, the mappers reconstruct the pattern object of size k a long with the static data structures and generates the candidates from the current pattern. In Line 4-9, the mappers iterate over all possible candidates of size $k + 1$ and on success in isomorphism and occurrence list test mappers emit the key-value pair for the reducer. Reducer mining function computes the aggregate support (Line 2) of the pattern and if the pattern is frequent, reducers write back the key, value pairs to HDFS for the mappers of the next iteration.



```
// key    = min-dfs-code
// value  = Byte-stream of pattern object for
iteration i-1
Mapper_mining(Long $key$, BytesWritable
$value$):
1. $p$ = reconstruct_pattern($value$)
2. reconstruct_all_data-structures($value$)
3. $P$ = Candidate_generation($p$)
4. forall $P_i$ in $P$:
5.   if pass_isomorphism_test($P_i$) = true
6.     if $length(P_i.OL) > 0$
7.       $intermediate\_key$ = min-dfs-code($P_i$)
8.       $intermediate\_value$ = serialize($P_i$)
9.     emit($intermediate\_key, intermediate\_value$)

// key     = min-dfs-code
// values  = List of Byte-stream of a pattern
object in all partitions
Reducer_mining(Text $key$, BytesWritable
$\langle values \rangle$):
1. for all $value$ in $values$:
2.   $support$ += get_support($value$)
3. if $support \geq minimum\_support$
4.   for all $value$ in $values$:
5.     write_to_file($key, value$)
```

Figure IV-15 : Mining Phase.

IV.10 Implementation Details:

We used Cloudera's open source Distribution with Hadoop CDH 15-4, that include Hadoop version 2-6-0, as a platform for running the application. The baseline mining algorithm is written in java, as well as the map and the reduce function for both the preparation and the mining phases. A custom input reader is used instead of the default ones that came built-in with Hadoop.

To improve the execution time data is compressed when written to HDFS. we used global counters provided by Hadoop to monitor and track the stopping point of the iterative mining task.

IV.10.1 Map reduce job configuration:

Success of the job depends on the accurate configuration of it, and since the type of the value that is read by a mapper and emit by the reducer is ByteWritable, FSM-H sets the input and output format of each job as SequenceFileInputFormat and SequenceFileOutputFormat respectively. Another job property, named `mapred.task.timeout` also need to be set properly for better execution of FSM-H. This parameter controls the duration for which the master node waits for a data node to reply. If the mining task that FSM-H commence is computationally demanding, the default timeout which is 10 minutes may not be enough. To be on the safe side, FSM-H sets the timeout of the job to 5 hours (300 minutes). FSM-H also sets the `mapred.output.compress` property to true. This configuration lets the output of a MapReduce job to be compressed which eventually decreases network load and improves the overall execution time. The codec that is used for compression is `BZip2Codec` instead of the default one. `BZip2Codec` is shipped with Hadoop. FSM-H also increases the heap size of a job using `mapred.child.java.opts` property. The same configuration is used for both the preparation and mining phase of FSM-H.

A list of some of the main configuration options that may enhance the performance of the execution of jobs could be found in the appendix.

Key Points – Chapter 04 :

- We introduced the chapter by defining the general formulation of FSM problem where the input data is a database containing small to medium sized transactions (graphs).
- We highlighted the theoretic approaches adopted along with the different data structures that is maintained by FSM-H in order to perform candidate generation, isomorphism checking and support counting.
- We highlighted the pseudo code for the mapper and the reducer of FSM-H with respect to a configuration where we have a fully distributed system.
- We presented the general framework and execution flow of FSM-H for instance partition, preparation and mining phases.
- We concluded the chapter by presenting some tuning parameter that once configured allow for best execution of the jobs.

Chapter V:

Experiments and Results

V. Chapter 05:

Experiments and Results

V.1 Experiments:

In this Section we present experimental results that demonstrate the performance of FSM-H for solving frequent subgraph mining task where we have a graph database containing a collection of small – to – medium sized graphs.

We have done several experiments on real datasets, taking into account a variation of multiple factors (number of data nodes, number of mappers, reducers, …. etc.).

For each test results we analyses it and demonstrate the efficiency of FSM-H.

V.2 Experimental setup:

V.2.1 Datasets:

In chemistry graphs can represent different chemical objects: molecules, reactions, crystals, polymers, clusters, etc. The common feature of chemical systems is the presence of *sites* and *connections* between them. Sites may be atoms, electrons, molecules, molecular fragments, groups of atoms, intermediates, orbitals, etc. The connections between sites may represent bonds of any kind, bonded and no bonded interactions, elementary reaction steps, rearrangements, van der Waals forces, etc. Chemical systems may be depicted by chemical graphs using a simple conversion rule:

Site → vertex

Connection→ edge

A special class of chemical graphs are *molecular graphs*. Molecular graphs are chemical graphs which represent the *constitution* of molecules. They are also called *constitutional graphs*. In these graphs vertices correspond to individual atoms and edges to chemical bonds between them.

So as input we use six real-world graph datasets which are taken from an online source that contains graphs extracted from the PubChem website. PubChem is an open chemistry database at the National Institutes of Health (NIH). It provides information on biological activities of small molecules and the graph datasets from PubChem represent atomic structure of different molecules.

Table V-1: highlight some statistics about these real world graph datasets:

Table V-1 : statistics of real life graph datasets.

Name of Transaction Graph dataset.	*Assay ID*	*# Transactions (Graphs)*	*Tumor Description*	*Average size of each graph*
SN12C	*145*	*40004*	*Renal*	*27.7*
NCI-H23	*1*	*40353*	*Non-small Cell Lung*	*28.6*
OVCAR-8	*109*	*40516*	*Ovarian*	*28.1*
SF-295	*47*	*40271*	*Central Nerv syst*	*28.0*
YEAST	*167*	*79601*	*Yeast Anticancer*	*22.8*

- ***Name of Transaction Graph dataset*:** refer to the name of the anticancer screen test, the graphs in each dataset represent chemical compounds that were exposed to some test cell lines in laboratory.
- ***Assay id*:** refers to the bioassay ID as it is identified in the PubChem database.
- ***# Transactions (Graphs):*** represent the number of transactions (graphs) in each dataset.
- ***Tumor description:*** Refers to the cancer type that these chemical compounds (graphs in our case) were tested against.
- ***Average size of each graph***: refers to the average size (number of edges) of graphs in each dataset.

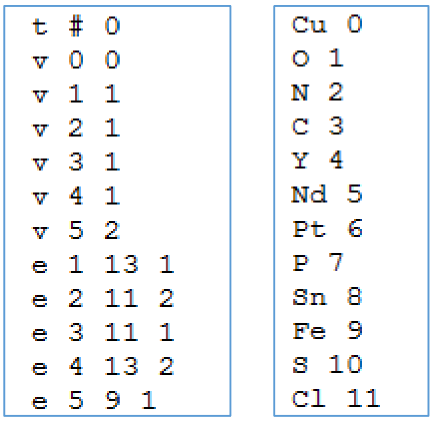
Rq: the graphs in each dataset (chemical compounds) are grouped into two categories depending on the bioactivity outcome:

- ***Active:*** means that the tested chemical molecule (compound) has an active outcome with respect to the objective of the test which is in general the growth inhibition of the tumor in the cells tested.
- ***Inactive:*** means that the tested chemical compound didn't present any activity against the cell that it was exposed to.

Performing frequent subgraph mining against these chemical graph datasets could reveal the main component (frequent subgraph: frequent compounds) that are shared amongst them, which could be of huge value because these frequent patterns help in the fabrication of drugs for the treatment of malignant, or cancerous diseases.

V.2.1.1 Graph representation in machine:

Each graph from the graphs mentioned in Table V-1 and their mappings to chemical structures are represented and stored in text files as captured in the figure V-1 below:



(a)

```
t # 0
v 0 0
v 1 1
v 2 1
v 3 1
v 4 1
v 5 2
e 1 13 1
e 2 11 2
e 3 11 1
e 4 13 2
e 5 9 1
```

(b)

```
Cu 0
O 1
N 2
C 3
Y 4
Nd 5
Pt 6
P 7
Sn 8
Fe 9
S 10
Cl 11
```

Figure V-1 : (a) Exerpt from the yeast graph dataset file.
(b) Exerpt from the mapping text file that correspond to yeast graph dataset.

- (a): represent a graph (a chemical compound):
  - `t # 0`: refers to transaction number `0` (first graph in the dataset).
  - `v 0 0`: vertex `0` has a label `0` (labels here correspond to atoms example: `O`, `C`, `H`, `Br`, …. etc.

  - `e 1 13 1`: there is an edge between vertex `0` and vertex `13` that has a label of `1`.
  - Labels can be represented by an integer 1 or `2`, labels define the type of the bond that exist between atoms(vertexes)
    - `1`: define simple bond between elements(atoms).
    - `2`: define double bonds between two elements (atoms)

- (b): correspond to an excerpt from the file mapping.txt that store the mapping of chemical elements(atoms) to an integer id: for example, `C 3` in the file means that `C` (carbon) has an integer id of `3`, so whenever we find in the graph dataset a vertex with label `3` we know that it represents `C` (carbon) and from this observation we can define the chemical structure that we are dealing with, that is represented here as a transaction.
- It is important to note here that mapping.txt does not include the Hydrogen atom and thus the type of graphs that we are dealing with are called "hydrogen-suppressed molecular graphs", example of such graphs are presented in the example below.

Example:

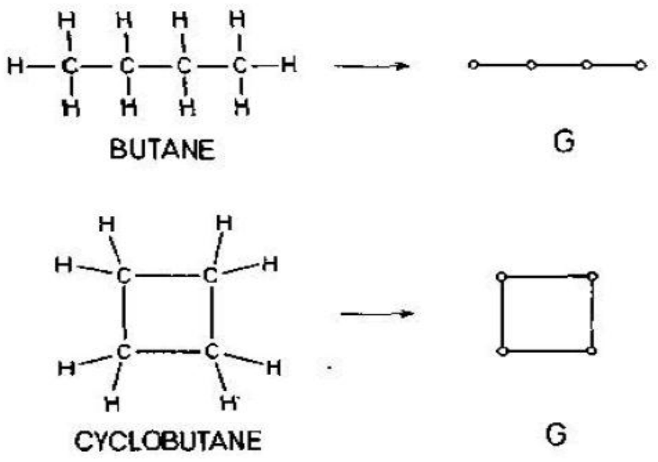


Figure V-2 : Example of two hydrogen-suppressed molecular graphs depicting butane and cyclobutane.

.

V.2.2 Implementation platform:

We used Cloudera's distribution with Hadoop CDH 15-4, that include Hadoop version 2.6.0 as a platform for running the program, note also that all experiments were conducted on real Cluster composed of four nodes, running each of them Cent-OS version 7.0.

Each of the four nodes is equipped with 12 Core Xeon, 2.5 Ghz CPU and having 125 Gb of memory and 1TB or storage space.

Note that for each of the tests (see next section) we keep each partition with approximately 100 graphs. And balances the graphs in each of them to be having approximately the same number of edges.

V.3 Tests and Evaluations:

V.3.1 Runtime of FSM-H for different minimum support:

In this experiment, we analyze the runtime of FSM-H for varying minimum support threshold. We conduct this experiment for the real world datasets mentioned above. Here we fix the number of data nodes to 4 and keep 100 transactions for each partition. and we observe the running time of FSM-H for a minimum support threshold that vary between 50 and 120 (with values 50, 70, 90 and 120 respectively). In Figure V-3 (a-e) we show the result. As expected, the runtime decreases as minimum support threshold increases. In figure V-4(a-d), we show the overall running time of FSM-H distributed over “Map” and ”Reduce“ phases. We pick “yeast” and “SN12C” dataset for this experimentation. In all cases (different supports), the “Reduce” phase takes large time to execute than the ”Map” phase. More precisely, the running time of “Reduce“ phase is approximately 70% of overall running time.

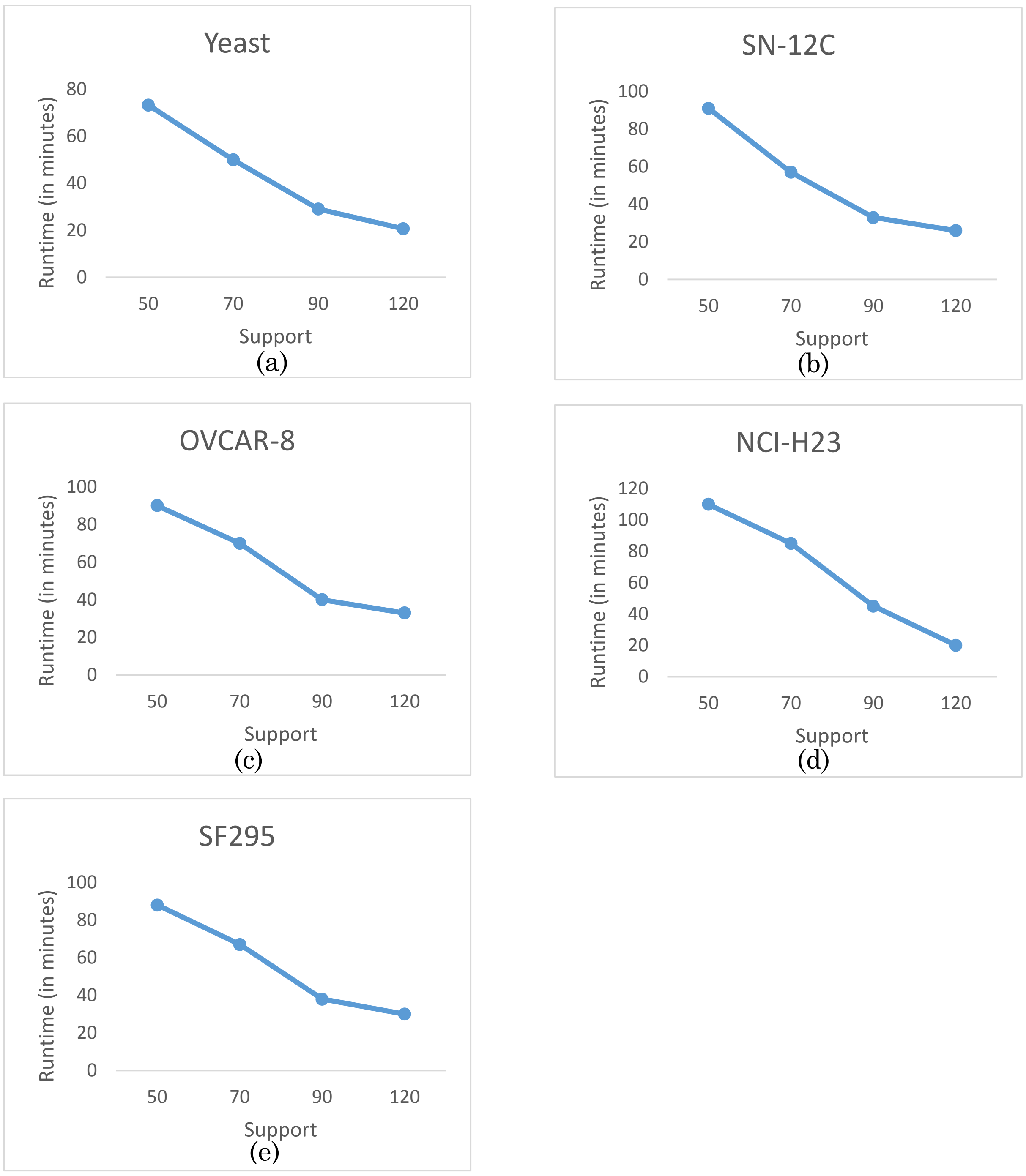


Figure V-3 : Line Plot Showing the relationship between the minimum support threshold and the running time n minutes for (a) Yeast, (b) SN12C (c) OVCAR-8 (d) NCI-H23 and (e) SF295.

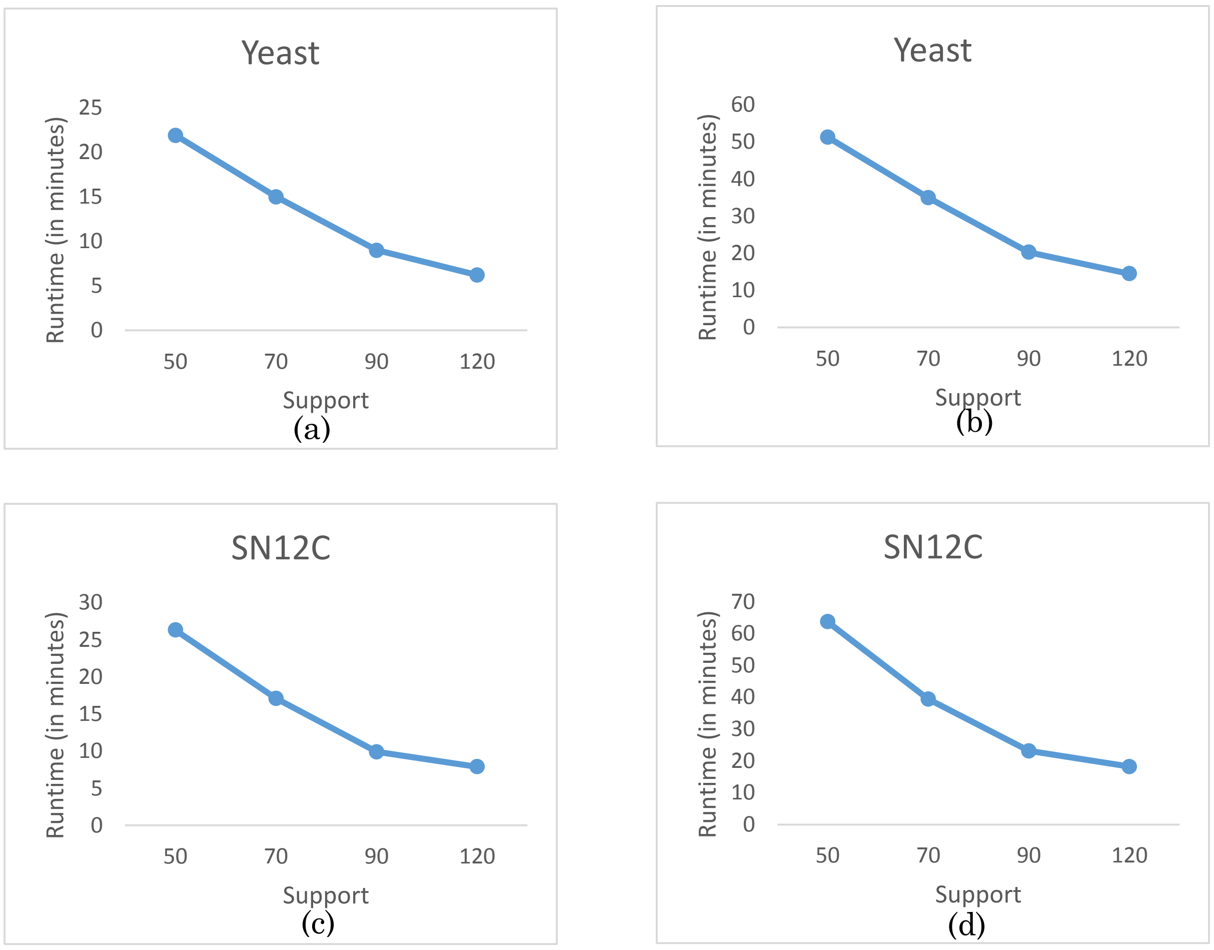


Figure V-4 : Line Plot showing the relationship between the minimum support threshold and the running time of Map and Reduce phase of FSM-H in (a)(b) Yeast and (c)(d) SN12C

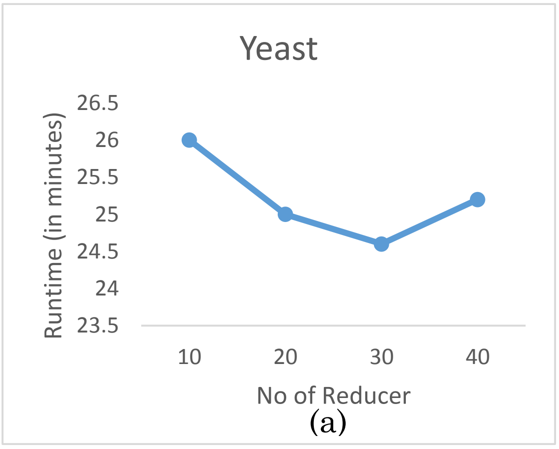
V.3.2 Runtime of FSM-H for varying number of Reducers:

The number of reducer plays an important role in the execution of MapReduce job in Hadoop. While writing data (output) in HDFS, a MapReduce job follows a convention of naming the output file with the key word “part”. Reducer count determines how many “part” files will be generated to hold the output of a job. If the number of reducer is set to 1, entire output will be written in a single file. Since FSM-H is an iterative algorithm, where output of the current job is used as an input of the next job, the number of reducer has a significant effect on the execution time of FSM-H. If we set reducer count to a small value then there will be fewer number of output files that are large in size; these large files will be a burden over the network when they are transferred between data nodes.

On the other hand, large number of reducers might create many output files of zero size (reducer is unable to output any frequent pattern for the next stage Mapper). These zero size output files will also become an overhead for the next stage mappers as these files will still be used as input to a mapper. Note that, loading an input file is costly in Hadoop.

In this experiment, we measure the runtime of FSM-H for various configurations where we set the number of reducers to, 10, 20, 30 and 40 respectively. We run the experiment on biological datasets for a minimum support threshold of 100 and we keep approximately 100 database graphs in each partition.

Figure V-5 (a-b) shows the relationship between execution time and the number of reducers using bar charts. As we can see, 30 is the best choice for the number of reducers in our cluster setup. This finding is actually intuitive, because we have 4 data nodes each having 12 reduce slots (12 core processor), yielding 48 processing units. So keeping a few units for system use and other services, 30 is the best choice for the number of reducers.



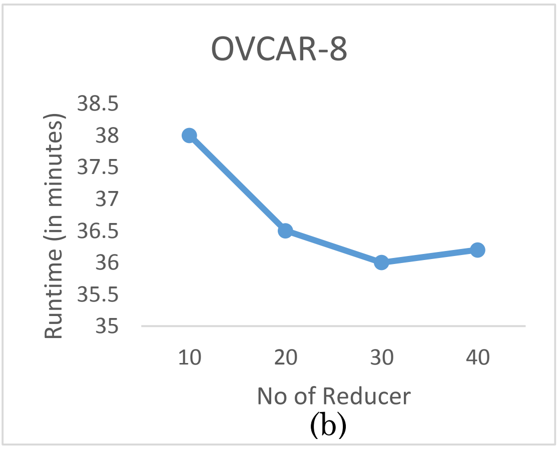
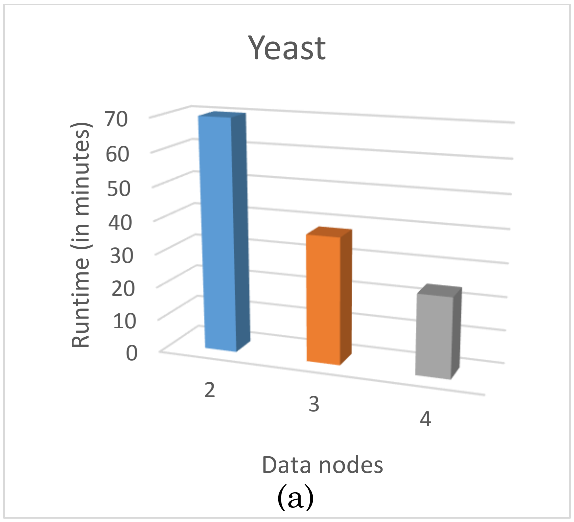


Figure V-5 : Bar Plot showing the relationship between the number of Reducer and the running time of FSM-H in (a) Yeast (b) OVCAR-8..

V.3.3 Runtime of FSM-H on varying number of data nodes:

In this experiment, we demonstrate how FSM-H's runtime varies with the number of active data nodes (slaves). We use the Yeast dataset and 100 minimum support threshold and keep 100 database graphs in one partition. We vary the count of data nodes among 2, 3 and 4 and record the execution time for each of the configurations. As shown in Figure V-6 (a) the runtime reduces significantly with an increasing number of data nodes. In Figure V-6 (b) we plot the speedup that FSM-H achieves with an increasing number of data nodes, with respect to the 2-datanodes configuration. We can see that the speedup.



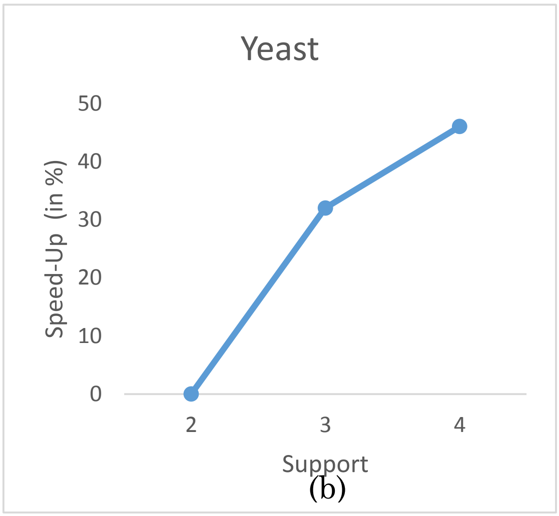


Figure V-6 : Relationship between the execution time and the number of data nodes : (a) Bar plot shows the execution time (b) Line plot shows the speedup with respect to the execution time using 2 data nodes configuration .

V.3.4 Effect of partition scheme on runtime:

An important requirement for achieving the optimal performance of a Hadoop cluster is to find the appropriate number of mappers. In such a cluster, the setup and scheduling of a task wastes a few seconds. If each of the tasks is small and the number of tasks is large, significant amount of time is wasted for task scheduling and setup. So the experts advise that a mapper should execute for at least 40 seconds Another rule of thumbs is that the number of mappers should not over-run the number of partitions.

In our cluster setup, we have 4 data nodes, each with 12 cores that allow us to have 48 mappers. Then, the perfect number of input partitions should be less than or equal to 48. But this rules do not fit well for frequent subgraph mining task. For example, the Yeast dataset has close to 80, 000 graphs and if we make 30 partitions, then each partition ends up consisting of 2666 graphs. Since, frequent subgraph mining is an exponential algorithm over its input size, performing a mining task over these many graphs generally becomes computationally heavy. In this case, the map function ends up taking more time than is expected.

As a result, the optimal number of partitions for an FSM task should set at a much higher value (compared to a tradition data analysis task) so that the runtime complexity of the mappers reduces significantly. Note that, the higher number of partitions also increases the number of key-value pairs for a given pattern which should be processed by the reducers. However, the performance gain from running FSM over small number of graphs supersedes the performance loss due to the increased number of key-value pairs. This is so, because the gain in execution time in the mappers follows an exponential function, whereas the loss in execution time in the reducers and the data transmission over the network follow a linear function.

On the other hand, selecting the number of partitions in such a way so that, each mapper gets to process only one transaction will not be an optimal choice. The reason is, average processing time of only one transaction will be much less than average task scheduling and setup time.

We will see in this experiment that increment of the number of partitions has negative effects on overall running time.

The following experiment validates the argument that we have made in the above paragraph. In this experiment, we run FSM-H on Yeast dataset for different number of partitions and compare their execution time.

Figure V-7 shows the result using bar charts. The charts show that as we increase the partition count, the performance keeps improving significantly until it levels off at around 1000 partitions. When the partition count is 1561, there is a slight loss in FSM-H’s performance compared to the scenario when the partition count is 796. The strategy of finding the optimal number of partitions depends on the characteristics of input graphs that control the complexity of the mining task, such as the density, number of edges, number of unique labels for vertices and edges in an input graph and so on.

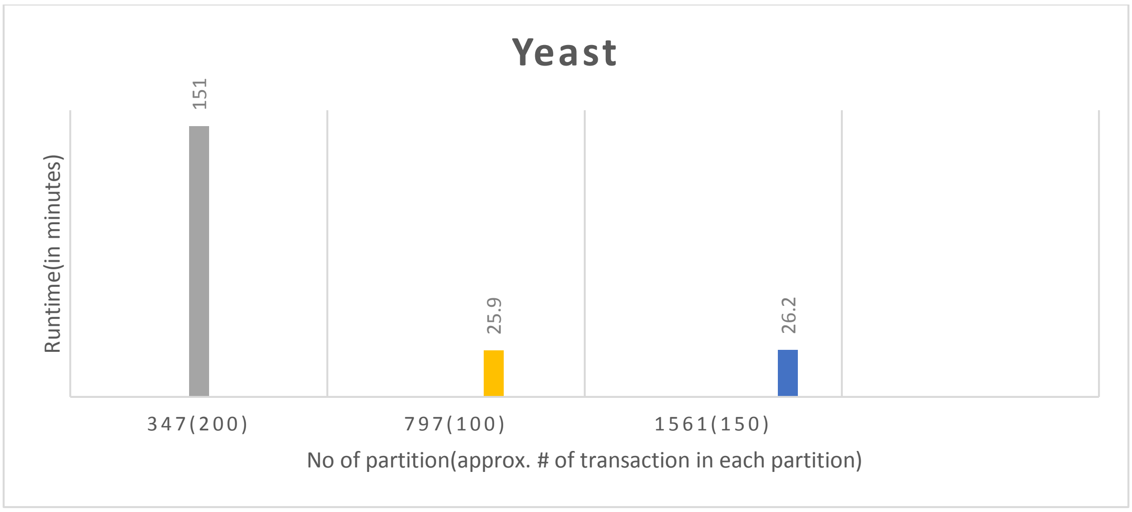


Figure V-7 : Bar plot showing the relationship between the partition count and the running time of FSM-H for Yeast dataset.

VI. Conclusion:

The term “Big Data” refers to the large amounts of data in which traditional data processing procedures and tools would not be able to handle, data is constantly generated from various business and scientific fields, and this data data comes in multiple forms : structured and unstructured.

Contrary to much of the traditional data types, most of the Big Data is unstructured or semi-structured in nature, which requires different techniques and tools to process and analyze them.

Graphs are common data structures used to represent / model real-world systems and the data associated with it. Graph Mining is one of the arms of Data mining in which voluminous complex data are represented in the form of graphs and mining is done to infer knowledge from them. This thesis was focused in the particular problem of frequent subgraph mining.

Frequent sub graph mining or for short (FSM) is extensively used for graph classification, building indices and graph clustering purposes, the purpose of an FSM algorithm is to discover subgraphs that appears frequently in a set of graphs or a single large graph.

The research goals of FSM are directed at: (*i*) effective mechanisms for generating candidate subgraphs (without generating duplicates) and (*ii*) how best to process the generated candidate subgraphs so as to identify the desired frequent subgraphs in a way that is computationally efficient and procedurally effective.

The thesis presented a survey for the most FSM algorithms that are reported in the literature, and as in the case of frequent tree mining, candidate generation and support counting are key issues of such algorithms. Since subgraph isomorphism detection is known to be NP-complete, a significant amount of research work has been directed at various approaches for effective candidate generation. The mechanism employed for candidate generation is the most significant distinguishing feature of such algorithms.

In this thesis we studied a novel approach for frequent subgraph mining called FSM-H, this algorithm adopt an iterative map reduce based approach for mining graph datasets, this allows for load balancing and performance gains.

We evaluated the effectiveness of FSM-H on real graph datasets in terms of the performance and the quality of results.

VII. References:

1. Chen M, Mao S, Zhang Y, Leung VCM. Big Data - Related Technologies, Challenges and Future Prospects [Internet]. Springer; 2014. 89 p. Available from: http://www.springer.com/gb/book/9783319062440

2. Rojo S. Big Data vs. Business Intelligence In Analytics | Arcadia Data [Internet]. [cited 2018 Feb 13]. Available from: https://www.arcadiadata.com/blog/big-data-and-business-intelligence-differences/

3. Singh M. Effective Big Data Management and Opportunities for Implementation [Internet]. IGI Global; 2016 [cited 2018 Feb 15]. 324 p. Available from: https://books.google.com/books?hl=en&lr=&id=vVOiDAAAQBAJ&oi=fnd&pg=PR1&dq=Effective+Big+Data+Management+and+Opportunities+for+Implementation&ots=j__fDpC6FT&sig=uoGAzd-HZZDoEe3cA5GZJtOpxT4

4. Marr B. Why only one of the 5 Vs of big data really matters | IBM Big Data &amp; Analytics Hub [Internet]. [cited 2018 Feb 12]. Available from: http://www.ibmbigdatahub.com/blog/why-only-one-5-vs-big-data-really-matters

5. Dietrich D, Heller B, Yang B, editors. EMC Data Science and Big Data Analytics. Wiley. Jhon Wiley & Sons, Inc.; 2015. 435 p.

6. Buyya R, Calheiros RN, Dastjerdi AV. Big Data: Principles and Paradigms. Elsevier I. Big Data: Principles and Paradigms. Cambridge: Todd Green; 2016. 1-468 p.

7. Hurwitz J, Nugent A, Halper F, Kaufman M. Big Data for Dummies. Wiley. Jhon Wiley & Sons, Inc.; 2013. 339 p.

8. Big Data 101 : Streaming Data - YouTube [Internet]. Wiley. [cited 2018 Jun 15]. Available from: https://www.youtube.com/watch?v=AyqRk2zrmxA

9. Tariq RS NT, RS T. Big Data Challenges. Comput Eng Inf Technol

[Internet]. 2015 Jul 29 [cited 2018 Jun 2];04(03). Available from: http://scitechnol.com/big-data-challenges-Vfcv.php?article_id=3549

10. Big Data 101 : Big Data Technology Stack Architecture - YouTube [Internet]. [cited 2018 Feb 18]. Available from: https://www.youtube.com/watch?v=DVMsneOBWl8

11. Azure Data Architecture Guide | Microsoft Docs [Internet]. [cited 2018 Mar 11]. Available from: https://docs.microsoft.com/en-us/azure/architecture/data-guide/

12. Big Data 101 : Virtualization and Cloud Computing in Big Data - YouTube [Internet]. [cited 2018 Jun 15]. Available from: https://www.youtube.com/watch?v=kWdzc-DxYUY

13. Aridhi S. Distributed Frequent Subgraph Mining in the Cloud. Engineering Doctoral School of Clermont Ferrand; 2013.

14. Müller DE. Lesematerial | Big Data Analytics | openHPI [Internet]. [cited 2018 May 25]. Available from: https://open.hpi.de/courses/bigdata2017/items/4TO9c3oDe1AhP9tecEUDp5

15. Washio T, Motoda H. State of the art of graph-based data mining. ACM SIGKDD Explor Newsl [Internet]. 2003;5(1):59. Available from: http://portal.acm.org/citation.cfm?doid=959242.959249

16. Holder LB, Cook. Substructure Discovery in the SUBDUE System. J Chem Inf Model. 2013;53(9):1689–99.

17. Xifeng Yan, Jiawei Han. gSpan: graph-based substructure pattern mining. EEE Int Conf Data Min [Internet]. 2002;1(d):721–4. Available from: http://ieeexplore.ieee.org/document/1184038/

18. Inokuchi A, Washio T, Motoda H. An Apriori-Based Algorithm for Mining Frequent Substructures from Graph Data. 2000;13–23. Available from: http://link.springer.com/10.1007/3-540-45372-5_2

19. Ozaki T, Ohkawa T. Mining correlated subgraphs in graph databases. In: Pacific-Asia Conference on Knowledge Discovery and Data Mining. 2008. p.

272–83.

20. Yan X, Cheng H, Han J, Yu PS. Mining significant graph patterns by leap search. Proc 2008 ACM SIGMOD Int Conf Manag data - SIGMOD '08 [Internet]. 2008;433. Available from: http://portal.acm.org/citation.cfm?doid=1376616.1376662

21. Chen C, Yan X, Zhu F, Han J. gApprox: Mining frequent approximate patterns from a massive network. Proc - IEEE Int Conf Data Mining, ICDM. 2007;445–50.

22. Yan X, Cheng H, Han J, Xin D. Summarizing itemset patterns. Proceeding Elev ACM SIGKDD Int Conf Knowl Discov data Min - KDD '05 [Internet]. 2005;314. Available from: http://portal.acm.org/citation.cfm?doid=1081870.1081907

23. Huan J, Wang W, Prins J, Yang J. Spin: mining maximal frequent subgraphs from graph databases. In: Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining. 2004. p. 581–6.

24. Flake GW, Tarjan RE, Tsioutsiouliklis K. Graph clustering and minimum cut trees. Internet Math. 2004;1(4):385–408.

25. Huang Y, Niu B, Gao Y, Fu L, Li W. CD-HIT Suite: a web server for clustering and comparing biological sequences. Bioinformatics. 2010;26(5):680–2.

26. Yan X, Yu PS, Han J. Graph indexing: a frequent structure-based approach. In: Proceedings of the 2004 ACM SIGMOD international conference on Management of data. 2004. p. 335–46.

27. Yan X, Yu PS, Han J. Substructure similarity search in graph databases. In: Proceedings of the 2005 ACM SIGMOD international conference on Management of data. 2005. p. 766–77.

28. Shasha D, Wang JTL, Giugno R. Algorithmics and applications of tree and graph searching. In: Proceedings of the twenty-first ACM SIGMOD-SIGACT-SIGART symposium on Principles of database systems. 2002. p.

39–52.

29. Gärtner T, Flach P, Wrobel S. On graph kernels: Hardness results and efficient alternatives. In: Learning Theory and Kernel Machines. Springer; 2003. p. 129–43.

30. Borgwardt KM, Kriegel H-P. Shortest-path kernels on graphs. In: Data Mining, Fifth IEEE International Conference on. 2005. p. 8--pp.

31. Kashima H, Tsuda K, Inokuchi A. Marginalized kernels between labeled graphs. In: Proceedings of the 20th international conference on machine learning (ICML-03). 2003. p. 321–8.

32. Chakrabarti S, Dom BE, Kumar SR, Raghavan P, Rajagopalan S, Tomkins A, et al. Mining the Web's link structure. Computer (Long Beach Calif). 1999;32(8):60–7.

33. Kosala R, Blockeel H. Web mining research: A survey. ACM Sigkdd Explor Newsl. 2000;2(1):1–15.

34. Getoor L, Diehl CP. Link mining: a survey. Acm Sigkdd Explor Newsl. 2005;7(2):3–12.

35. Kleinberg JM. Authoritative sources in a hyperlinked environment. In: In Proceedings of the ACM-SIAM Symposium on Discrete Algorithms. 1998.

36. Brin S, Page L. The anatomy of a large-scale hypertextual web search engine. Comput networks ISDN Syst. 1998;30(1–7):107–17.

37. Greco G, Guzzo A, Manco G, Sacca D. Mining and reasoning on workflows. IEEE Trans Knowl Data Eng. 2005;17(4):519–34.

38. Hu H, Yan X, Huang Y, Han J, Zhou XJ. Mining coherent dense subgraphs across massive biological networks for functional discovery. Bioinformatics. 2005;21(suppl_1):i213--i221.

39. Yan X. Mining, indexing and similarity search in large graph data sets. 2006; Available from: https://www.ideals.illinois.edu/handle/2142/11256

40. Kavitha D, Rao BVM, Babu VK. A Survey on Assorted Approaches to Graph Data Mining. Int J Comput Appl. 2011;14(1):43–6.

41. Trlnajstic N. CHEMICAL GRAPH THEORY. Randie M, Klein DJ, Mezey P 0., Trinajstic N, editors. 323 p.

42. Aldrich H, Bates T, Kuhn T. Open HPI Mooc Courses. 2001. p. 1–5.

43. Chuntao Jiang FC and MZ. A Survey of Frequent Subgraph Mining Algorithms. Knowl Eng Rev. 2004;00(January):1–24.

44. Walks, Trails, Paths, Cycles and Circuits - Mathonline [Internet]. [cited 2018 Jun 3]. Available from: http://mathonline.wikidot.com/walks-trails-paths-cycles-and-circuits

45. Gutman I, Polansky OE. Mathematical concepts in organic chemistry. Springer Science & Business Media; 2012. 28 p.

46. Agrawal R, Srikant R, others. Fast algorithms for mining association rules. In: Proc 20th int conf very large data bases, VLDB. 1994. p. 487–99.

47. Agrawal R, Srikant R. Fast Algorithms for Mining Association Rules in Large Databases. J Comput Sci Technol [Internet]. 1994;15(6):487–99. Available from: http://portal.acm.org/citation.cfm?id=645920.672836

48. Garey MR, Johnson DS. Computers and intractability: a guide to NP-completeness. WH Freeman and Company, San Francisco; 1979.

49. Ullmann JR. An algorithm for subgraph isomorphism. J ACM. 1976;23(1):31–42.

50. Schmidt DC, Druffel LE. A fast backtracking algorithm to test directed graphs for isomorphism using distance matrices. J ACM. 1976;23(3):433–45.

51. McKay BD, others. Practical graph isomorphism. 1981;45–87.

52. Cordella LP, Foggia P, Sansone C, Vento M. Subgraph transformations for the inexact matching of attributed relational graphs. In: Graph based representations in pattern recognition. Springer; 1998. p. 43–52.

53. Cordella L Pietro, Foggia P, Sansone C, Vento M. An improved algorithm for matching large graphs. In: 3rd IAPR-TC15 workshop on graph-based representations in pattern recognition. 2001. p. 149–59.

54. Pong CPTC, Shapiro LG, Haralick RM. A facet model region growing algorithm. In: Pattern recognition and image processing Proc IEEE Computer Society conference, Dallas, 1981,(IEEE, New York; CH1595 8). 1981.

55. Bunke H, Allermann G. Inexact graph matching for structural pattern recognition. Pattern Recognit Lett. 1983;1(4):245–53.

56. Christmas WJ, Kittler J, Petrou M. Structural matching in computer vision using probabilistic relaxation. IEEE Trans Pattern Anal Mach Intell. 1995;17(8):749–64.

57. Messmer BT, Bunke H. A new algorithm for error-tolerant subgraph isomorphism detection. IEEE Trans Pattern Anal Mach Intell. 1998;20(5):493–504.

58. Conte D, Foggia P, Sansone C, Vento M. Thirty years of graph matching in pattern recognition. Int J pattern Recognit Artif Intell. 2004;18(03):265–98.

59. Miyazaki T. The complexity of McKays canonical labeling algorithm. In: Groups and Computation II. 1997. p. 239–56.

60. Han J, Pei J, Yin Y. Mining frequent patterns without candidate generation. In: ACM sigmod record. 2000. p. 1–12.

61. Read RC, Corneil DG. The graph isomorphism disease. J Graph Theory. 1977;1(4):339–63.

62. Inokuchi A, Washio T, Motoda H. An apriori-based algorithm for mining frequent substructures from graph data. In: European Conference on Principles of Data Mining and Knowledge Discovery. 2000. p. 13–23.

63. Inokuchi A. A fast algorithm for mining frequent connected subgraphs. IBM Res Rep. 2002;

64. Kuramochi M, Karypis G. Frequent subgraph discovery. In: Data Mining, 2001 ICDM 2001, Proceedings IEEE international conference on. 2001. p. 313–20.

65. Huan J, Wang W, Washington A, Prins J, Shah R, Tropsha A. Accurate

classification of protein structural families using coherent subgraph analysis. In: Biocomputing 2004. World Scientific; 2003. p. 411–22.

66. Vanetik N, Gudes E, Shimony SE. Computing frequent graph patterns from semistructured data. In: Data Mining, 2002 ICDM 2003 Proceedings 2002 IEEE International Conference on. 2002. p. 458–65.

67. Gudes E, Shimony SE, Vanetik N. Discovering frequent graph patterns using disjoint paths. IEEE Trans Knowl Data Eng. 2006;18(11):1441–56.

68. Kuramochi M, Karypis G. Finding frequent patterns in a large sparse graph. Data Min Knowl Discov. 2005;11(3):243–71.

69. Huan J, Wang W, Prins J. Efficient mining of frequent subgraphs in the presence of isomorphism. In 2003. p. 549.

70. Chi Y, Wang H, Yu PS, Muntz RR. Moment: Maintaining closed frequent itemsets over a stream sliding window. In: Data Mining, 2004 ICDM'04 Fourth IEEE International Conference on. 2004. p. 59–66.

71. Nijssen S, Kok JN. A quickstart in frequent structure mining can make a difference. In: Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining. 2004. p. 647–52.

72. Chaoji V, Al Hasan M, Salem S, Zaki MJ. An integrated, generic approach to pattern mining: data mining template library. Data Min Knowl Discov. 2008;17(3):457–95.

73. Chakravarthy S, Beera R, Balachandran R. DB-Subdue: Database approach to graph mining. In: Pacific-Asia Conference on Knowledge Discovery and Data Mining. 2004. p. 341–50.

74. Chakravarthy S, Pradhan S. Db-fsg: An sql-based approach for frequent subgraph mining. In: International Conference on Database and Expert Systems Applications. 2008. p. 684–92.

75. Srichandan B, Sunderraman R. Oo-FSG: An object-oriented approach to mine frequent subgraphs. In: Proceedings of the Ninth Australasian Data Mining Conference-Volume 121. 2011. p. 221–8.

76. Wu B, Bai Y. An efficient distributed subgraph mining algorithm in extreme large graphs. In: International Conference on Artificial Intelligence and Computational Intelligence. 2010. p. 107–15.

77. Liu Y, Jiang X, Chen H, Ma J, Zhang X. Mapreduce-based pattern finding algorithm applied in motif detection for prescription compatibility network. In: International Workshop on Advanced Parallel Processing Technologies. 2009. p. 341–55.

78. Cook DJ, Holder LB, Galal G, Maglothin R. Approaches to parallel graph-based knowledge discovery. J Parallel Distrib Comput. 2001;61(3):427–46.

79. Wang C, Parthasarathy S. Parallel algorithms for mining frequent structural motifs in scientific data. In: Proceedings of the 18th annual international conference on Supercomputing. 2004. p. 31–40.

80. Parthasarathy S, Coatney M. Efficient discovery of common substructures in macromolecules. In: Data Mining, 2002 ICDM 2003 Proceedings 2002 IEEE International Conference on. 2002. p. 362–9.

81. Meinl T, Wörlein M, Urzova O, Fischer I, Philippsen M. The parmol package for frequent subgraph mining. Electron Commun EASST. 2007;1.

82. Philippsen M, Worlein M, Dreweke A, Werth T. Parsemis: the parallel and sequential mining suite. Available www2 Inform uni-erlangen de/EN/research/ParSeMiS. 2011;

83. Wang J, Hsu W, Lee ML, Sheng C. A partition-based approach to graph mining. In: Data Engineering, 2006 ICDE'06 Proceedings of the 22nd International Conference on. 2006. p. 74.

84. Nguyen SN, Orlowska ME, Li X. Graph mining based on a data partitioning approach. In: Proceedings of the nineteenth conference on Australasian database-Volume 75. 2008. p. 31–7.

85. Bhuiyan MA, Al Hasan M. An iterative MapReduce based frequent subgraph mining algorithm. IEEE Trans Knowl Data Eng. 2015;27(3):608–20.

86. Lakshmi K, Meyyappan T. Frequent Subgraph Mining Algorithms - a

Survey and Framework for Classification. Cs It. 2012;04:189–202.

87. Holder LB, Cook DJ, Djoko S, others. Substucture Discovery in the SUBDUE System. In: KDD workshop. 1994. p. 169–80.

88. Kuramochi M, Karypis G. Grew-a scalable frequent subgraph discovery algorithm. In: Data Mining, 2004 ICDM'04 Fourth IEEE International Conference on. 2004. p. 439–42.

89. Borgelt C, Berthold MR. Mining molecular fragments: Finding relevant substructures of molecules. In: Data Mining, 2002 ICDM 2003 Proceedings 2002 IEEE International Conference on. 2002. p. 51–8.

90. Menon R. Cloudera Administration Handbook. PACKT; 2014. 254 p.

91. Sammer E. Hadoop Operations. Vol. 53, Journal of Chemical Information and Modeling. 2012. 283 p.

92. Big Data 101 : Storing Files in HDFS - YouTube [Internet]. [cited 2018 Jun 18]. Available from: https://www.youtube.com/watch?v=xj3_27hRPXM

93. Wu S. Big Data Processing with MapReduce. 2015;295–313.

94. Cutting D. Hadoop the Definitive Guide. White T, editor. 2009. 805 p.

VIII. Appendices:

01-The application as mentioned earlier in chapter 05 works on a four node Hadoop cluster, each machine runs CentOS v7 and Cloudera's Distribution with Hadoop CDH V15.4.

Each machine has a:

12 Core Intel Xeon Processor.

125 GB of RAM.

And 1.5TB of disk storage.

Yealding : 48Core for Processing, 500 GB of RAM in Total and 6TB of disk space across the Cluster.

One of the node serves as the master as well as a slave node having the :

NameNode, and RssourceManager and DataNode Roles.

The remaining Three have each :

DataNode and the NodeManager Roles.

The following lists the `/etc/hosts` file on each of the machines:

```
10.42.0.2  master.FSMCluster.local master
10.42.0.3  datanode1.FSMCluster.local datanode1
10.42.0.4  datanode2.FSMCluster.local datanode2
10.42.0.5  datanode3.FSMCluster.local datanode3
```

02-We used for the purpose of running the application: 32 Cores and a total of 320 GB of RAM across the Cluster, and a 6TB of disk space for the purpose of DFS Storage, the remaining resources are reserved to the system overhead.

Here are some configuration parameters (organized in groups) that were necessary for getting the best performance according to our setup :

A- YARN Container Configuration Property (Vcores) :

Configuration parameter	Value
yarn.scheduler.minimum-allocation-vcores	1
yarn-scheduler.maximum-allocation-vcores	1
yarn.scheduler.increment-allocation-vcores	1

B- YARN Container Configuration Property (Memory):

Configuration parameter	Value
yarn.scheduler.minimum-allocation-mb	1024
yarn.scheduler.maximum-allocation-mb	10240
yarn.scheduler.increment-allocation-mb	512

C- MapReduce Configuration:

Configuration parameter	Value
yarn.app.mapreduce.am.resource.cpu-vcores	1
yarn.app.mapreduce.am.resource.mb	10240
ApplicationMaster Java Maximum Heap Size (available in CM)	10240
mapreduce.map.cpu.vcores	1
mapreduce.map.memory.mb	10240
mapreduce.map.java.opts.max.heap	10240
mapreduce.reduce.cpu.vcores	1
mapreduce.reduce.memory.mb	10240
mapreduce.reduce.java.opts	10240
mapreduce.task.io.sort.mb	256