INSTITUTO SUPERIOR DE ENGENHARIA DO PORTO

MESTRADO EM ENGENHARIA INFORMÁTICA

Open Source Platforms for Big Data Analytics

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Outubro de 2017

POLITÉCNICO
DO PORTO

Instituto Superior de Engenharia do Porto

OPEN SOURCE PLATFORMS FOR BIG DATA ANALYTICS

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Dissertação para obtenção do Grau de Mestre em Engenharia Informática, Área de Especialização em Sistemas de Informação e Conhecimento

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Porto, outubro 2017

Resumo

O conceito de *Big Data* tem tido um grande impacto no campo da tecnologia, em particular na gestão e análise de enormes volumes de informação. Atualmente, as organizações consideram o *Big Data* como uma oportunidade para gerir e explorar os seus dados o máximo possível, com o objetivo de apoiar as suas decisões dentro das diferentes áreas operacionais.

Assim, é necessário analisar vários conceitos sobre o *Big Data* e o *Big Data Analytics*, incluindo definições, características, vantagens e desafios.

As ferramentas de *Business Intelligence* (BI), juntamente com a geração de conhecimento, são conceitos fundamentais para o processo de tomada de decisão e transformação da informação.

Ao investigar as plataformas de *Big Data*, as práticas industriais atuais e as tendências relacionadas com o mundo da investigação, é possível entender o impacto do Big Data Analytics nas pequenas organizações. Este trabalho pretende propor soluções para as micro, pequenas ou médias empresas (PME) que têm um grande impacto na economia portuguesa, dado que representam a maioria do tecido empresarial.

As plataformas de código aberto para o *Big Data Analytics* oferecem uma grande oportunidade de inovação nas PMEs. Este trabalho de pesquisa apresenta uma análise comparativa das funcionalidades e características das plataformas e os passos a serem tomados para uma análise mais profunda e comparativa.

Após a análise comparativa, apresentamos uma avaliação e seleção de plataformas Big Data Analytics (BDA) usando e adaptando a metodologia QSOS (Qualification and Selection of software Open Source) para qualificação e seleção de software open-source.

O resultado desta avaliação e seleção traduziu-se na eleição de duas plataformas para os testes experimentais. Nas plataformas de software livre de BDA foi usado o mesmo conjunto de dados assim como a mesma configuração de hardware e software. Na comparação das duas plataformas, demonstrou que a HPCC Systems Platform é mais eficiente e confiável que a Hortonworks Data Platform.

Em particular, as PME portuguesas devem considerar as plataformas BDA como uma oportunidade de obter vantagem competitiva e melhorar os seus processos e, consequentemente, definir uma estratégia de TI e de negócio.

Por fim, este é um trabalho sobre Big Data, que se espera que sirva como um convite e motivação para novos trabalhos de investigação.

Palavras-chave: Big Data, Big Data Analytics, BI, Big Data Platforms.

Abstract

The concept of Big Data has been having a great impact in the field of technology, particularly in the management and analysis of huge volumes of information. Nowadays organizations look for Big Data as an opportunity to manage and explore their data the maximum they can, with the objective of support decisions within its different operational areas.

Thus, it is necessary to analyse several concepts about Big Data and Big Data Analytics, including definitions, features, advantages and disadvantages.
Business intelligence along with the generation of knowledge are fundamental concepts for the process of decision-making and transformation of information.

By investigate today's big data platforms, current industrial practices and related trends in the research world, it is possible to understand the impact of Big Data Analytics on small organizations. This research intends to propose solutions for micro, small or medium enterprises (SMEs) that have a great impact on the Portuguese economy since they represent approximately 90% of the companies in Portugal.

The open source platforms for Big Data Analytics offers a great opportunity for SMEs. This research work presents a comparative analysis of those platforms features and functionalities and the steps that will be taken for a more profound and comparative analysis.

After the comparative analysis, we present an evaluation and selection of Big Data Analytics (BDA) platforms using and adapting the Qualification and Selection of software Open Source (QSOS) method. The result of this evaluation and selection was the selection of two platforms for the empirical experiment and tests. The same testbed and dataset was used in the two Open Source Big Data Analytics platforms.

When comparing two BDA platforms, HPCC Systems Platform is found to be more efficient and reliable than Hortonworks Data Platform.

In particular, Portuguese SMEs should consider for BDA platforms an opportunity to obtain competitive advantage and improve their processes and consequently define an IT and business strategy.

Finally, this is a research work on Big Data; it is hoped that this will serve as an invitation and motivation for new research.

Keywords: Big Data, Big Data Analytics, BI, Big Data Platforms.

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Acronyms

API	Application Programming Interface
BD	Big Data
BDA	Big Data Analytics
BI	Business Intelligence
BJSON	Binary JavaScript Object Notation
CRM	Customer Relationship Management
CSV	Comma-separated value
DM	Data Mart
DSL	Domain Specific Language
DW	Data Warehouse
ECL	Enterprise Control Language
ELT	Extract Load Transform
ESP	Enterprise Services Platform
ETL	Extract Transform Load
GUI	Graphical User Interface
HDFS	Hadoop Distributed File System
ICT	Information and Communications Technology
IMDB	In-memory database
IoT	Internet of Things
IT	Information Technology
JSON	JavaScript Object Notation
ML	Machine Learning
MPP	Massive Parallel Processing
NoSQL	Non-Relational Databases

OSS	Open Source Software
PDF	Portable Document Format
QSOS	Qualification and Selection of software Open Source
SQL	Structured Query Language
RDBMS	Relational Database Management Systems
RDD	Resilient Distributed Dataset
SQL	Structured Query Language
SSH	Secure Shell
UDF	User-Defined Functions
UI	User Interface
VM	Virtual Machine
XML	eXtensible Markup Language

1 Introduction

Today we observe huge volumes of data that are in constant growth, due to the evolution of technology together with the massive exchange of information. Therefore, it is needed one or more sophisticated platforms to deal with this massive quantity of data. The human being is just one of the main characters within this context, s/he every day handles, stores and manage all kinds of information, accompanied by technological advances and new challenges in data analysis, discovering and above all understanding a little beyond what the traditional platforms can provide.

There are two types of platforms available for handling Big Data - Open Source and Proprietary Software - which are used by all types of organizations to manage their information. However, many of them they do not know the benefits, advantages, and disadvantages that these platforms offer in cost, operation, and management of information.

In recent times all type of organizations are present on the Internet and this channel has a great impact on their business, taking care of what customers want and also serving as a guide for new products and what is offered. This process also highlights the huge deal of information in what has to do with products and services for sale to their consumers.

It is for all this that the main reason to carry out this research work is to analyse in particular the Open Source platforms for Big Data Analytics that best fit in Small and Medium-sized Enterprises (SMEs) and Non-governmental organization (NGO).

1.1 Problem

Nowadays, organizations and companies have opted for the adoption of open source and proprietary software platforms oriented to Big Data to solve problems of handling, management, storage, and analysis of information.

In order to justify this research work, a comparative analysis will be carried out between the open source platforms that can be adopted by SMEs that cannot afford or do not wish to acquire proprietary platforms, with the aim of discovering what kind of platforms and tools would be most suitable for their work environment, the large amount of information they handle and the analysis they need to support their business.

In addition, the present research will help solve problems within the context of Big Data, such as variety, the velocity of data, complementing with the new knowledge that the organizations finally obtain by analysing the data.

Furthermore, the consolidation of existing knowledge in conjunction with the new knowledge that will be obtained as the present work develops.

1.2 Objectives

The main objectives of this work are:

- Perform a comparative analysis and investigation of existing open source platforms for Big Data Analytics (BDA);
- Study current industrial practices and related trends in the research area;
- Describe how BDA platforms can be adopted by SMEs.

Moreover we can define the following specific objectives:

- Investigate concepts related to Big Data.
- Identify benefits, advantages, and challenges of open source platforms within the context of Big Data.
- Analyse aspects related to Business Intelligence and generation of knowledge.
- Investigate and explain the reality of SMEs in Portugal.
- Compare, analyse and test a solution adjusted to the reality of SMEs.

1.3 Document structure

This document is structured as follows: The first part (chapters 1, 2 and 3) of this work gives an introductory overview of the problem behind the research, the followed research objectives, value analysis, context, related work and concepts utilized in this work. In the second part (chapters 6, 7, 8) are explained the research method and agenda, the selection and evaluation, and the tests and experiment. The major conclusions and future work are summarized in chapter 9.

2 Value Analysis

In recent years, intellectual capital and intangible assets have been given more importance, giving rise to new questions and studies aimed at evaluating the implications for companies that care about understanding the new business processes, legislators, accountants, and economists. A holistic view of intellectual capital offers today the possibility of redefining value and revenue both at the corporate level and at the macroeconomic level. If we define value only in monetary terms, we do not evolve since the industrial age. However, to really understand how intangibles create value, there are two very important dimensions. The first dimension is how intangibles enter the market as negotiable. The second dimension is how intangibles function as transactional in key transactions that take place in a certain business model ("V. Allee, 'A Value Network Approach for Modeling and Measuring Intangibles,' Transparent Enterprise, Madrid, 2002. - References - Scientific Research Publish," n.d.). If we redefine value according to an intangible perspective, we can think of value in a broader way. Thus, we can exchange knowledge by knowledge or by tangible assets, services or money. Or even by other intangible assets such as customer loyalty. In this new economy, both value and money begin to gain new forms and appearances (Allee, 2000).

The value must be managed, this has the purpose of motivating people, developing skills and promote synergies and innovation, with the ultimate purpose of maximizing the overall results of an organization. Focusing on each process, product/service of a company can improve its overall results, mitigate risks, and increase the competitiveness (Moebius and Staack, n.d.).

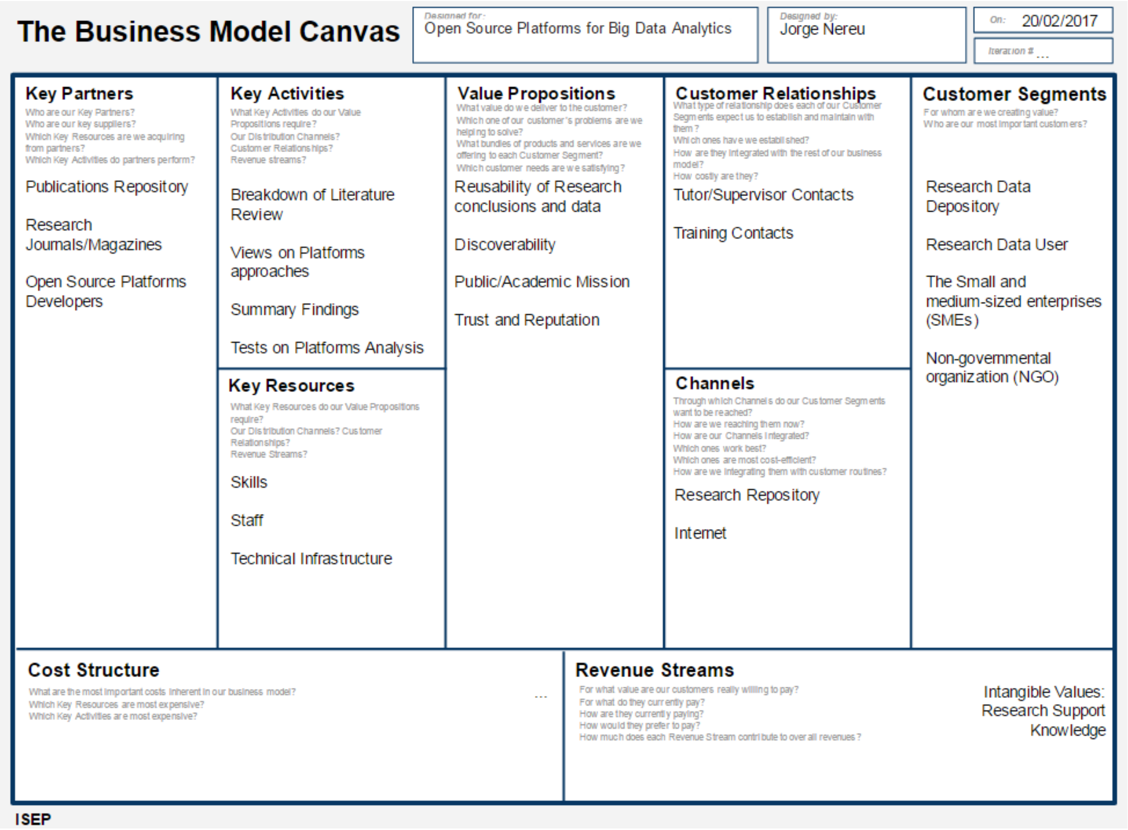
2.1 Value Networks

To convert tangible and intangible assets in outputs that are sent to other roles through the execution of the transaction. And, the value is obtained by companies when they convert inputs into earnings. We can visualize the sets of roles, interactions, and relationships that generate economic or social value in value networks. Thus, any organization or activity can be understood in the value network, by analysing the network uncovers the roles, how these interact and the patterns that create (Allee, 2008).

2.2 Value Proposition

Our intangible asset is a study (review and evaluation) through which organizations can decide if they want to have an Open Source Platform for Big Data for Analytics. The target customers for this study are the Small and medium-sized enterprises (SMEs) and Non-governmental organization (NGO) in Portugal. This study will help the SMEs and NGO that need to manage, visualize and gain insights from his Big Data, shared data and Open Data. This will save costs to the organization from the cost of Acquisition and Ownership. On the other hand, the study will provide a good option for those who want a platform through can build Big Data valuable information which becomes an asset for making good business decisions and by that gain more competitiveness. This study is unique in that it does not only provide a review of Open Source Big Data Platforms, but it also evaluates the platforms in features, advantages, and challenges.

2.3 Canvas Model



The Business Model Canvas

Designed for: Open Source Platforms for Big Data Analytics

Designed by: Jorge Nereu

On: 20/02/2017

Iteration # ...

Key Partners

Who are our Key Partners?
Who are our key suppliers?
Which Key Resources are we acquiring from partners?
Which Key Activities do partners perform?

Publications Repository

Research Journals/Magazines

Open Source Platforms Developers

Key Activities

What Key Activities do our Value Propositions require?
Our Distribution Channels?
Customer Relationships?
Revenue streams?

Breakdown of Literature Review

Views on Platforms approaches

Summary Findings

Tests on Platforms Analysis

Key Resources

What Key Resources do our Value Propositions require?
Our Distribution Channels? Customer Relationships?
Revenue Streams?

Skills

Staff

Technical Infrastructure

Value Propositions

What value do we deliver to the customer?
Which one of our customer's problems are we helping to solve?
What bundles of products and services are we offering to each Customer Segment?
Which customer needs are we satisfying?

Reusability of Research conclusions and data

Discoverability

Public/Academic Mission

Trust and Reputation

Customer Relationships

What type of relationship does each of our Customer Segments expect us to establish and maintain with them?
Which ones have we established?
How are they integrated with the rest of our business model?
How costly are they?

Tutor/Supervisor Contacts

Training Contacts

Channels

Through which Channels do our Customer Segments want to be reached?
How are we reaching them now?
How are our Channels integrated?
Which ones work best?
Which ones are most cost-efficient?
How are we integrating them with customer routines?

Research Repository

Internet

Customer Segments

For whom are we creating value?
Who are our most important customers?

Research Data Depository

Research Data User

The Small and medium-sized enterprises (SMEs)

Non-governmental organization (NGO)

Cost Structure

What are the most important costs inherent in our business model?
Which Key Resources are most expensive?
Which Key Activities are most expensive?

...

Revenue Streams

For what value are our customers really willing to pay?
For what do they currently pay?
How are they currently paying?
How would they prefer to pay?
How much does each Revenue Stream contribute to overall revenues?

Intangible Values:
Research Support
Knowledge

ISEP

Figure 1 – Business model canvas of Osterwalder for the present work

From this Figure 1, it can be verified in the block 'Key Partners' the potential stakeholders of this research work. Comparing with the 'Customer Segments', one critical factor can be identified: the involvement of SMEs and NGO. The model showed that SMEs and NGO are not involved, while this research work is intended for use both by interested researchers and organizations, as can be seen in the block ' Customer Segments' in Figure 1. The other critical factor that can be derived regard the 'Key Activities', can all the significant Platforms be covered by this research?

3 Context

In organizations, data is created, which brings about the need for large storing capacity and the need for extracting it to obtain its value. In this chapter presents the context of the study, SMEs and related work.

3.1 Context of the work

This research work, therefore, provides an analysis of big data analytics. We also discuss appropriate and open source tools that are used in this analysis of big data as well as the technologies that are applied and how they are applied. For instance, there are issues to do with storage, capture, sharing, search, visualizing as well as analytics. Presently, organizations explore large data volumes that are highly detailed to discover the facts that they were not aware of initially. Therefore, the analytics of big data is where improved data analytics are used in huge sets of data. However, the larger the data set, the more the complexity of managing it (Morshed et al., 2016).

In this work, it is important to figure out the data waste due to inefficient storage; which means that the data about people, organizations or any other incidents, different transactions performed, or other aspects that need to be storage are lost directly after they are used. In this aspect, organizations would find it difficult to get back important data as well as the knowledge that they may need in future after they were used. Also, organizations would find it difficult to perform a detailed analysis and provide new advantages and opportunities to their stakeholders. Some data that ranges from names of customers, as well as their addresses to the available products to the purchases acquired as well as the employees recruited, has become important for daily operations of organizations ("Ventana Research," 2014). Data is the building block on which all organizations thrive (Elgendy and Elragal, 2014).

With this data, it is even more evident that technology is imperative in data storage and its recovery. Technological advancements contribute to an increase in capabilities to store more data as well as more methods of collecting this data. Additionally, huge data amounts have been made easily accessible (Inoubli et al., 2016). Many organizations still deal with the flood of data created by IT systems and internet. Which includes data generated by the social interactions, sensor data but also by business systems(Belo et al., 2013). This flood is not a problem but an opportunity for companies in particular for SMEs that can have an opportunity for growth if they can turn that data into knowledge with the right tools. Although the data is too much and difficult to manage and analyze, companies know that data and its analysis can become a strategic and competitive advantage (Sivarajah et al., 2017).

3.2 SMEs

Information and Communications Technology (ICT) has a significant impact on organizations, SMEs are trying to adopt IT systems to support their business. The adoption of these systems in SMEs is distinct from adoptions in larger organizations, due to their specific characteristics, such as resources constraints (Ghobakhloo et al., 2012). In the next section the most important definitions and characteristics, as well the strategy and innovation in Portuguese SMEs are discussed.

3.2.1 Definition of SMEs

According to European Union (EU) (European Union, 2016) for a company is considered SME; the company must be included in three categories:

- Micro company: less than ten employees and an annual turnover or balance sheet of fewer than two million euros.
- Small company: less than fifty employees and an annual turnover or balance sheet of fewer than ten million euros.
- Medium-sized company: less than two hundred and fifty employees and an annual turnover of fewer than fifty million euros or a balance sheet of fewer than forty-three million euros.

Only 10% of all business in EU is from large companies, thus, SMEs represent 90% of all businesses. The SMEs stimulate the entrepreneurial and innovative spirit and help to promote competitiveness, economic growth, and employment in Europe.

3.2.2 Portuguese SMEs

According to Arendt (2008), all SMEs in Portugal have computers, and almost all have an internet connection. The SMEs use ICT mainly for customer relations such as email communication, sending pricelists, invoices, also use for marketing, logistics, customer Attention, HR management, payments, resource management, training and financial management, but with less expression. In Portugal, SMEs are ready to use ICT for logistical purposes, HR management, and business resources management.

It is clear that SMEs are investing in ICT for business purposes, and most importantly, training employees with e-learning officers. Today the knowledge and training of IT skills of entrepreneurs, managers, and employees are crucial in to reduce the digital divide between SMEs and large companies (Arendt, 2008). Having IT-skilled employees in a given technology is significantly determinant in the decision-making process of adopting this IT technology (Barbosa and Faria, 2008). If the companies do not have the necessary skill must ponder adopting and diffusing new IT systems from a strategic point of view and evaluating them like any other investment. Some SMEs are conscious of the potential of ICTs, especially in the technology and retail sectors, who believe that the adoption of new systems increases their performance in process integration, efficient management and rapid response to demand. (Belo et al., 2013)

Arendt (2008), presented a comprehensive survey of the adoption of ICT by the Portuguese SMEs, and conclude that the most significant obstacle to adopting new ICTs is the lack of financial resources, and others such as lack of appropriate software, knowledge, and ISP.

Although some Portuguese SMEs are well equipped with ICT, they do not take advantage of the opportunities ICT offers (Arendt, 2008).

3.2.3 SMEs Innovation as opportunity to grow

According to Salavou, Baltas and Lioukas, SMEs preferably use product innovations to gain competitive advantage contrasting with large companies that use other paths, such as economies of scale, diversification and investment in new products (Barbosa and Romero, 2014).

Effective use of Information and Communications Technology (ICT) by enterprises it is a decisive factor for success in their competitiveness, innovation, and growth (Morais et al., 2011).

Recognizing the importance of SMEs as the backbone of EU economy, the EU and its members periodically introduce incentive programs for SMEs, such as research, competitiveness and innovations (European Union, 2016). Example of this kind of programmes is the 'Portugal 2020'[1] which focuses on the alteration of certain points such as: strengthening of the organization and management capacities of SMEs, specific qualification of assets in areas relevant to the strategy of innovation, internationalization and modernization of enterprises, in order to promote the development of more productive activities in Knowledge and creativity and with a strong incorporation of national added value. This program identifies the need of Insertion of SMEs in the digital economy with the use of ICT. Thus, there is a great incentive and opportunity for SMEs for a Big Data Analytics strategy.

3.3 Related Work

Multiple research works have been done to compare and evaluate existing Big Data platforms some research focus on a specific capability, technology or purpose.

[1] http://www.poci-compete2020.pt/portugal2020

Almeida and Bernardino (2015) focus on the capability of mining data, and in a mix of technical parameters and features that are suitable for Small and Medium Enterprise environments.

On the other hand, Morshed and others (2016) focused their work on Platforms addressing distributed real-time data analytics, and concluded that the platforms present on their research do not cover all the features that are required for distributed computation in real-time.

Miller, Bowman, Harish, & Quinn, concentrate their work on platforms written in a certain programming language, in this case SCALA, that is a new programming language that supports both the object-oriented and functional programming paradigms built on top of JAVA (Miller et al., 2016).

Landset et al. (2015) presented a comprehensive survey of open source tools for machine learning with big data in the Hadoop ecosystem to researchers or professionals in machine learning but is inexperienced with big data. Also, Inoubli et al. (2016) discuss and presents the best practices using Big Data platforms in the domain of machine learning, graph processing and other applications, this was accomplished by doing an experimental evaluation and comparative study of three Big Data platforms.

Sagiroglu and Sinanc (2013) provides an overview of big data such as samples, methods, advantages and challenges. They compare Hadoop and HPCC by their architectures, primary languages, and indexes in a Distributed File System, data warehouse abilities and performance tests where HPCC shows the best results.Another recent paper describes an experiment with 40-node using Hadoop Platforms (Hortonworks, Cloudera or Apache), Spark for streaming data processing, HBase and OpenTSDB to store time series sensor data. The authors present the characteristics, requirements, and configurations of Hadoop platforms (Liu et al., 2016).

Bhadani and Jothimani (2017) present a comprehensive view of areas that can benefit from Big Data Analytics its advantages and limitations. They also analyse the Big Data tools and point out issues and future directions.

Yang et al. (2016) focus their research on Big Data tools and how they can be applied in the industrial context, and propose an architecture for the development of an open source platform for Big Data analytics to use in the industry.

In Chang et al. (2017) introduce new approaches to integrate analytics tools that use the R programming and so them to create a high-performance Big Data analytics platform and also they develop a method for job scheduling using MSHEFT algorithm. They conclude that their approach is capable of integrating new analytics platforms by adding tools that use R programming.

Cao et al. (2017) propose a unification framework that allows a generic abstraction at the top of the Big Data platforms that resulted from the comparison of some Big Data platforms.

In kejariwal et al. (2015) present an in-depth overview of streaming analytics in Big Data, discuss applications, algorithms and open source platforms. Finally, they identified future and current challenges.

Memon et al. (2017) point out the advantages and the simple way to use "big data platforms" in a distributed environment. They also do a systematic review of new developments in the area of "big data" technologies, giving some focus on the application of "big data" in the area of health.

So these were few related works which do evaluate based on specific capability, technology or purpose. Our work contributes into the identification of the Big Data platforms for analytics that may be suitable for SMEs in their operations.

4 Big Data Concepts

This chapter contains some of the essential concepts in Big Data, Big Data Storage and Management, Big Data Analytics, Big Data Ecosystems in order to systematize the concepts associated with this work.

4.1 Big Data

The appearance of the term “Big Data” might be traced back to the early 1980’s of the by the time scientists acknowledged that they failed to build the tools to analyze datasets of big size (Yan, 2013). During that era, Big Data was just quite a few hundreds of megabytes. However, currently, datasets of terabytes are frequent. Today the term Big Data still draws much attention, but behind the exaggerated publicity, there is a simple story. For decades, companies have been making business decisions based on transactional data stored in relational databases. In addition to the critical data, however, is a potential treasure trove of non-traditional data, less structured: blogs, social media, email, sensors, and photographs where we can extract useful information (Dijcks, 2013).

Big Data alludes to new ways for government and business organizations to combine miscellaneous digital data sets and after that use statistics and other data mining techniques to extract from them both occult information and astonishing correlations (Rubinstein, 2012).

According to Beyer, Big Data is “High volume, high velocity, and/or high variety information assets that require new forms of processing to enable enhanced decision making, insight discovery and process optimization” (Beyer and Laney, 2012).

Dumbill defines Big Data as “data that exceeds the processing capacity of conventional database systems. The data is too big, moves too fast, or doesn’t fit the strictures of your database architectures. To gain value from this data, you must choose an alternative way to process it.” (Dumbill, 2013).

In short, Big Data is a slogan that describes an enormous volume of structured, semi-structured and unstructured data that is so big that it’s difficult or impossible to process using traditional database systems and software techniques, in other words, Big data refers to a large data set due to its complex characteristics is difficult to be acquired, processed, stored and analysed in order to satisfy to what we intend in time with traditional technologies and techniques.

For many, there is no difference in the use of the term's "Big Data" and "Big Data analytics". In general opinion "Big Data" does not simply allude to the issue of data overburden (engineering problem), but additionally alludes to analytical tools used to deal with the flood of data and transform that flood into a source of gainful and useable data (Maltby, 2011). In this respect, the McKinsey Global Institute describes Big Data as "datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyse" (*Big data*, 2011).

4.1.1 Types of Big Data

Organizations collect all sorts of data; these are structured, semi-structured and unstructured (Gandomi and Haider, 2015). But typically the types of Big Data are loosely structured. With the constant addition of new types of data, the structure and relationship between the data are constantly evolving. The technological advances of the last years lead to high rate of data generation. In organizations, the source of unstructured data is internal (Sensor-data) and external (Social-Media) (Gandomi and Haider, 2015) and both (Activity-Transactional).

4.1.1.1 Sensor-Data (Internet of Things – IoT)

The huge deployment of connected devices such as cell phones, cars, RFID readers, webcams, and sensor systems adds a countless of autonomous data sources (Sharma and Navdeti, 2014). This machine data could be web logs, computer logs, mobile devices location (Sabapathi and Yadav, 2016), networking hardware devices, sensors from smart cities, such as utility poles, water lines, transportations and traffic lights. This type of data is a meaningful source of Big Data (Inoubli et al., 2016). With cloud computing becoming more and more omnipresent, it is anticipated that machine-generated data will grow by 40% of digital universe by 2020 (Kejariwal et al., 2015).

4.1.1.2 Social-Media Data

This type of Big Data is human sourced and less structured data, it is generated from various types of Internet Applications such as blogs, social networks, business networks, shared photographs and videos (Inoubli et al., 2016). It is a potential treasure trove of non-traditional data where we can extract useful information (Dijcks, 2013).

4.1.1.3 Activity-Transactional Data

Structured Data from traditional databases, generated from business transactions with information about customers, suppliers, and activities, e.g., Customer Relationship Management – CRM, e-commerce environments, (Prasad and Agarwal, 2016), and logs (e.g., web and network logs) (Sivarajah et al., 2017).

4.1.2 Big Data Characteristics

Big data can be defined by three characteristics of the data (Khan et al., 2014; Laney, 2001; Zikopoulos et al., 2011), first introduced by Doug Laney in 2001:

- Volume, the quantity of data;
- Variety, the types of structured data and unstructured;
- Velocity, the rate of generation, catchment, processing, and transmission.

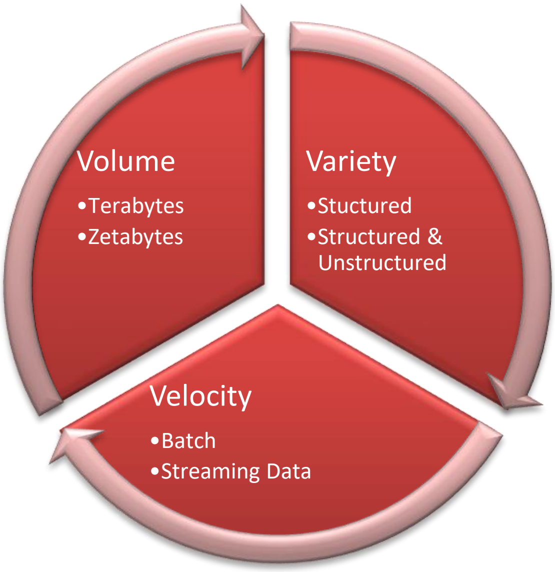


Figure 2 – Big Data characteristics (3Vs)

Beyond the exponential increase in volume, two other characteristics of the data changed significantly.

- Data flood, a consequence of machine data, this device create continuous data streams without human intervention, expanding the velocity of data collection and velocity needed for all processes (real-time and batch processing) (Sharma and Navdeti, 2014).
- Data is very varied. Almost all of newly created data comes from camera images, video, and surveillance footage, blogs, social networks, forums, and e-commerce catalogues. All of these unstructured data sources contribute to a much higher variety of data types (Jeseke et al., 2013).

Oracle characterizes Big Data as huge datasets that are challenging to store, search, share, visualize, and analysing. At the first look, seems that those orders of magnitude exceed data processing from conventional technologies and the largest Data Warehouses (DW) (Oracle, 2013).

With the development of discussion and enhancing interest in Big Data, considering Big Data analytics and developing Big Data strategy, the first three characteristics (three V's) have been expanded with the following (Rijmenam, 2013; Yan, 2013):

- Veracity, integrity of data;
- Value, usefulness of data;
- Complexity, degree of interconnection among data structures;
- Variability, unpredictability of data;
- Visualization, seeing the data;
- Veracity, the integrity of data.

In conclusion, by reviewing the existing literature, it was found that big data can have these seven characteristics in forms of Vs, in the next points these Vs will be described in detail.

4.1.2.1 Volume

As mentioned above, managing large and rapidly increasing volumes of data has been a challenging issue for many years. The term “Big” in big data suggests to massive volumes of data, users must view this as a relative term (Olofson and Vesset, 2012). The size of a conventional structured DW is sized in terabytes and petabytes, Big Data is sized in petabytes or exabytes, and maybe soon in zettabytes (Oracle, 2013). This size used to determine if a particular dataset is considered Big Data is not solidly characterized and continues to change over time. This is a bit a moving target increasing with available computing power. Moreover "big" volume is not just relying on the available computing, but additionally on other characteristics and usage of data. (Maier, 2013). The volume of data, is exploding (Akerkar, 2014), in which data created inside organizations, outside or both and it can originate from devices, networks and people interaction on the internet like social networks that plays a key role, and also the volume of data that will be analysed is immense (Sharma and Navdeti, 2014).

4.1.2.2 Variety

The complex nature of Big Data is principally determined by the unstructured nature of a great part of the data that is produced by a huge number of different data sources with diverse data types, like that from:

- social networks, e.g., Twitter responses, Facebook Likes, Pinterest;
- sensors and machine data, e.g., biosensors, ventilation equipment, smart meters; RFID Readers;
- vehicles, e.g., planes, trucks;
- web searches, emails, website links, pictures;
- computers, cell phones, and others.

Some of this data is called semi-structured because it does not have any defined format, but their structures can be derived based on various patterns of the data (Gudipati et al., 2013). In most instances, so as to successfully use of Big Data, it must be joined with structured data (transactional) from multiple conventional business applications such as Enterprise Resource Planning (ERP) or Customer Relationship Management (CRM) (Navint, 2012). The variety characteristic of big data is all about trying to acquire all of the data that relevant to the decision-making process (Zikopoulos et al., 2013). Traditional data formats have the trend to be well defined by a data schema and to have slow changes. In opposition, non-traditional data formats have a high rate of change. As new services are added, new sensors deployed, or new marketing campaigns executed, new data types are needed to capture the resultant information (Dijcks, 2013).

4.1.2.3 Velocity

The speed of creation of new data, this characteristic of Big Data is mostly due to the universal nature of present day on-line (data in motion), increasing channels, real-time data capture/creation systems, devices and networks, and in addition the need to integrate streaming information into business processes and decisions. It is normal that this rate of grown will keep on increasing for a long time to come (Oracle, 2013)(Navint, 2012)(Schroeck et al., 2012). Velocity means how data flow, at high rates, in increasingly distributed technologies and nodes. Velocity must handle and react with the streaming data, we can distinct two data stream:

- streams of new data (potentially from a variety of sources and types) being progressively incorporated into existing (huge) datasets;
- streams of query results (potentially huge) to user requests (Cuesta et al., 2013);

Often time-sensitive, streaming data must be analysed with millisecond response times to support real-time decisions (Soares, 2013). So, velocity signifies how rapidly data is generated, required and served (Cuesta et al., 2013).

As the perception of what is considered "big" volume changed over time, today the perception of real-time is not the same as it was in the mid-1990s when real-time was usually used for almost instantaneous monitoring, updating, or some activities that are around timely data processing. Today in an ultra-fast world without wires, this perception has assumed a new dimension (Kudyba, 2014).

4.1.2.4 Variability

The unpredictability of data and how these may change over time (Akerkar, 2014). Can be really pertinent when executing sentiment analyses. Variability signifies that the meaning can be altering (quickly). In the same tweets, a word can have a completely different significance, for example, the word "impact" can be used as a noun or a verb. So as to perform an appropriate sentiment analyses, algorithms need to have the capacity to comprehend the context and have the capacity to find the exact meaning of a word in that context (Rijmenam, 2013). Can exist changes from the structure of the data and how users need to think of that data (Fan and Bifet, 2013);

The variability may be present in the inconsistency of data streams, the rate of these flows can be quite variable, i.e., daily, seasonal or due to events peaks loads can be challenging to manage (Troester, 2012),(Katal et al., 2013),(Inukollu et al., 2014).

4.1.2.5 Visualization

Doing all of that vast quantity of data understandable in a manner that will be clear to see. Using the correct analyses and visualizations, raw data might be used in other case data continues to be useless. Having the ability to combine interactive data explorations with some analytics and visualization could create new insights that were probably hidden (Akerkar, 2014), e.g., a dataset of geo-located crimes or flu cases, or real-time data with local info from feeds can be analysed in a map. Thus, we can see where crimes happen or the source of the outbreak, or prevent something that could occur in location based information from feeds. This can be a hard aspect of Big Data;

4.1.2.6 Veracity

This is uncertain data, refers to the level of reliability regarding certain types of data (Schroeck et al., 2012), or the degree of that one leader has to be able to use certain information to make a decision (Zikopoulos et al., 2013). Possessing plenty of data in various volumes arriving in high velocity can be useless in a case in which data is incorrect. Thus, due to the high rate of arrival of these large volumes of data which need to be processed is difficult to cleanse them consistently and perform the pre-processing to improve data quality. This effect is more pronounced when dealing with the variety (Cuesta et al., 2013). To mitigate this effect is essential to assure the consistency and cleanliness of the unstructured data and the variety of many sources (Ebbers et al., 2013). Many data is inherently uncertain, e.g., sentiment and truthfulness in humans (typed human errors, ill intentions); GPS sensors bouncing, weather conditions (Schroeck et al., 2012). Completely wrong data could cause a plenty of problems for organizations and also for consumers.

In Big Data the quality issues are a reality, and veracity is what generally is used to refer to this problem domain (Ebbers et al., 2013). It is believed that one in three business leaders do not trust the information that they use to make decisions is a strong indicator that veracity is a very important aspect in Big Data (Maier, 2013; Zikopoulos et al., 2013).

However, even with uncertainty, the data still includes valuable information (Schroeck et al., 2012). Consequently, organizations must make sure that this data is right and also the analyses done on the data are right (Rijmenam, 2013);

4.1.2.7 Value

This characteristic measures the data utility in decision making (Kaisler et al., 2013). Big Data technologies are now seen as facilitators to create or capture value from data than other technologies have not been fully explored ("Big Data - A New World of Opportunities," 2012), e.g., capturing and processing a larger data set of non-traditional data, can unveil good information can unveil hidden good information. Thereby, it can bring a business value that offers the organization a real advantage, as a result of the capacity of making decisions based on giving answers to questions which were thought in the past that were out of reach (Fan and Bifet, 2013).

4.2 Big Data Storage and Management

Organizations need to deal with a few perspectives when managing this data. In the last few years, the amount of data used in organizations has become tremendous (Elgendy and Elragal, 2014; Khalifa et al., 2016). Firstly, knowing how and where this data is stored after it is acquired. To deal with structured data the conventional methods are Relational Database Management Systems (RDBMS), Data Marts (DM), as well Data Warehouses (DW). Under these, data is moved to storage from its operational systems making use of some methods, such as Extract, Transform, Load (ETL) or Extract, Load, Transform (ELT). These two unique methods are utilized to extract data from outside sources, and then transform the data to fit the operational needs, and at the end load that data to databases, DM or DW. At long last, this data is transformed, organized before it is made accessible for mining and or additionally for online analytics (Elgendy and Elragal, 2014). But, the present Big Data platforms also requires the utilization of Magnetic, Agile and Deep (MAD) analyses techniques (Elgendy and Elragal, 2014; Sharma et al., 2017). These analytics techniques are unique in relation to the traditional Enterprise DW platforms, in MAD all type of sources aren't limited to traditional sources (structured) that must be cleansed and integrated. In any case, because of data omnipresence these days, Big Data platforms should be Magnetic, which implies that they may captivate new sources of data paying little attention to their quality. Moreover, given the increasing number of data sources as well as the sophistication of data analysis, Big Data storage should enable analysts to easily produce and adapt data quickly. It is required an Agile database that easily ingests, digest, produce and adapt data quickly with data evolution, and also need deep data analyses, to study huge datasets by drilling up and down in data repository (Elgendy and Elragal, 2014; Sharma et al., 2017).

In such manner, a few solutions are given, and they run from systems that are distributed and with Massively Parallel Processing (MPP) databases, which is utilized in Big Data platforms to permit high query performance and platform scalability to non-relational or in-memory databases. Recently, non-relational databases, generally known as NoSQL databases, capable of store and manage unstructured, and non-relational data. These databases are capable of massive scaling, schema free, and simply to develop and deploy (Miller et al., 2016). Another great advantage over relational databases is the separation of the data management and data storage in the application and organization. These databases focus on high-performance scalable data storage and let data management tasks to the application layer. Also, perform in-memory database they do not require data input and data output on disk, and that saves a lot of response time from a database (Elgendy and Elragal, 2014). For a better understanding of the mentioned technologies, in the following subsections of this subchapter, will be described NoSQL databases and In-Memory Databases.

4.2.1 Non-relational databases

One of the most important information management style to handle Big Data are the NoSQL systems which are ideal for handling multi-structured data (Chandrasekhar et al., 2013).

In the last years, the use of non-relational databases considerably increased due to the advantages, such as scalability, highly available, fault-tolerant, and capable of handle heterogeneous data (Murthy and Bowman, 2014).

The non-relational databases or Not Only SQL (NoSQL) can be placed into four categories according to different optimizations (Kabakus and Kara, 2016; Kune et al., 2016):

- Key-value store: uses a set of key-value (k, v) pairs. In this concept, the table is known as "hash table" has two columns, one for the key and the other column for the value. The value can be a single value or a data block with various values.
- Document store: It is a document-oriented database, this database store, retrieve and manage document oriented and semi-structured data. Also uses key-value (k, v) pairs to encode or encapsulate other key-value pairs in some standard such as eXtensible Markup Language (XML), JavaScript Object Notation (JSON) or Binary JavaScript Object Notation (BJSON).
- Column family: Rather store single key-value (k, v) pairs, they are organized according to the relationship of data and stored as a set of rows and columns.
- Graph database: Data is stored and modelled as a graph representing a collection of nodes and edges to represent relationships between nodes.

4.2.2 In-Memory Databases

It is a current trend to use In-memory database (IMDB) in the field of processing large volumes of data (Brusakov and Botvin, 2017) quickly (Stimmel, 2014). An In-memory database is a database management system, these systems store data in the RAM memory of the machine, thus avoiding storing data on disk input/output (Scheffler and Otyepka, 2014). The in-memory database should only save data (e.g. logs and snapshots) to disk to guarantee system reliability, all operations must be carry out completely in RAM (Brusakov and Botvin, 2017).

This allows faster responses times, almost in real-time (Elgendy and Elragal, 2014; Scheffler and Otyepka, 2014). IMDB supports structured and unstructured data witch benefits in-memory analytics, with useful response time for real-time analytic visualization and data exploration (Stimmel, 2014).

4.3 Big Data Analytics

Big Data Analytics is becoming more and more a trending practice that many companies are adopting with a purpose to build Big Data valuable information (Sivarajah et al., 2017). The main objective of Big Data Analytics is to become an asset for making business decisions, making possible to data scientists, and other analytics professionals to analyze enormous volumes of transaction data, also other formats of data that may be other Business Intelligence (BI) can't explore (Sabapathi and Yadav, 2016).

Presently, organizations explore large data volumes that are highly detailed to discover the facts that they were not aware of initially. Therefore, the analytics of big data is where improved data analytics are used in huge sets of data. However, the larger the data set, the more the complexity of managing it (Morshed et al., 2016). Platforms oriented to Big Data Analytics are the greater promoters of the paradigm shift of Big Data. These platforms manage large volumes of data and also work as an application of various analytical techniques to make sense from large volumes of data (Miller et al., 2016).

To extract useful information from large data volume tools, it is appropriate to collect, store and process data for various analytical perspectives (Prasad and Agarwal, 2016). The usual process flow diagram for Big Data Analytics is shown in Figure 3.

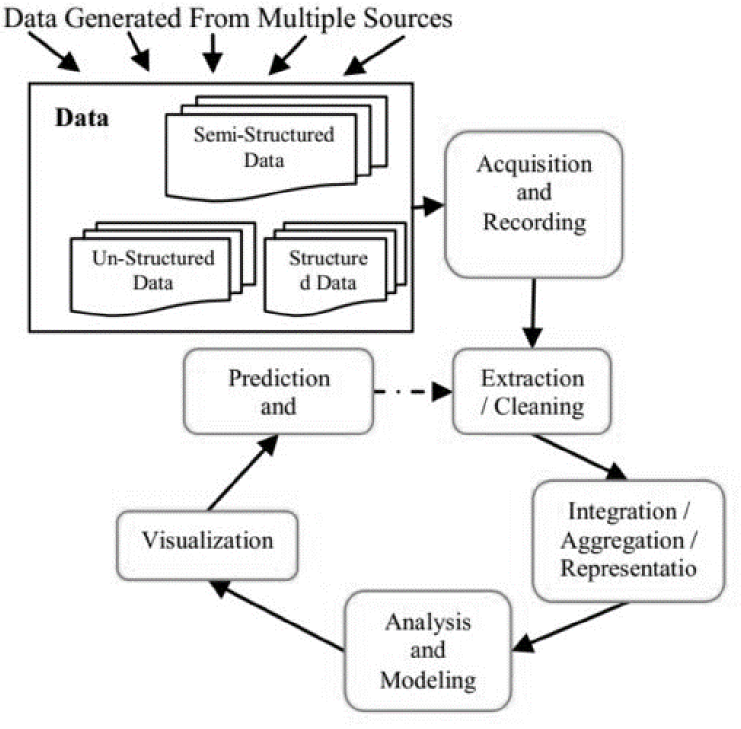


Figure 3 – Process flow diagram for Big Data Analytics (Prasad and Agarwal, 2016)

In this following sections, will be present some aspects related to Big Data Analytics such as In-Memory analytics, Real Time analytics, Big Data Analytical Methods and Decision Making.

4.3.1 In-Memory analytics

The utilization of IMDB has brought an improvement in analytic processing. As a matter of fact, many organizations are raising Hybrid Transaction/Analytical Processing (HTAP) that allows transactions and analytic processing in the same in-memory database (Sabapathi and Yadav, 2016). The results of analytics are more faster with better query response times, thus BI applications can support faster business decisions (Kune et al., 2016).

4.3.2 Real Time analytics

The high velocity that today the data flows from diverse real-time data sources bring a huge opportunity for streaming analytics (Kejariwal et al., 2015), an example of some use cases are:

- Visualization of business metrics in real-time
- Providing highly personalized experiences
- Providing a response during catastrophe or emergencies.

This real-time interactive analytics are normally exploratory in nature, the user is online and submits a query and expects to receive the results in seconds. It is critical a low response time in such applications that supports real-time analytics, contrasting with offline and batch-oriented analytics tools that are unfit for this real-time analytics (Zhang et al., 2014).

4.3.3 Big Data Analytical Methods and Decision Making

In this section is described the analytical methods and the opportunities for decisions makers that Big Data Analytics brings to companies.

4.3.3.1 Methods

The current technologies developments as well as the expansion in large numbers of data produced every day, it is required analytical methods more efficient and faster for support decisions. It is already recognized that BD can help and improve decision making and increase productivity in organizations, it is possible when selecting appropriate analytical methods to extract the meaning of the data, such as (Sivarajah et al., 2017):

- Predictive analytics: It is related to forecasting and statistic modelling to determine future scenarios.
- Prescriptive analytics: It is related to optimization and random testing to assess how the business can improve its service levels while lowering its costs.
- Descriptive analytics: This method examines the data and information to define the current state of the business, where what is happening is based on incoming data. The developments, patterns, and exceptions are evident. Usually, reports, dashboards, and alerts are used.

- Inquisitive analytics: Is concerned in discerning data to accept or reject a business hypothesis, questions such as, what, how, what if. For example, analytical drill/drowns, statistical analysis, and factor analysis.

4.3.3.2 Big Data Analytical Decision Making

Elgendy and Elragal identify the opportunities that Big Data Analytics brings to companies which include Small and Medium-sized Enterprises (SMEs), those include:

- Customer Intelligence: BDA can benefit business areas such as retail, banking, and telecommunications. By analyzing the data, the companies will be able to segment the customers based on their socio-economic characteristics and also to increase the levels of customer satisfaction. Also, companies could decide and make better-target social-influencer marketing and identification of sales and market opportunities.
- Supply Chain: BDA can help predict demand shifts, and according to demand adjust supply. Areas of business such as manufacturing, retail, transport, and logistics-related industries may benefit from these forecasts.
- Performance Management: Performance management can be optimized by the healthcare industries due to the increasing need to improve productivity, and staff performance information can be monitored and predicted. In companies can be monitored and predict the performance of staff with predictive analysis, thus aligning all departments in the strategic objectives which lead to increased efficiencies.
- Quality Management and Improvement: Big Data Analytics can be used in quality management and increase profits, reduce costs by improving the quality of products and / or services. Areas of business such as manufacturing, energy and utilities and telecommunications could benefit of quality management, e.g., in the manufacturing process the performance variability can be mitigated by doing applying predictive analytics, but also to avoid quality problems by giving early warning. In the area of health with the storage of records about patients and the healthcare provided along with the use of BDA, there is an opportunity to mine the data (without identification of the patients) to assess the quality of the healthcare, as well as manage the diseases and health services.
- Risk Management: BDA offers opportunities in risk management benefits companies from the banking, investment, and insurance sectors. For the financial investment sector, Big Data Analyses can be made to aid in the selection of investments based on the probability of gains and losses.
- Fraud Detection: Big Data Analytics can be used to detect and prevent fraud in areas of industries such as banking and insurance, and government departments. Thus, using BDA systems with prevalent fraud pattern data allows systems to learn new types of fraud and delivery alerts.

4.4 Big Data Ecosystems

The ecosystem of big data includes several aspects such as data, the lifecycle models of big data, and finally the infrastructure that is used for support (Murthy and Bowman, 2014).

The maturity of big data and predictive analysis leads to more open source contributors to the technologies used to empower the solutions. Presently, all types and sizes of vendors are making use of open sources for big data processing and the predictive analytics process (Pääkkönen and Pakkala, 2015). In some cases, the cloud, as well as open sources for storage and computing, is the technological catapults that enable start up and an emergence of small companies to compete with the more established ones (Sen et al., 2016).

Granville and Sqrrl[2] (2013) points out 11 large segments (see. Figure 4) that the Big Data Ecosystem consists, such as:

1. Hardware: Providers of hardware systems and disks for Big Data software.
2. Services: Providers of services to support strategy and implementation of Big Data solutions.
3. Cloud: Some organizations run their Big Data in public, private or both clouds.
4. Enterprise Data Warehouse (EDW): Vendors of relational databases.
5. Data Integration: Vendors of solutions that assist in getting data into Big Data Platforms or Scale-Out databases.
6. Hadoop: Hadoop commercial platforms with HDFS and related Apache projects.
7. Security: Vendors of security tools for encryption and key management, expressly created for Big Data.
8. Scale-Out Database: Vendors of NoSQL and NewSQL databases.
9. Horizontal Big Data Platforms: Some of these platforms are built on top of Hadoop and provide additional data analysis capabilities that go beyond those existent in Hadoop.
10. Vertical Big Data Platforms: Comparable to Horizontal Big Data Platforms, but concentrated for a particular vertical industry.
11. Business Intelligence and Visualization: Tools for interpretation and visualization of queries results on dashboards and static reporting for data present in Hadoop.

[2] https://sqrrl.com/

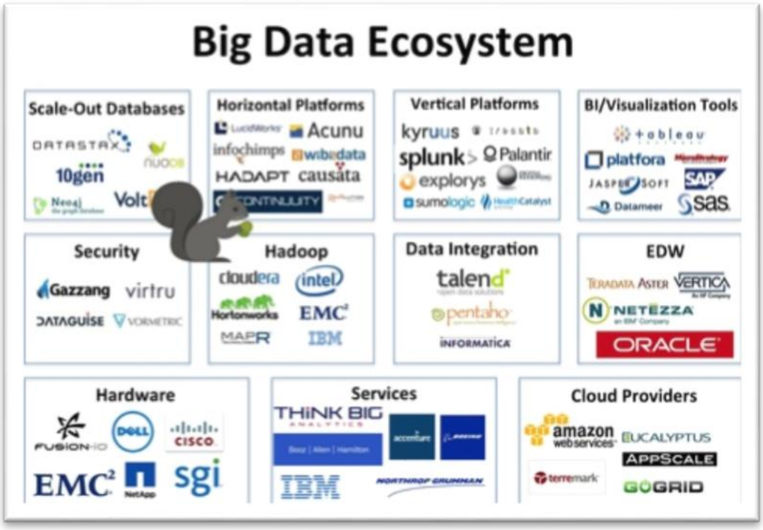


Figure 4 – Big Data Ecosystem (Granville, 2013)

Big Data open source platforms are divided into several categories, which are data storage and access, development tools, and platforms for analytics and reporting (Miller et al., 2016).

5 Open Source Big Data Platforms

In this chapter, several concepts and aspects with respect to the platforms of Big Data will be present. For this, the literature used is mostly from the scientific community, together with publications of a technical nature related to this thematic.

For Gupta and Gupta (2014), any platform that of support the massive amount of data that other traditional database tools cannot support can be considered a Big Data Platform (Almeida and Bernardino, 2015).

A Big Data platform should be a solution that is specifically designed to meet the needs of the organization in mind (Chandrasekhar et al., 2013). Thus, the basic functionalities that should be offered are:

- Full-Stack: It should provide a wide foundation for the support of all three Big Data tasks - Volume, Variety, and Velocity.
- Enterprise-ready: It should incorporate the features driven for performance, security, usability and reliability.
- Incorporated: It should easily simplify and accelerate the implementation of Big Technological innovation for organizations.
- Open Source based - It should be an enterprise-class product in both performance and integration.
- Updates and Low latency flows
- Solid and fault-tolerant
- Scalability
- Extensible
- Allows ad-hoc queries
- Little maintenance.

This work highlights the working characteristics of some Platforms for Big Data, and also aim to explain the working advantages of open source analytical platforms that are not limited to their ecosystem but also complement each other such as:

- Apache Hadoop
- Cloudera Impala
- HPCC System
- Apache Spark
- Hortonworks Data Platform (HDP)
- Apache Apex
- Apache Storm
- Apache Solr
- Apache Drill

Other platforms have been identified but are not currently in the study, such as:

- Apache Kudu
- Lumify
- Flink
- Samza
- Apache Ignite
- Nvidia Cuda
- MLPACK
- Mahout
- Berkeley Data Analytics Stack
- S4
- R Project
- Pegasus
- Graphlab
- CreateTM
- Chukwa
- Elasticsearch
- Ikanow
- Pentaho Community
- Apache Tez.

5.1 Apache Hadoop

The Apache Hadoop is a free software library, a project of the Apache foundation that implements the MapReduce[3] paradigm and the Hadoop Distributed File System (HDFS) as a filesystem.

This open source platform allows distributed processing of large data sets across clusters of servers using simple programming models, which one cluster is designated as the master node and other as slave node (Prasad and Agarwal, 2016).

This platform has been projected to scale from one server to thousands of servers where each has local processing and storage ("Apache™ Hadoop®," 2016).

The two most important components that characterize the platform are MapReduce and HDFS, where MapReduce supports analysis of data and HDFS supports storage of data (Saraladevi et al., 2015). HDFS is at the base of the architecture as shown in Figure 5.

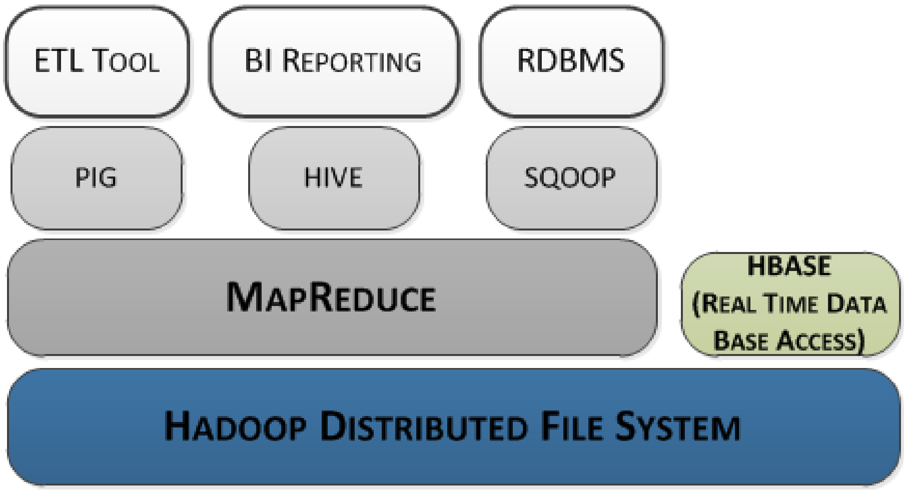


Figure 5 – Hadoop Architecture (Saraladevi et al., 2015)

5.1.1 MapReduce

The main advantage of MapReduce is the accomplishment of parallelization and failover successfully, by splitting the work into multiple units (Chandrasekhar et al., 2013; Miller et al., 2016). MapReduce jobs are done by only using two user defined functions: map and reduce functions, which uses a set of key-value (k, v) pairs. The map function is grouped by key and is received as a single group in the Reduce function. The improvement of the Hadoop MapReduce is that users typically only have to define the functions map and reduce. Another significant advantage of Hadoop MapReduce pointed by authors is that it permits non-expert users an easy way to run analytical jobs over Big Data.

[3] https://hadoop.apache.org/docs/r1.2.1/mapred_tutorial.html#Purpose

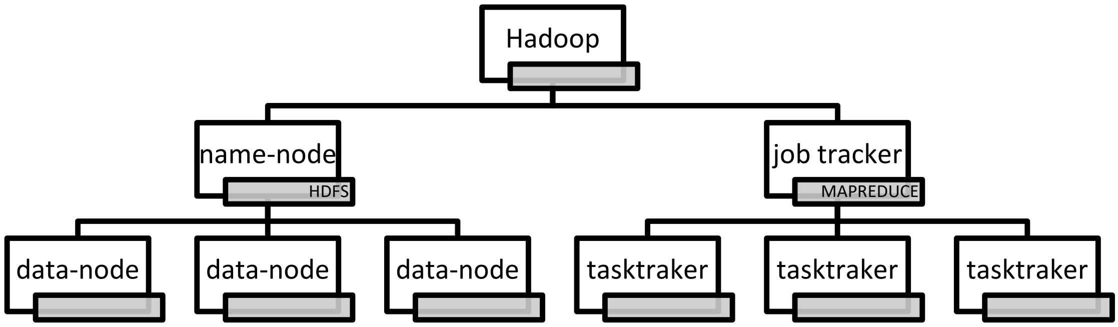


Figure 6 – MapReduce and HDFS Daemons (Inoubli et al., 2016)

They found that through scaling out to multiple computing nodes Hadoop MapReduce jobs attain good performance though (Dittrich and Quiané-Ruiz, 2012). The component for coordinating the tasks within the node is the job tracker and several task trackers as shown in Figure 6 Figure 6 – MapReduce and HDFS Daemons(Inoubli et al., 2016).

5.1.2 Hadoop Distributed File System (HDFS)

This platform uses a distributed file system to read and write its data, usually for data storage uses Hadoop Distributed File System - HDFS which is also open source, and HDFS is based on the distributed Google File System – GFS. It supports scalable distributed file system that stores huge files in various and distributed machines in a reliable and efficient way (Inoubli et al., 2016).

The HDFS is distributed and reliable system, self-healing, highly scalable storage, extends through every node in Hadoop cluster for data storage on commodity hardware, and by linking together the file systems on various local nodes it creates a huge file system.

The HDFS automatically replicates data across various nodes for fault tolerance and so there is no need for backup (Inukollu et al., 2014). There are two types of nodes in a cluster. The first is the name-node (master) and the second is the data-node (slave), the name-node manages files, blocks, and mapping in a formation of the data-nodes as seen in Figure 6, the data-node is responsible for storing data from a block unit into a number of locations separately. HDFS files are also replicated in multiple in order to provide parallel processing of large amounts of data (Khan et al., 2014).

The strengths of the Apache Hadoop include scalability as it stores as well as distribute large sets (Katal et al., 2013). It is also a cost-effective method and well resilient to failure. The weaknesses of this tool are that its design makes it vulnerable to security attacks. Additionally, this tool has several issues with stability. The opportunities that it provides are that it offers storage for big data in a cost-effective manner. The threats of the tool are posed by its weaknesses, which include security breaches.

5.2 Cloudera

Cloudera is the most well-known platform based on Apache Hadoop, which offers an effective platform that empowers organizations to gain insights from all their data (structured or unstructured) (Chandrasekhar et al., 2013).

Cloudera is on the front line of the data management. Furthermore, Cloudera is the most innovative and contributes most for the open source Apache Hadoop platform (Sabapathi and Yadav, 2016). Cloudera is the leader in Hadoop-based platforms (Chandrasekhar et al., 2013) has the same methods, functions, and main properties present in Hadoop, but it includes other efficient tools for social media (Murthy and Bowman, 2014). Cloudera maximizes the capabilities of Hadoop in storage, retrieval, and analysis (Murthy and Bowman, 2014) and enables enterprises to take advantage of features for SQL tools to achieve real-time analytics (Prasad and Agarwal, 2016).

Where this platform stands out from the original Hadoop system is that it offers big data processing at faster speeds (Prasad and Agarwal, 2016), and has a user-friendly interface with many features and useful tools like Cloudera Impala. The Cloudera Impala status can be identified in the Hadoop Stack in Figure 7.

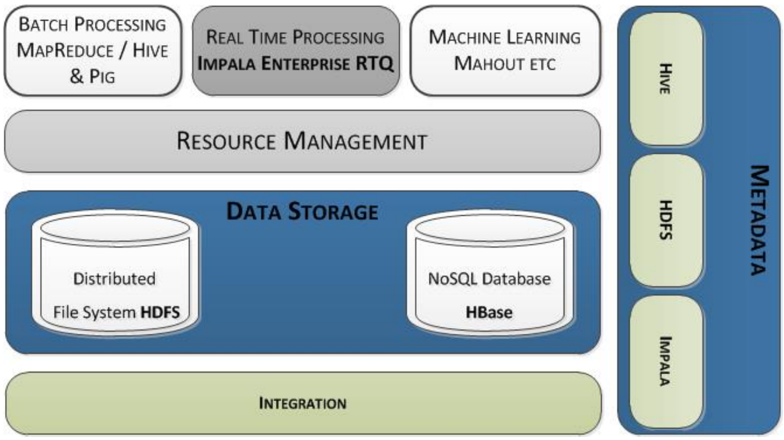


Figure 7 – Cloudera Impala Status in Hadoop Stack (Prasad and Agarwal, 2016)

Impala is a real-time, parallelized processing engine with an SQL-based interface that queries the storage (HDFS and HBASE). Impala is seen as the fastest querying engine present in the Hadoop-based platforms. Moreover, is not just the Impala that stands out from the other platforms; the Cloudera Manager is more stable and complete in features than the Ambari (HDP) and resource manager (Hadoop) (Azarmi, 2015).

The strength of this platform is that it offers to process big data at faster speeds than the original Hadoop system. The weakness that it has is that there are incompatibilities with some systems. Its opportunities are reliability as a result of faster data processing. The threats posed to this tool are issues with security.

5.3 Hortonworks Data Platform (HDP)

Hortonworks Data Platform (HDP) is another open source platform based on Apache Hadoop, is an important influencer of the Apache Hadoop project, and offers its free and open source version of Hadoop along with services and training (Dinsmore, 2016), HDP agglutinates the stable components instead of distributing the latest version of the Hadoop project (Azarmi, 2015). Contrasting with Cloudera, HDP is 100% open source and totally free. It is an excellent choice for organizations that need the capability and cost-effectiveness of Apache Hadoop, with ready business tools (Chandrasekhar et al., 2013; "HDP," 2016).

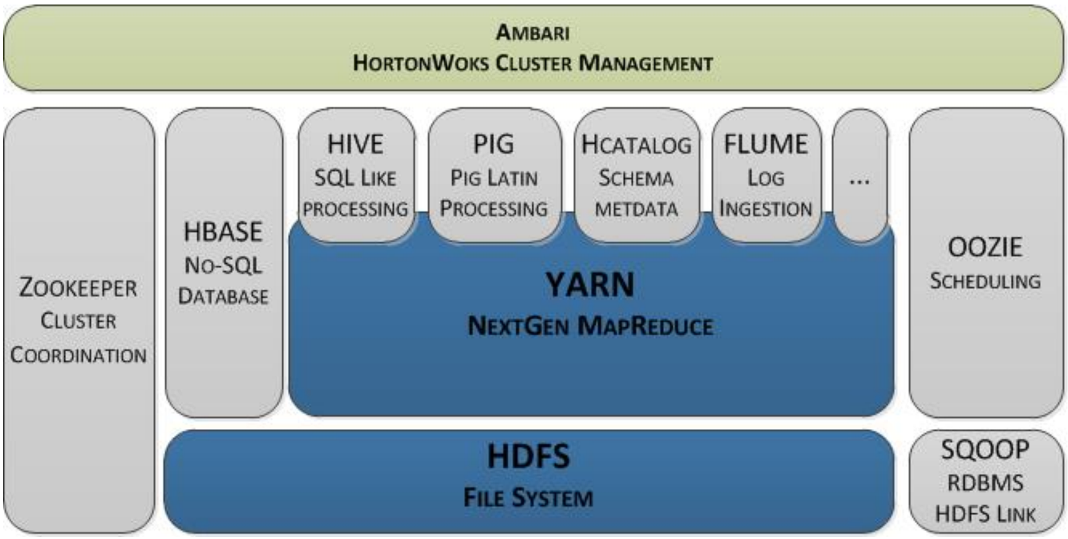


Figure 8 – Hortonworks Distribution (Azarmi, 2015)

As seen in Figure 8, HDP contains an integrated solution composed of open source tools such as Hadoop, Pig, Hive, Spark, Yarn, etc (Khalifa et al., 2016). The components of Hadoop core stack are represented in blue, the components of the Hadoop Ecosystem project are in grey, and the specific component from HDP is represented in green (Azarmi, 2015). To deal with the performance issues, the HDP promotes Apache Tez as a performance optimizer (Dinsmore, 2016). This platform does not view the Hadoop as an alternative to traditional data management platforms thus focuses on offering integration components for traditional data management platforms ("HDP," 2016). HDP look for Hadoop as a tool to complement the existing data platforms, a similar vision with the Proprietary Software vendors.

HDP offers secure distribution on a centralized architecture and it is the only Hadoop Distribution that supports Windows as its strengths. Its main weaknesses are security breaches and a basic management interface. Its opportunity is that it focuses on the reliability and stability of the Apache Hadoop.

5.4 HPCC System

The High-Performance Computing Cluster (HPCC) Systems Big Data is an open source framework that is used for manipulating, querying, transforming, as well as data warehousing. This framework is tipically used as a choice instead the Hadoop-based platforms, and there are two versions of the platform, one paid and one free (Chandrasekhar et al., 2013).

The HPCC uses the Linux operating system to support the layers of custom-built middleware components, thus providing an environment for running and supporting the distributed file system for data-intensive computing.

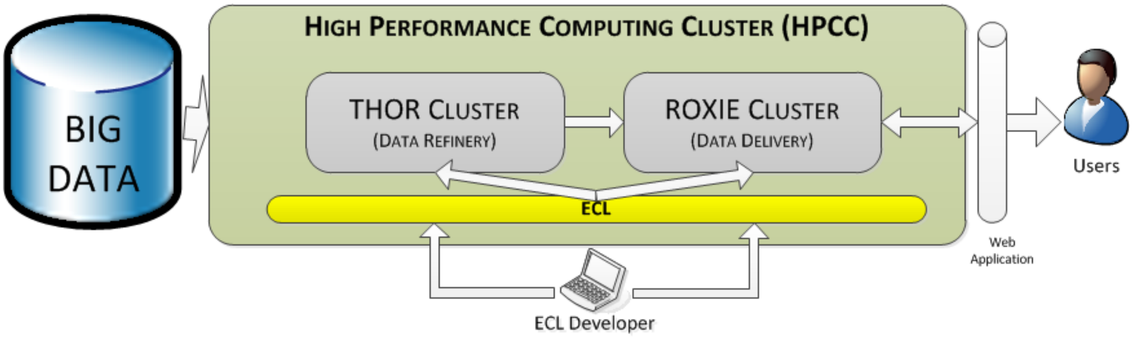


Figure 9 – HPPC environment system (adapted from Furht and Villanustre, 2016).

As shown in Figure 9, HPPC makes use of Thor[4] data refinery that is identical to the Hadoop-MapReduce combination, with its functions and capabilities, however, with similar configurations, it offers a much better performance (Furht and Villanustre, 2016). The HPPC data delivery engine Rapid Online XML Inquiry Engine (Roxie)[5] as the name suggests is an online high performance structured query and analysis tool that supports parallel data access processing requests per node per second with sub-seconds response times (Furht and Villanustre, 2016) as well supports the ECL – Enterprise Control Language. This is an Easy-to-learn and consistent programming language (ECL) which is designed specifically for big data processing. There is another framework called the community edition, which is a free HPCC version and is also supported by active developers and enthusiasts' community through online forums of discussion. HPCC Systems platform has the same core technology that LexisNexis[6] has used for years to analyse huge data sets for its customers in industry, law enforcement, government, and science ("HPCC Systems Platform," 2016).

Due to the high-performance and cost-effectiveness of its implementation, the HPCC has been adopted by several government agencies, companies and research laboratories (Furht and Villanustre, 2016).

[4] https://hpccsystems.com/resources/faq/what-thor

[5] https://hpccsystems.com/resources/faq/what-Roxie

[6] http://www.lexisnexis.com/en-us/gateway.page

The HPCC identified the need for a new computing paradigm to address its growing volumes of data, his design approach comprehended the definition of a new highlevel language (ECL) for parallel data processing based on the Dataflow architecture ("HPCC Systems Platform," 2016). As we can verify in Figure 9 ECL is a crucial and transverse component of HPCC.

The HPCC is also a solution to consider in an early stage of BDA (Tsai et al., 2015).

5.5 Apache Apex

Apex is an Enterprise Grade platform and a Hadoop YARN[7] native platform which has oriented to unifying stream and batch processing. Apex processes big data-in-motion (streaming) in a scalable, fault-tolerant, secure, distributed, and easily operable manner.

Apex states that the platform has a low barrier entry by providing a simple API to developers for writing or re-use generic Java code, thus decreasing the knowledge necessary to develop big data applications, also uses Malhar[8] a free library to facilitate integration with 300 commonly used operators and applications templates ("Apache Apex," 2016). The platform high-level architecture can be seen in Figure 10.

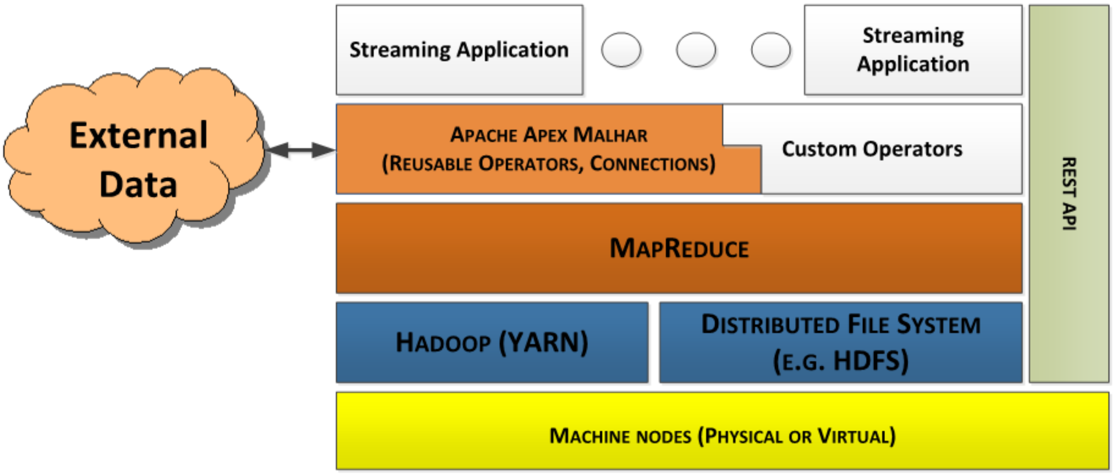

Streaming Application
Streaming Application
External Data
APACHE APEX MALHAR (REUSABLE OPERATORS, CONNECTIONS)
Custom Operators
REST API
MAPREDUCE
HADOOP (YARN)
DISTRIBUTED FILE SYSTEM (E.G. HDFS)
MACHINE NODES (PHYSICAL OR VIRTUAL)

Figure 10 – Apache Apex Architecture ("Apache Apex," 2016)

Apache Apex includes key features such as in-memory performance, fault tolerance, and hadoop-native Yarn and HDFS (as can be seen in Figure 10) as its strengths. Its opportunity is that it focuses on closing the gap between batch and stream-processing.

[7] https://hadoop.apache.org/docs/current/hadoop-yarn/hadoop-yarn-site/YARN.html

[8] https://apex.apache.org/docs/malhar/

5.6 Apache Storm

In its early stage, Apache Storm was promoted as the "Hadoop of real-time" and the first of its kind (Wingerath et al., 2016). The Apache storm is an open source computation system for distributed systems and allows the user to process structured and unstructured streams of data that are not bounded in a reliable manner (Inoubli et al., 2016). Its programming model provides an abstraction for stream-processing identical to what MapReduce paradigm does for batch-processing (Wingerath et al., 2016).

Apache Storm is comparable with Hadoop but is focused for rapid and efficient event processing system in real-time, by sending data directly from one worker to another, Apache Storm can process millions of tuples per node per second (Miller et al., 2016; Morshed et al., 2016). This platform creates a graph of real-time computation named topology (Figure 11), this graph is feed by streaming data into the cluster of the nodes called spouts. These nodes distribute the tuples between worker nodes called bolts for processing, write data to external storage and distribute tuples further downstream themselves (Wingerath et al., 2016). Apache Storm is indicated for rapid event processing system granting the increasing of computation (Morshed et al., 2016).

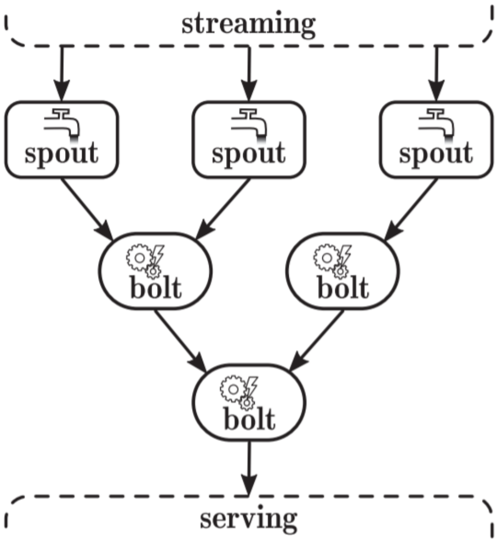


Figure 11 – Storm topology (Wingerath et al., 2016)

This platform has a wide user-base and supports many JVM-based languages such as Java, Python, Scala, Perl and others (Morshed et al., 2016; Wingerath et al., 2016).

Apache Storm supports the real-time distribution of computation is indicated for quick event processing that offers increasing computation and has adapters for several languages as its strengths. Its weaknesses are the dependency of a reliable and durable data source for at least once processing.

5.7 Apache Drill

The Apache Drill is an open source implementation of Google BigQuery[9], Drill is a structured query language engine that is used to explore this data, supporting queries and joins of data from various sources (Khalifa et al., 2016).

This framework is designed to support analysis on a high-performance level on the data that is semi-structured and rapidly evolves that originates from modern applications of Big Data, such as NoSQL databases and file systems, with a simpler query Apache Drill can join data from various sources. ("Apache Drill - Schema-free SQL for Hadoop, NoSQL and Cloud Storage," n.d.; Khalifa et al., 2016).

Apache Drill does not use a master-slave concept. As we can see in Figure 12 any Drill node (Drillbit) when accepts queries requests and assumes the role of root server (driving Drillbit), in this way, eliminates the problem of a single point of failure ("Apache Drill - Schema-free SQL for Hadoop, NoSQL and Cloud Storage," n.d.; Khalifa et al., 2016).

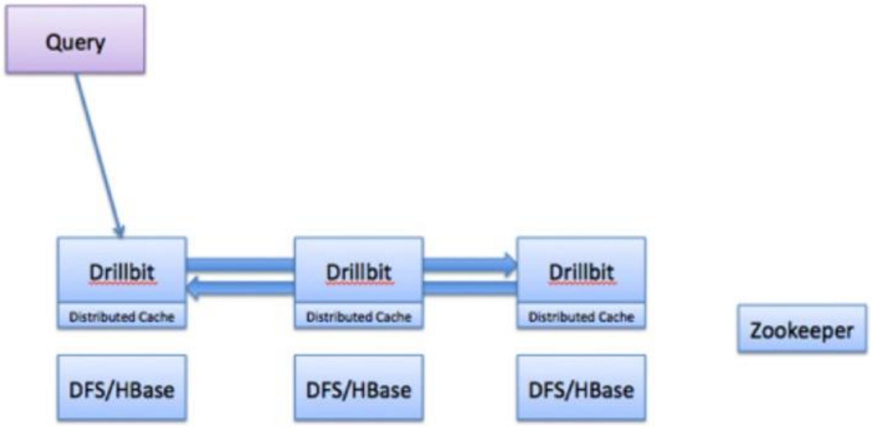


Figure 12 – Flow of Apache Drill query ("Architecture - Apache Drill," 2017)

The coordination of the nodes, the planning of the query planning, also the optimization, scheduling, and execution are performed and distributed (Hausenblas and Nadeau, 2013).

The main strengths of this platform are that it is a distributed system and its extensibility, the ability to join in a query multiple and diverse sources of data.

5.8 Apache Solr

The Apache Solr is a popular open source made to be highly reliable, tolerate faults, and scalable. It provides for indexing in a distributed system, replication as well as query balancing of loads, automated failover, and recovery (Ma et al., 2017; Sabapathi and Yadav, 2016).

[9] https://cloud.google.com/bigquery/

Solr is very fast and intended to be an enterprise search platform (Sabapathi and Yadav, 2016) used to power the features for navigation for many global internet sites, and it is designed on the Apache's Lucene[10] technology that is based on Java for search technology as well as indexing ("Apache Solr," 2017) and runs as a standalone full-text search server ("Apache Solr," 2017; Yadav et al., 2013).

Its search engine includes full-text search, hit highlighting, faceted search, geospatial search, dynamic clustering, database connections, near real-time indexing, and the index accepts data from multiple and diverse sources, such as files in common format Portable Document Format (PDF), Comma-Separated value (CSV) files, Microsoft Word files, XML (Yadav et al., 2013).

The concept of Solr is analogous to a search engine, that is, the more information or documents available to Solr, it is more likely to find the information later through the query.

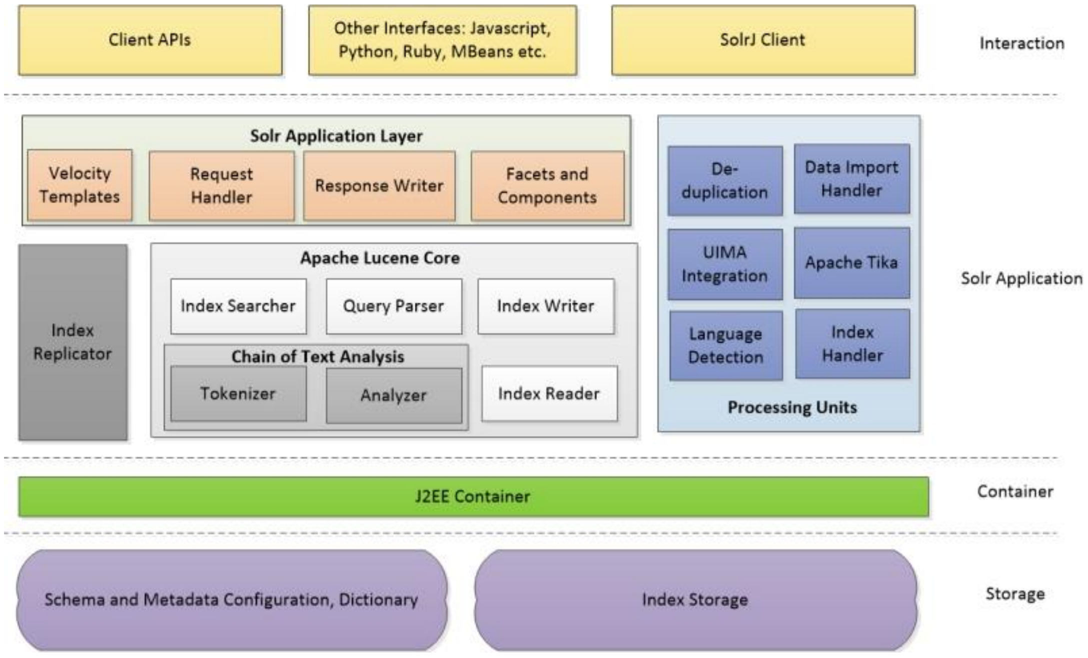


Figure 13 – Apache Solr Conceptual Architecture (Karambelkar, 2013)

Apache Solr has various modules as can be seen in Figure 13, some of the modules are other projects in themselves (Karambelkar, 2013).

Apache Solr is highly modular, reliable, scalable and fault tolerant as its strengths. Its weakness is the verticality in BDA platforms.

[10] https://lucene.apache.org/core/

5.9 Apache Spark

Spark is an open source framework that was originally developed at UC Berkley in 2009 (Inoubli et al., 2016). This platform stands out for running programs faster than Hadoop MapReduce on disk or memory.

Spark API supports Java, Scala, Python and R to develop quickly applications, and can be integrated with others platforms or work standalone ("Apache Spark™," 2016).

Apache Spark is particularly appropriate and efficient for the analytics of heterogeneous data (Inoubli et al., 2016) and for stateful computations when precisely a delivery is useful indifferent whether it takes too long or not. Spark supports real-time distributed features, and integrates a complete SQL interface (Spark-SQL). It uses Hive[11] for standard query languages, and also Domain Specific Language – DSL for query structured data (Morshed et al., 2016). It is similar to Impala in features and performance (Azarmi, 2015).

Spark uses a resilient distributed dataset (RDD) as a basic abstraction for a distributed dataset. The core operations (map, reduce and groupByKey) can be accomplished on the elements of the RDD and any one of those operations is evaluated lazily (transformations) or eagerly (actions). The distinct property of RDD is that they are unchangeable; operations on the RDDs create new RDDs (Miller et al., 2016).

As seen in Figure 14 – SPARK system overview (Inoubli et al., 2016)Figure 14, Apache Spark cluster is based on master-slave architecture and have three main components:

- Driver Program;
- Cluster Manager;
- Worker Nodes.

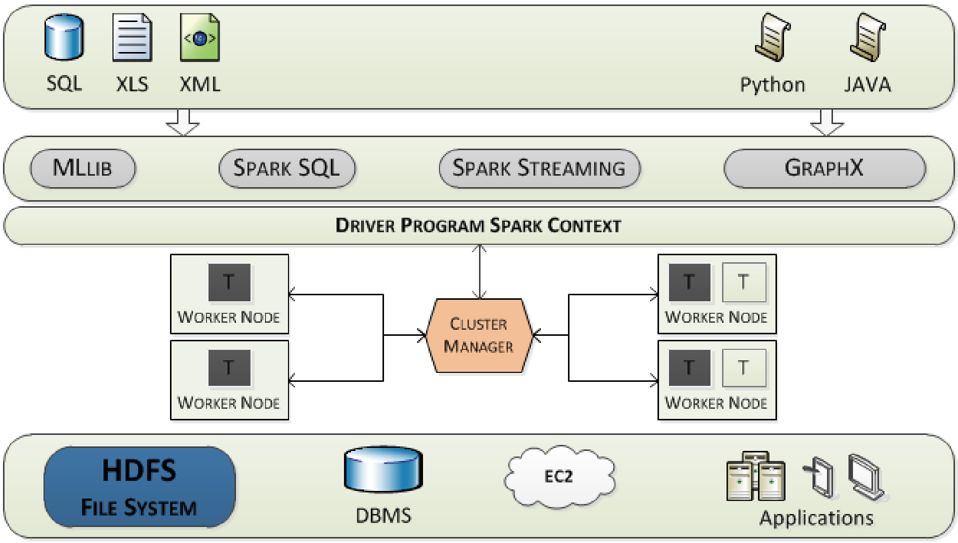


Figure 14 – SPARK system overview (Inoubli et al., 2016)

[11] https://hive.apache.org/

Apache Spark is best suitable for near real-time data processing, and not for real-time processing because Spark uses mini batches that are not suitable for event level processing. The most attrative feature of Spark is the capacity of Machine Learning (ML) efficiently, due to its memory caching capacity that is impressive. Almost all of the popular streaming data sources can be easily integrated into Spark API (Morshed et al., 2016).

5.10 OS Big Data Platforms Comparison

The Open Source Big Data Platforms described in the previous sections, provide a certain number of functionalities for a comparison.

This section explains the reasons behind the criteria chosen for comparison among them. To ensure a logical thread in the comparison, the criteria chosen can be useful for business or IT managers understand which platform could be appropriate for their purposes. Some of the functionalities supported by each tool that has been taken into consideration are:

- Full-Stack: Have all the functionalities for processing, storing and analysing data in an application stack;
- SQL-based interface: A query engine that uses a query language similar to SQL.
- API support: API to access and manage components.
- Real-time analytics: Ability to perform real-time analysis, analysing the data almost at the same time as it enters the system.
- Ready-Business Tools: It integrates seamlessly with the tools/systems your business already uses.
- Graphical User Interface (GUI): Graphical user interface via browser or software.

Table 1 below presents the list with the presence of these functionalities for each platform.

Table 1 – Big Data Platforms – comparative table

	Full-Stack	Sql-based Interface	API support	Real-time Analytics	Ready-Business Tools	GUI
Hadoop	Yes	Hive	Yes	No	No	Yes
Cloudera	Yes	Hive	Yes	Yes	Yes	Yes
Hortonworks	Yes	Hive	Yes	Yes	Yes	Yes
HPCC	Yes	Add-on	Yes	Yes	Yes	Yes
Apex	No	Apex-Calcite	Yes	Yes	Yes	No
Storm	No	Storm SQL	Yes	Yes	No	Yes
Drill	No	ANSI SQL	Yes	No	Yes	Yes
Solr	No	Parallel SQL	Yes	Yes	No	Yes
Spark	No	Spark SQL	Yes	Yes	No	Yes

Following our comparison and analysing the features we have chosen we can conclude that Hadoop, Cloudera, Hortonworks, and HPCC are the only platforms that are full-stack and ideal for most organizations. The Apex, Storm, Drill, Solr, and Spark could be considered to complement another full-stack platform due to its vertical nature.

Regarding real-time analytics, Hadoop do not have this functionality, only with the use of third-party tools.

All of them have support for API to access and manage the system or components. It was verified that the platforms Cloudera, Hortonworks, HPCC, and Drill have tools to integrate into existing business systems easily.

Most platforms already have interfaces to SQL; only the HPCC needs an add-on to do so. It was verified that almost all platforms have a graphic user interface via browser or application, with the exception of Apache Apex.

5.11 Summary

The first ten parts of the chapter present and analyse nine of the most popular open source Big Data platforms describing some of the more significant qualities, characteristics, capabilities, and functionalities of each platform.

Table 2 shows a succinct description of the platforms and the key features, contributing to the identification of the Big Data platforms for analytics that may be suitable for SMEs in their day-to-day business operations.

Table 2 – Big Data Platforms – strong points

BDP	Description	Strong Points
Apache Hadoop	The most popular platform that implements the MapReduce paradigm and uses the HDFS.	-Largest community -Popularity -Forefront
Cloudera	The most well-known Hadoop-based platform. Same methods, functions, main properties as Hadoop, but more efficient in storage, retrieval, and analysis.	-Innovative -Efficient tools for social media -SQL tools for real-time analytics -User-friendly interface -Stability -Training & Support
HDP	This platform is also Hadoop-based but only uses the stable components. Promotes the Apache Tez to deal with performance issues and the Apache Ambari as the cluster manager.	-Training & Support -Stability -Ready business tools -Low complexity for integration into an IT infrastructure -Microsoft Windows support
HPCC System	Typically chosen as alternative to Hadoop-based platforms, uses Thor data refinery as a distributed file system and for processing data across several nodes.	-High-performance -Consistent programming language (ECL) -Experienced -Robust solution

Apache Apex	Oriented to unify stream and batch processing, provides developers with a simple API to reuse Java code.	-Low barrier entry -Free library with connectors -In-memory performance
Apache Storm	Focused for rapid and efficient event processing system in real-time.	-Supports many JVM-based languages -Rapid event processing
Apache Drill	This platform is a SQL engine to explore data, supporting queries and joins of data from various sources.	-Query and Joins multiple sources -Avoid a single point of failure
Apache Solr	It is intended to be an enterprise search platform which includes full-text search, hit highlighting, faceted search, geospatial search, dynamic clustering, database connections, near real-time indexing of data from multiple and diverse sources.	-Fast engine -Indexes data from multiple and diversified sources.
Apache Spark	This platform runs programs faster than MapReduce on disk or memory and can be integrated to work with others platforms.	-Supports several programming languages -Integration with other BDA -Efficient analytics -Memory caching capacity -Complete SQL interface

6 Methodology

This chapter details the methodology applied to achieve the research aim and objectives. The chapter comprises the following sections: research agenda and research design method. For every section, first the concept is described and next the justification behind selection of process is discussed.

6.1 Design Method

The following subsections describes the Research Method, Method for Selecting and Evaluation and finally the Testing Method.

6.1.1 Research Method

Being this research work in the area of Information Systems, the adoption of Design Science Research Methodology for Information Systems seems appropriate. Considering the background and objectives of the research that will be done, the method represented in Figure 15 will be used.

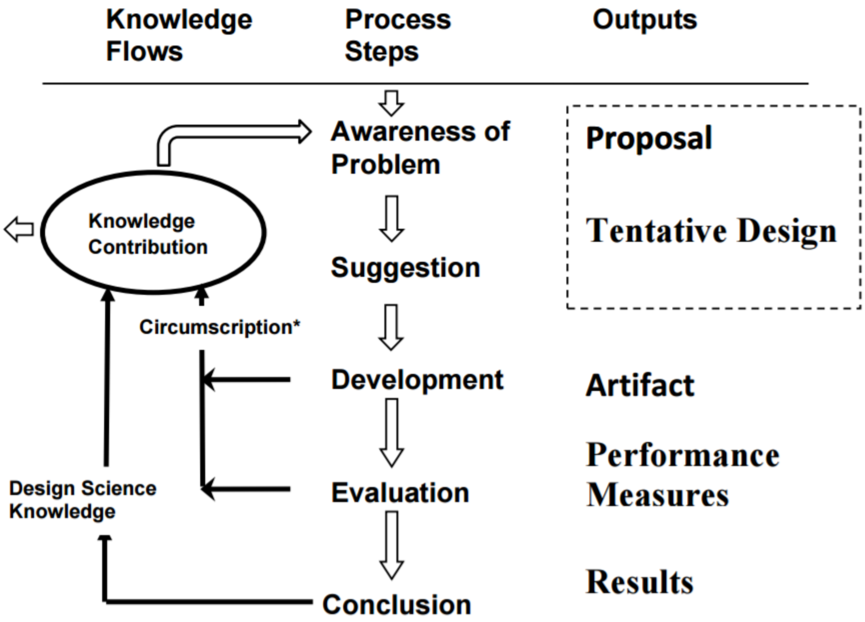


Figure 15 – Design Science Research Process Model (Vaishnavi and Kuechler, 2012)

This model is very flexible, allowing to any research work starts at any process step. In this research work, we begin in the first process step the ‘Awareness of problem’ where the research began.

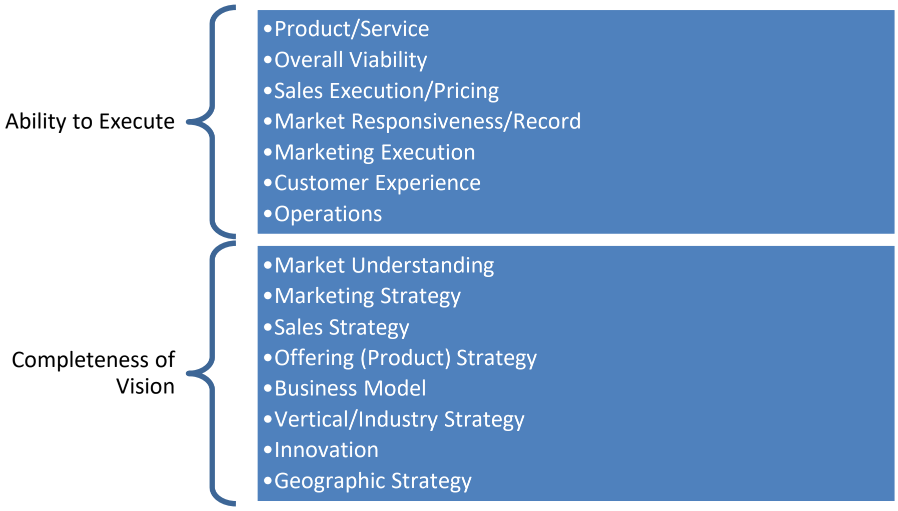
6.1.2 Method for Selecting and Evaluation

Many software evaluation methodologies were created by various organizations in the world. Each methodology is intended for different purposes or focused on distinct aspects of software such as maturity, durability or functionality itself.

Firstly, it was considered the use of and adapt the criteria’s from the 2017 Gartner Magic Quadrant for Data Warehouse Data Management Solutions for Analytics, although it is more suitable for proprietary software, it indicates what to expect from a data management and analytics solution. For a qualitative evaluation, it is essential to mention some key factors (criteria’s) on which platforms must respond to be considered functional. It will be used and adapted the criteria’s from the 2017 Gartner Magic Quadrant for Data Warehouse Data Management Solutions for Analytics. However, it is necessary to use an assessment method that quantifies those key factors and features, and the method QSOS (Qualification and Selection of software Open Source) was considered the most suitable for the type of software that will be evaluated and oriented to the adoption of OSS in SMEs. The two following subsections present 2017 Gartner Magic Quadrant for Data Warehouse Data Management Solutions for Analytics and QSOS respectively.

6.1.2.1 2017 Gartner Magic Quadrant for DW Data Management Solutions for Analytics

The Gartner uses two dimensions to classify the 2017 criteria, such as the ability to execute and completeness of vision. All criteria can be seen in the following figure.



Ability to Execute

- Product/Service
- Overall Viability
- Sales Execution/Pricing
- Market Responsiveness/Record
- Marketing Execution
- Customer Experience
- Operations

Completeness of Vision

- Market Understanding
- Marketing Strategy
- Sales Strategy
- Offering (Product) Strategy
- Business Model
- Vertical/Industry Strategy
- Innovation
- Geographic Strategy

Figure 16 – 2017 Gartner evaluation criteria (Gartner, 2017)

Ability to Execute is mainly related with the ability and maturity of the product and the vendor. Criteria under this title either look for portability of the product, its scalability, and its ability to run in different environments, thus allowing to the customer several options. These ability to execute criteria are critical to customer satisfaction and product success, so customer references are weighted heavily throughout the process (Black and Thomas, 2013; Gartner, 2017).

Completeness of Vision describes a supplier’s ability to understand the functions needed to put in place a product strategy that meets market needs, understands the general market trends, and influences or leads the market when needed. For the long-term viability of the business, it is needed a visionary role, this vision is strengthened by its willingness to broaden its influence across the market by working with independent third-party application software supplier’s that provide complementary solutions. A successful supplier will be capable to not only comprehend the competitive scenario of its product field but also be a game changer of this field with the appropriate focus of its capabilities for future product development (Black and Thomas, 2013; Gartner, 2017).

6.1.2.2 QSOS

This methodology was conceived by Atos SE[12] to qualify, select and compare free or open-source software in an objective, traceable and fact based (Ferreira et al., 2012).

The method is currently in version 2.0 with a GNU Free Documentation License and is maintained by an open community[13], which also offer a tool called O3S that help in the

[12] https://atos.net/pt-pt/portugal

[13] http://www.qsos.org/Community.html

application of the method (ATOS, Origin., 2013). The QSOS model is partial derived from ISO/IEC 9126 quality model (Adewumi et al., 2013).

This model has the well-defined methods and is practical in nature, follow an interactive process and the scoring is strict (0 to 2) (Umm-e-Laila et al., 2017).

The general process of QSOS consists of four iterative steps (ATOS, Origin., 2013): Definition, Evaluation, Qualification and Selection as seen in Figure 17 – QSOS Figure 17.

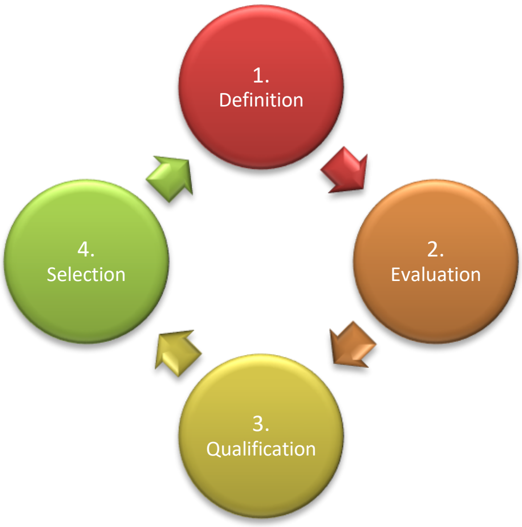


Figure 17 – QSOS Steps (ATOS, Origin., 2013)

6.1.2.2.1 Definition

In this initial step, it is critical to describe the software in at least three recommendations:

- Type of software reference: the type of software that exists and meets the general requirements divided into two axes: maturity analysis and functionality coverage analysis. In version 2.0 of QSOS it is mandatory to use the maturity criteria defined in the method shown in Figure 18.
- Community: identify the type of community involved in the development of the project, e.g., an open community or a company.
- Type of licence: verify the type of licence, e.g., BSD or GPL.

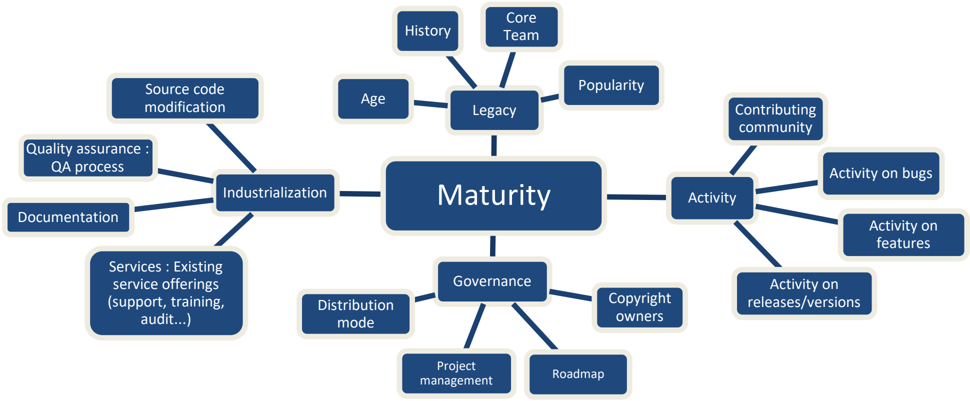


Figure 18 – Maturity criteria of a project (ATOS, Origin., 2013)

6.1.2.2.2 Evaluation

The goal of this step is to evaluate each OSS with each evaluation criterion previous identified in definition step with score points from 0 to 2.

It is created a grid or analysis model and thus resulting in a criteria tree.

6.1.2.2.3 Qualification

In this step it must be assigned the weights to each criterion according with the strategic objectives of the organization. Also, the context of the use of the OSS must be set, thus it can't be added one or more filters:

- Identity filter
  - e.g., select only a software with a certain distribution licence or of a specific type.
- Maturity filter
  - Filter by maturity of the OSS, it is subjective and depends of the context.
- Functional coverage filter
  - For each functionality described in the evaluation step must be specified a level of requirement, such as: required functionality; optional functionality; not required functionality.

6.1.2.2.4 Selection

This method specifies two types of selection:

- Strict selection – This selection is made by process of elimination if an OSS does not meet the requirements:
  - exclusion of the OSS that do not go through the identity filter;
  - exclusion of the OSS that do not fit the expected functionalities;

  - exclusion of the OSS in which the maturity criterion do not reach the level of relevance defined by the user, in the method it is defined that for a relevant criterion the score must be equal to or greater than 1, and for a critical criterion the score must be equal to 2;

- Loose Selection – This selection is less rigorous than the strict selection because it does not eliminate the OSS that is not eligible and classifies them concerning the previously defined filters.

Result of the product of the assigned weights and the score points of each evaluation of the OSS.

This general process step by step, the evaluation of criterion and the model of scoring allows one objective and traceable selection of the OSS.

6.1.3 Testing Process

These tests and experiments comparison process consists in to examine and functionally explore the Open Source Platforms for BDA and compare their performance and tools.

Han and Lu (2014) suggests that any Big Data benchmark should consist of five steps: Planning; Generating data; Generate tests; Execution; Analysis and evaluation. An adaptation of this process can been seen in Figure 19.

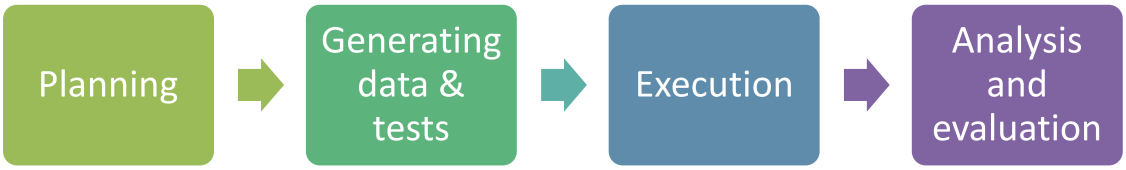


Figure 19 – Testing Process (Han and Lu, 2014)

Thus, the steps of the testing process are as follows:

- Planning: In this step, the evaluation object, application domain, and evaluation metrics are determined.
- Generating data/Generate tests: In these steps, the data to be used is obtained, and the tests are generated.
- Execution: In this step, the test is performed and then reported.
- Analysis and evaluation: Finally, in this step, the results are analysed and evaluated.

6.2 Agenda for Selection, Evaluation, and Tests

The first step is to select from the reviewed platforms the ones that will be tested during this research. The second are identifying the key features that will be used to explore each platform. Then, the datasets and some queries from the SMB's domain are selected to be employed for testing the analytics and query capabilities of every selected platform.

6.2.1 Platforms Selection

There are some platforms that are intended to be an all-in-one solution to deal with Big Data (BD) and Analytics; others are specific solutions for Big Data Analytics (BDA). A thorough investigation of the existing open source BDA platforms was done, and a few were chosen to evaluate them.

6.2.2 Platforms Evaluation

It is clear that for any comparative analysis is necessary to establish criteria and choose a method. For the evaluation of the BDA platforms, were choose the QSOS (Qualification and Selection of software Open Source), this method allows to qualify and evaluate the OSS, according to the analysis of the requirements and the restrictions (technical, functional and strategic).

6.2.3 Platforms Tests

In this research, the two BDA platforms chosen to test will be the two best classified using one assessment methodology the QSOS. Several tests will be performed, such as queries, and some selected visual reports.

7 Evaluation and Selection of BDA Platforms

This chapter presents the evaluation and selection of Big Data Analytics (BDA) platforms using and adapting the Qualification and Selection of software Open Source (QSOS)(ATOS, Origin., 2013) method. We consider this method as the best and most appropriate for our evaluation and selection of the two platforms for the empirical experiment and tests.

This method was developed by Atos Origin and is intended to qualify, select and compare tools and open source platforms. The QSOS method consists of four stages definition, evaluation, qualification and selecting, and can be used interactively.

This chapter is organized as follows: in section 7.1 the QSOS method are described, in section 7.2 the method implementation are shown, in section 7.3 the chapter conclusions are summarized in section 7.3.

7.1 QSOS Method

The method adopted for the evaluation and selection of the BDA platform for the tests is the QSOS. This decision is justified by the fact that methodology is available freely under the GNU General Public License on the Web, allowing its adaptation to the present research work.

The choice of software, OSS or proprietary software, has to be based on the purpose of the software. It is imperative to know the functional needs and limitations of the software, after this it is possible to apply the QSOS method and adapt if necessary.

The QSOS method proposes four iterative stages (as seen in Figure 20) namely: definition, evaluation, selection and qualification (Adewumi et al., 2013).

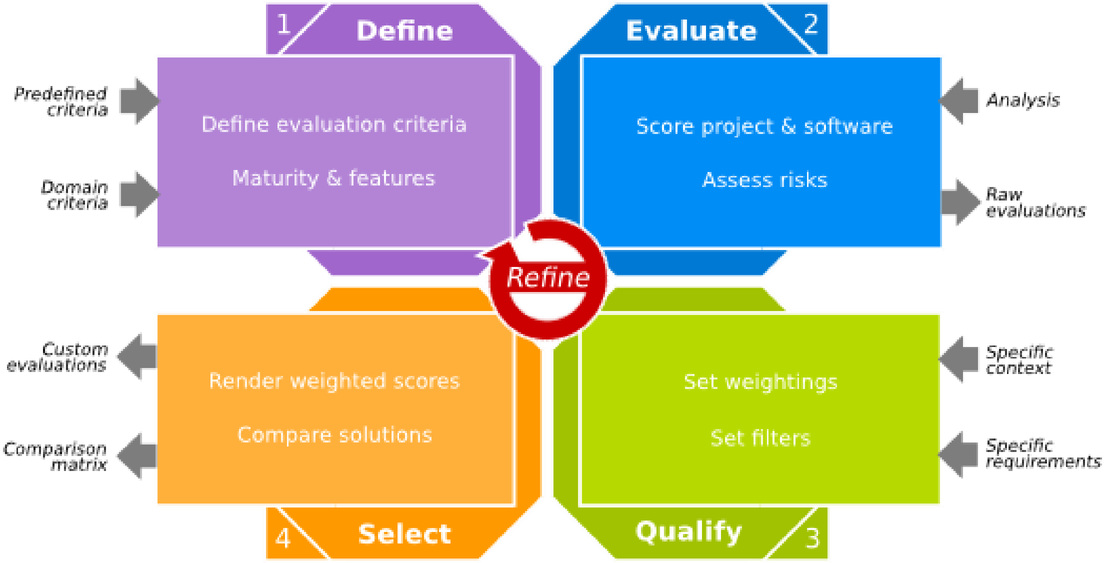


Figure 20 – General approach (ATOS, Origin., 2013)

7.1.1 Definition

At this step all the criterion will be organized. In chapter 5, it was identified some of the free and open source Big Data Analytics platforms which must be suitable for SMEs strategic needs, their licenses type and communities type. Each maturity criterion (predefined criteria) and functionality criterion (domain criteria) will be identified.

7.1.1.1 Maturity criteria

The maturity criteria are already defined by the method and are as follows:

- Legacy – Project's history and heritage: Age; History; Core Team; Popularity;
- Activity – Activity inside and around the project: Contributing community; Activity on bugs; Activity on features; Activity on releases/versions;
- Governance – Project's strategy: Copyright owners; Roadmap; Project management; Distribution mode;
- Industrialization – Industrialization of the project: Services – existing service offerings (support, training, audit...); Documentation; Quality assurance – QA process; Source code modification;

7.1.1.2 Functionality criteria

After the previous theoretical explanation the basic functionalities/aspects identified were:

- Full Stack (Solution Stack): This links several software and applications required for doing particular tasks, and additionally as infrastructure software, in the case of BDA platforms (tools for storage, management and analytics).
- Enterprise-ready: It should incorporate the features driven for performance, security, usability and reliability.
- Incorporated: It should easily simplify and accelerate the implementation of Big Technological innovation for organizations.
- Real-time Analytics: It involves analysing the data almost at the same time as it enters the system.
- Solid and fault-tolerant: Configuration that prevents a BDA platform from fail due an unexpected problem or event.
- Scalability: Platform able to grow by adding more resources and at the same time be able to manage it.
- Paid Version: Includes software support and advanced components.
- User-friendly Management: End-to-end application for managing all solution stack.

In this stage, all evaluation criteria will be organized, and all the OSS selected for evaluation will have an Identity Card with license type, version, and website.

7.1.2 Evaluation

For each identified criterion in previous step it is assigned a discrete score. The evaluation model imposes a discrete scale of 3 values. The sources to find the presence of each criterion are the scientific literature, BDA platforms documents/manuals and websites.

The evaluation templates suggest the significance of the three scores 0, 1 and 2 for each criterion.

For evaluation the criteria of maturity, the scale is 0 to 2. The scoring rule is normally as shown in Table 3.

Table 3 – QSOS Maturity criteria (ATOS, Origin., 2013)

Maturity criterion				Description
Legacy	Age	Score	0	Less than three months
			1	Between three months and three years
			2	More than three years
	History	Score	0	The software has many problems which can be prohibitive
			1	No major crisis, or unknown history
			2	Good past experience in crisis management
	Core Team	Score	0	Very few identified core developers
			1	Few active core developers
			2	Important and identified core development team
	Popularity	Sc	0	Very few identified users
			1	Usage can be detected

			2	Many known users and references
Activity	Contributing community	Score	0	No real community nor activity (forum, mailing lists...)
			1	Community with significant activity
			2	Strong community with vivid activity in forums, with many contributors and supporters
	Activity on bugs	Score	0	Low reactivity in forums and mailing lists, or no mention about bug fixes in release notes
			1	Existing activity but without any clearly defined process or with long resolution times
			2	Strong reactivity based on roles and task assignments
	Activity on features	Score	0	Few or no new features
			1	Product's evolution is led by a dedicated team or by users, but without a clearly stated process
			2	Feature request process is industrialized, an associated roadmap is available
	Activity on releases or versions	Score	0	Very low activity on the production or development versions (alpha, beta)
			1	Activity on production or development versions (alpha, beta) with frequent minor corrective versions
			2	Important activity with frequent corrective versions and planned major versions linked with the roadmap
Governance	Copyright owners	Score	0	Rights are being held by a few individuals or commercial entities
			1	Rights are uniformly held by many individuals
			2	Rights are held by a legal entity or a foundation that the community trust (ex: FSF, Apache, ObjectWeb)
	Roadmap	Score	0	No roadmap is published
			1	Roadmap without planning
			2	Versioned roadmap with planning and delay measurements
	Project management	Score	0	No clear and apparent project management
			1	Project managed by an individual or a single commercial entity
			2	Strong independence of the core team, rights held by a recognized entity
	Distribution mode	Score	0	Dual distribution with a commercial version along with a functionally limited free one
			1	Subparts are only available under proprietary license (core, plugins...)
			2	Completely open and free distribution
Industrialization	Services	Score	0	No service offering identified
			1	Limited service offering (geographically, to a single language, to a single provider or without warranty)
			2	Rich ecosystem of services provided by multiple providers, with guaranteed results
	Documentation	Score	0	No user documentation
			1	Documentation exists but is partly obsolete or restricted to one language or to few details
			2	Documentation is up to date, translated and possibly adapted to several target readers (end user, sys admin, manager...)
	Quality assurance	Score	0	No QA process identified
			1	Existing QA processes, but they are not formalized or equipped
			2	QA process based on standard tools and methodologies
	Source code modification	Score	0	No convenient way to propose source code modifications
			1	Tools are provided to access and modify the code (eg SCM, forge...) but are not really used by core team to develop the product
			2	The contributing process is well defined, exposed and respected, it is based on clearly defined roles

For functional aspects, concerning to evaluation, it was considered a scale 0 to 2, and the scoring rule is normally as shown in Table 4. Thus if the functionality is not covered in the platform, the criterion is scored with **0** if it is present only is partially covered with **1**, but if the criterion is fully covered on the platform is scored with **2**.

Table 4 – Score of functional coverage (ATOS, Origin., 2013)

Score	Description
0	Not covered
1	Partially covered
2	Fully covered

The result of this step is two tables, one with the maturity criteria score and another with the functionality criteria.

7.1.3 Qualification

In this step, the primary goal is to qualify the evaluation through the organization of the criteria, according to the degree of importance of each one and according to the context of the use of BDA platforms in SMEs with this are created some filters that can be used in the selection step.

There are no guidelines on how factors should be given. The QSOS, however, presents suggestions as to whether these weights can be given.

For maturity the degree of importance of each criterion is based on the context, the QSOS suggests:

Table 5 – Maturity relevance (ATOS, Origin., 2013)

Weight	Degree of maturity
0	Not relevant criterion
1	Relevant criterion
3	Critical criterion

For functional coverage the level of requirement of each criterion is based on how important or critical it is for the use of a BDA platform in the context of SMEs daily based operations, the QSOS suggests:

Table 6 – Level of requirement (ATOS, Origin., 2013)

Weight	Level of requirement
0	Not required functionality
1	Optional functionality
3	Required functionality

The degree of relevance of each maturity criterion serves as the basis for the weighting factor. Thus, for each functional criterion, a weighting factor of +3 for required, for optional +1 and assign 0 points for not required functionality.

7.1.4 Selection

In this last step, the platforms are compared according to the weighted average, which is calculated by summing the multiplications between the scores (S) and weights (W) divided by the sum of the Weights, according to the following equation:

$$\bar{x} = \frac{\sum_{i=1}^{n} S_i * W_i}{\sum_{i=1}^{n} W_i} \qquad (1)$$

After performing the calculations, the two BDA platforms with the highest scores, according to the weighted average, are selected for tests.

7.2 Method Implementation

As identified in the chapter 5 we choose nine of existing BDA platforms for this research work that can be used in some of SMEs. The Open Source BDA platforms are the following: Apache Hadoop, Cloudera, Hortonworks Data Platform, HPCC System, Apache Apex, Apache Storm, Apache Drill, Apache Solr and Apache Spark.

Considering the objectives of our work and what type of BDA platform will be most appropriate for most SMEs, we consider the following functionalities criteria: Full Stack, Enterprise-ready, Real-time Analytics, Solid and fault-tolerant, Scalability, Paid Version and User-friendly Management.

Some of the platforms will be disregarded in this evaluation because our selection mode will be strict and we consider the Full-Stack criterion as eliminatory, and the excluded BDA platforms from de evaluation and selection are Apache Apex, Apache Storm, Apache Drill, Apache Solr and Apache Spark.

7.2.1 Definition

We consult the sites of the chosen platforms, and we gather information about the licenses of each platform, start date, the community involved in the project, the latest available version and release date, operating system, community website, wiki, forum, and download URL.

The set of this information generates an identity card of each platform. Table 7 presents this information for the 4 BDA platforms:

Table 7 – Platforms ID card

	Hadoop	Cloudera	Hortonworks	HPCC
Company	Apache Software Foundation	Cloudera, Inc.	Hortonworks, Inc.	LexisNexis
Creation	2007	2009	2012	2011
Product	Apache™ Hadoop®	CDH	Hortonworks Data Platform (HDP®)	HPCC Systems Platform
License	Apache	Apache	Apache	GNU Affero General Public License
Version	3.0.0-beta1	5.12.1	2.6.2	6.4.2
Release	03-10-2017	29-06-2017	01-04-2017	07-09-2017
Operating	Linux-compatible	Linux-compatible	Linux-compatible Windows	Linux-compatible installation, Windows and Mac OSX (ECL IDE and Client tools).
Community	https://hadoop.apache.org/who.html	http://community.cloudera.com/	https://community.hortonworks.com/	https://hpccsystems.com/community
Wiki	https://wiki.apache.org/hadoop	http://community.cloudera.com/t5/tkb/communitypage	-	https://wiki.hpccsystems.com/display/hpcc/Home

Forum	Mailing list	https://community.cloudera.com/t5/community/mobilecommunitypage/interaction-style/forum	https://community.hortonworks.com/topics/forum.html	https://hpccsystems.com/bb/
URL	http://hadoop.apache.org/releases.html	https://www.cloudera.com/downloads.html	https://hortonworks.com/downloads/	https://hpccsystems.com/download

Hadoop is the oldest platform of all, as is evident in the case of Hortonworks and Cloudera because they are based on Hadoop.

The Hadoop platform is only without commercial interests. Hadoop, Hortonworks, and Cloudera have an Apache License, and HPCC code is under GNU Affero General Public License.

It is possible to verify that all projects remain current and popular, their communities are active and interested and also with frequent updates and releases.

All BDA platforms evaluated allow installation in Linux environment. However, for the access to the platform all can be accessed by the web-browser.

It should be noted that Hortonworks has a version of the platform to run on Microsoft Windows environment and HPCC provides management and query tools to access the platform through the Windows environment.

7.2.2 Evaluation

Maturity criteria

For each identified maturity criterion defined by QSOS method, were scored according to the information collected during the entire research. Table 8 shows this.

Table 8 – Score of maturity criteria

Criterion	Hadoop	Cloudera	Hortonworks	HPCC
Age	2	2	2	2
History	1	2	2	2
Core team	2	2	2	2
Popularity	2	2	2	2
Contributing community	2	2	2	2
Activity on bugs	1	2	2	2
Activity on features	2	2	2	2

Activity on releases/versions	1	2	1	2
Copyright owners	2	0	0	0
Roadmap	1	1	2	2
Project management	2	1	1	1
Distribution mode	2	1	2	2
Services	2	2	2	2
Documentation	2	2	2	2
Quality assurance	1	2	2	2
Source code modification	2	2	2	2

In this context of maturity, it was possible to identify a significant difference between Hadoop platform and the others in the criterion “Copyright owners” because Hadoop is held by Apache a foundation that the community trust and the others platforms are held by a few individuals or commercial entities, although the Cloudera, Hortonworks and HPCC platforms are open source and free, the brand is a commercial entity.

Another aspect is the criterion “Quality assurance” it is difficult to identify the existing QA processes, but they are not formalized or equipped in Hadoop contrary to the QA process based on standard tools and methodologies of the other platforms.

Although the results are very similar, the HPCC platform stands out slightly in Activity on releases/versions, it is verified important activity with frequent corrective versions and properly identified in the release notes.

Functionality criteria

Each functionality criterion were scored according to the information collected during the entire research, and verified in the official websites and manuals. The “0” means that the functionality not covered, “1” functionality partially covered and “2” functionality fully covered. Table 9 shows the functionality criteria.

Table 9 – Score of functionality criteria

Criterion	Hadoop	Cloudera	Hortonworks	HPCC
Full Stack	2	2	2	2
Enterprise-ready	0	2	2	2
Real-time Analytics	0	2	2	2
Solid and fault-tolerant	1	2	2	2
Scalability	1	2	1	2
Paid Version	0	2	2	2
User-friendly Management	0	2	2	2

In this context of functionalities, Hadoop it was possible to identify a significant difference between Hadoop platform and the others in four criteria the Enterprise-ready, Real-time Analytics, Paid Version, User-friendly Management it is clear because this platform project is used as the base for other projects that explore each one of this criterion to differentiate themselves.

As we had previously identified, HPCC, Hortonworks and Cloudera have tools for easy integration with enterprise systems, so they score 2 points in Enterprise-ready criterion. Also, the User-friendly Management tools present in Hortonworks-Ambari, Cloudera-Cloudera Manager, and HPCC-ECL Watch are really end-to-end applications for managing all solution stack.

7.2.3 Qualification

Maturity criteria

For the weighting of the criteria of maturity, it was considered the importance that each one will have in any SMEs an assessment based on observation of the Portuguese reality. By way of illustration, in Portugal, many SMEs do not know how to consolidate several databases to create management reports. Because of this, they need someone who is capable of doing that or hiring consulting services (Belo et al., 2013). So it is necessary a rich ecosystem of services provided by multiple providers, with guaranteed results, to have a competitive market and not have such high costs when hiring outside services or investing in training.

The “0” means when it is a not relevant criterion, “1” when it is a relevant criterion and “3” when is a critical criterion.

Within this assumption, it can be considered that the criterion Age, History and Popularity is critical for SMEs because it indicates that the platform is widely used, has a positive track record and will be difficult to be abandoned in the short term.

The criteria associated with Activity inside and around the project, like bug fixes and development of new features are critical for businesses. Also, new versions are not relevant because they may interfere with platform stability. It is very important that the distribution criterion must be completely open and free distribution.

Almost all criterion of the industrialization of the project is critical. Having a rich ecosystem of services provided by multiple providers, with guaranteed results is critical for the business continuity, documentation up to date and for end-users, administrators and others is critical for an optimal administration and utilization of the platform.

Table 10 summarize the weights.

Table 10 – Weighting of maturity criteria

Criterion	Weight
Age	3
History	3
Core team	0
Popularity	3

Contributing community	3
Activity on bugs	3
Activity on features	3
Activity on releases/versions	1
Copyright owners	0
Roadmap	0
Project management	1
Distribution mode	3
Services	3
Documentation	3
Quality assurance	3
Source code modification	1

We consider that some criteria are not relevant to SMEs, such as the Roadmap, generally, companies when they adopt a software, only consider the immediate and which problem the software will solve or improve and do not consider very important what the product will do in the future. Also we considered the criterion Core team and Copyright owners a not relevant, and Project management criterion and Source code modification relevant. All other criteria such as Age, History, Popularity, Contributing community, Activity on bugs, Activity on features Activity on releases / versions, Distribution mode, Services, Documentation and Quality assurance are considered critical.

Functionality criteria

For the weighting of the criteria of maturity, it was considered the importance that each one will have in any SMEs an assessment based on observation of the Portuguese reality.

The “0” means when it is a not relevant criterion, “1” when it is a relevant criterion and “3” when is a critical criterion.

It is considered that the full-stack criterion is critical for an SME because it is important to have all the functionalities for processing, storing and analysing data in an application stack. It is also critical to be enterprise-ready having low complexity for integration into an IT infrastructure, and also incorporate the features driven for performance, security, usability, and reliability.

However having the ability to perform analytics that can access and use almost at the same time that data come into a system is a relevant criterion.

Solid and fault-tolerant and scalability criterion are relevant as well, because they must be an intrinsic property and something to expect on any BDA platforms.

User-friendly Management is a critical criterion in case of SMEs is critical possess an easy and intuitive end-to-end application for managing all solution stack.

Table 11 summarize the weights of functionality criteria.

Table 11 – Weighting of functionality criteria

Criterion	Weight
Full Stack	3
Enterprise-ready	3
Real-time Analytics	1
Solid and fault-tolerant	1
Scalability	1
Paid Version	1
User-friendly Management	3

7.2.4 Selection

In this step with the information of the points and weights of all the criteria, we calculate the weighted average, which is the sum of the product of the Weight by the Score divided by the sum of all weights. The comparison results are briefly listed in Table 12 and Table 13.

Table 12 – Comparison of total (Maturity)

Criterion	W	Hadoop		Cloudera		Hortonworks		HPCC	
		S	S*W	S	S*W	S	S*W	S	S*W
Age	3	2	6	2	6	2	6	2	6
History	3	1	3	2	6	2	6	2	6
Core team	0	2	0	2	0	2	0	2	0
Popularity	3	2	6	2	6	2	6	2	6
Contributing community	3	2	6	2	6	2	6	2	6
Activity on bugs	3	1	3	2	6	2	6	2	6
Activity on features	3	2	6	2	6	2	6	2	6
Activity on releases/versions	1	1	1	2	2	1	1	2	2
Copyright owners	0	2	0	0	0	0	0	0	0
Roadmap	0	1	0	1	0	2	0	2	0
Project management	1	2	2	1	1	1	1	1	1
Distribution mode	3	2	6	1	3	2	6	2	6

Services	3	2	6	2	6	2	6	2	6
Documentation	3	2	6	2	6	2	6	2	6
Quality assurance	3	1	3	2	6	2	6	2	6
Source code modification	1	2	2	2	2	2	2	2	2

Table 13 – Comparison of total (Functionality)

Criterion	**W**	**Hadoop**		**Cloudera**		**Hortonworks**		**HPCC**	
		S	**S*W**	**S**	**S*W**	**S**	**S*W**	**S**	**S*W**
Full Stack	3	2	6	2	6	2	6	2	6
Enterprise-ready	3	0	0	2	6	2	6	2	6
Real-time Analytics	1	0	0	2	2	2	2	2	2
Solid and fault-tolerant	1	1	1	2	2	2	2	2	2
Scalability	1	1	1	2	2	1	1	2	2
Paid Version	1	0	0	2	2	2	2	2	2
User-friendly Management	3	0	0	2	6	2	6	2	6

In general, three of the four systems have similar results except for Hadoop, which, although in the maturity criteria are following the others. The four platforms have several years of development, and there are no reports of instability or a history of defects or crisis situations that may discourage its selection, however at the criteria of functionalities, Hadoop fails almost in every criterion result.

The Table 14 presents the overall results of the QSOS method. After completing the calculation of the weighted average, the results are divided in the two criteria Maturity and Functionalities.

Table 14 – QSOS Evaluation results

Criteria	**Hadoop**		**Cloudera**		**Hortonworks**		**HPCC**	
	Avg	**Res**	**Avg**	**Res**	**Avg**	**Res**	**Avg**	**Res**
Maturity	$\frac{56}{33}$	1,70	$\frac{62}{33}$	1,88	$\frac{64}{33}$	1,94	$\frac{65}{33}$	**1,97**
Functionalities	$\frac{8}{13}$	0,24	$\frac{26}{13}$	0,78	$\frac{25}{13}$	0,76	$\frac{26}{13}$	**0,79**
TOTAL	1,96		2,66		**2,70**		**2,76**	

The Figure 21 shows a radar chart with the four platforms and their coverage in the four groups of maturity: Legacy-Project's history and heritage; Activity-Activity inside and around the project; Governance-Project's strategy; Industrialization-Industrialization of the project.

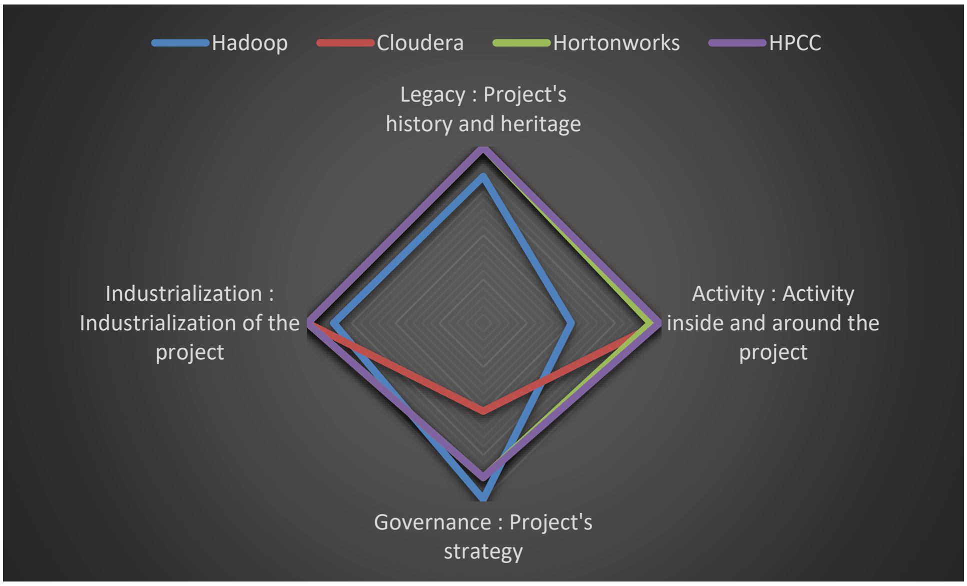


Figure 21 – Maturity coverage by group

Figure 22 shows a radar diagram with the four platforms and their coverage in the all seven functionalities: Full Stack; Enterprise-ready; Real-time Analytics; Solid and fault-tolerant; Scalability; Paid Version; User-friendly Management.

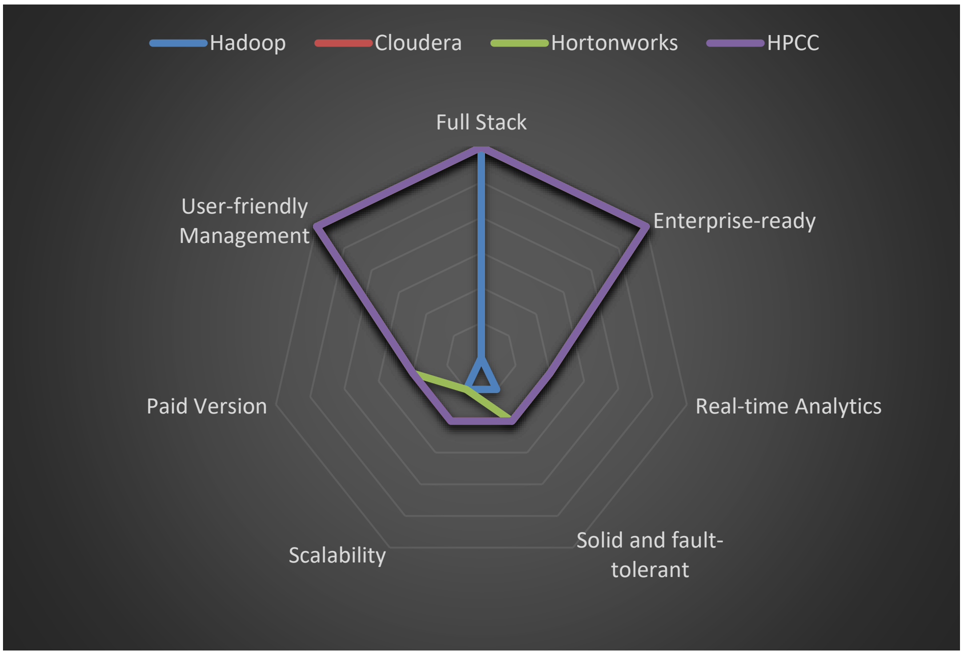


Figure 22 – Functionality coverage

It is confirmed that the platform HPCC and Cloudera have both the same and better functional coverage, and Hadoop the functional coverage.

7.3 Summary

This chapter evaluated four of the nine platforms described in this research work, focusing on their maturity and functionalities. These aspects are described considering the concepts of the BDA platforms for data analytics, their features, and components.

Due to its complete application stack and maturity, was performed one evaluation with the platforms Apache Hadoop, Cloudera-CDH, Hortonworks Data Platform, and HPCC Systems Platform, using the method QSOS. This model of evaluation and selection of open source software used is flexible and interactive and suitable for the selection of open source software.

The HPCC platform has more functionalities and maturity than the Hortonworks platform, the LexisNexis Company is more experienced than Hortonworks and because of that has a more mature platform.

It is important to note that Cloudera scored higher than Hortonworks on the functionalities, but lost in the maturity criteria. Especially for evidence that has more Scalability than Hortonworks.

Based on the evaluations and results obtained, it is noted that of the platforms evaluated, the least adequate to adopt as BDA platform is Apache Hadoop and the two to consider are the Hortonworks Data Platform and HPCC Systems Platform.

It is also clear that not always the software with more functionality coverage is one of the eligible, the maturity attributes have an essential influence on the final selection of the alternative, as is verified in the case of Cloudera and Hortonworks.

8 Tests and Experiment Comparison

This chapter summarizes the tests and findings related to the two open source BDA platforms selected in chapter 7. An experiment end-to-end with in virtual machines (VM) has been designed and performed to have experimental data and comparison of the BDA platforms. The dataset used in this experiment is from an open data repository from the United States (US) Government.

8.1 Testbed

In this empirical experiment the evaluation and tests was run in a virtual machine configured with the minimum and recommended hardware requirements of Hortonworks Data Platform (HDP) for a virtualization environment.

Table 15 shows the minimum and recommended Hardware and Software requirements for the VM of each platform:

Table 15 – Minimum Hardware and Software

Requirement	Hortonworks	HPCC
Host Operating System	Any 64-bit	32-bit/64-bit
Host Processor	Intel i5/ i7/ Xeon or AMD equivalent	Intel i5/ i7/ Xeon or AMD equivalent
Host Browser	Internet Explorer® 8, Google Chrome 10, or Firefox™ 3.0 (or later)	Internet Explorer® 8, Google Chrome 10, or Firefox™ 3.0 (or later)
Virtual Appliance File Size	9,7 GB	0,94 GB
Virtualiz. Software Support	Azure, VirtualBox or VMWare	VirtualBox
VM CPU	4	1
BDA Platform version	2.6.1	6.4.2
VM RAM	8 GB	1,5 GB
VM Disk Space	48,83 GB	5 GB
Virtualization Technology	Intel VT/AMD-V	Intel VT/AMD-V

For the purpose of this experiment, we chose to download and use the Virtual Machines available on the Platforms sites, this experiment only implements one node for each platform.

Also, Oracle VM VirtualBox® has also been chosen as the only virtualization software that is supported by both platforms appliances.

The host machine is a normal office laptop with an Intel® Core™ i7-4500U CPU, 16GB memory, Windows 10 (64-bit) and Oracle VM VirtualBox® 5.1.28.

8.2 Dataset

In this experiment, it is used one semi-structured data file containing real records from complaints filed by US citizens to US government (Consumer Financial Protection Bureau) about financial products and services.

This dataset is available online at address: https://catalog.data.gov/dataset/consumer-complaint-database and is intended for public access and use. The file, has the following details:

- Semi-structured data: Comma-Separated value (CSV)
- Size: 375MB
- Records: 879855
- Release date: May 2017)
- Complaints received on or after June 1, 2012.

The dataset fields are documented in the Table 16:

Table 16 – Dataset field reference

Field name	Data type
Date received	date & time
Product	plain text
Sub-product	plain text
Issue	plain text
Sub-issue	plain text
Consumer complaint narrative	plain text
Company public response	plain text
Company	plain text
State	plain text
ZIP code	plain text
Tags	plain text
Consumer consent provided?	plain text
Submitted via	plain text
Date sent to company	date & time
Company response to	plain text
Timely response?	plain text
Consumer disputed?	plain text
Complaint ID	number

8.3 Queries

Although the dataset used in both BDA platforms is the same, how queries are interpreted, optimized, and processed depends on the data processing of each platform. And also the integration of the data in the platforms can be inconsistent and produce errors in the processing of queries, something that has not been verified. Thus, to make the test more comprehensive a mixed set of queries has been created, with some queries more complex than others.

To cover the whole dataset all the queries should follow a rationale, something that is outside the scope of this research work, although we created this set of queries, as seen in Table 17.

Table 17 – Test queries

Query #	Description
Q1	Queries all the complaints in USA
Q2	Queries all the complaints of Wyoning (WY) state
Q3	Counts all the complaints of Wyoning (WY) state
Q4	Counts all the complaints of New York (NY) state
Q5	Queries all the complaints of Wyoning (WY) state order by ID
Q6	Counts the group of complaints of Wyoning (WY)
Q7	Queries with distinct of ID only four columns from Wyoning order by ID
Q8	Queries the total complaints for each Financial Product in Wyoming
Q9	Queries the total complaints for each Sub-Product of Mortgages in Wyoming
Q10	Queries the total complaints for each Financial Product in USA

8.4 Experiment Organization

For the purpose of verifying the functionalities described in its documentation and in our research. We structured the empirical experiment on the platform as follows:

- Cluster Manager: the interface with user and tool for managing the cluster.
- Data acquisition: how to acquire the dataset and load it into the HDFS in HDP and Data Refinery in the HPCC.
- Data Integration/Representation: transform the semi-structured, structured or unstructured data and deliver it to the platform.
- Analysis and Visualization: query data from the HDFS/ Data Refinery, and interpret the results in tabular form and in charts.
- Tests: execution of a comparable set of queries.

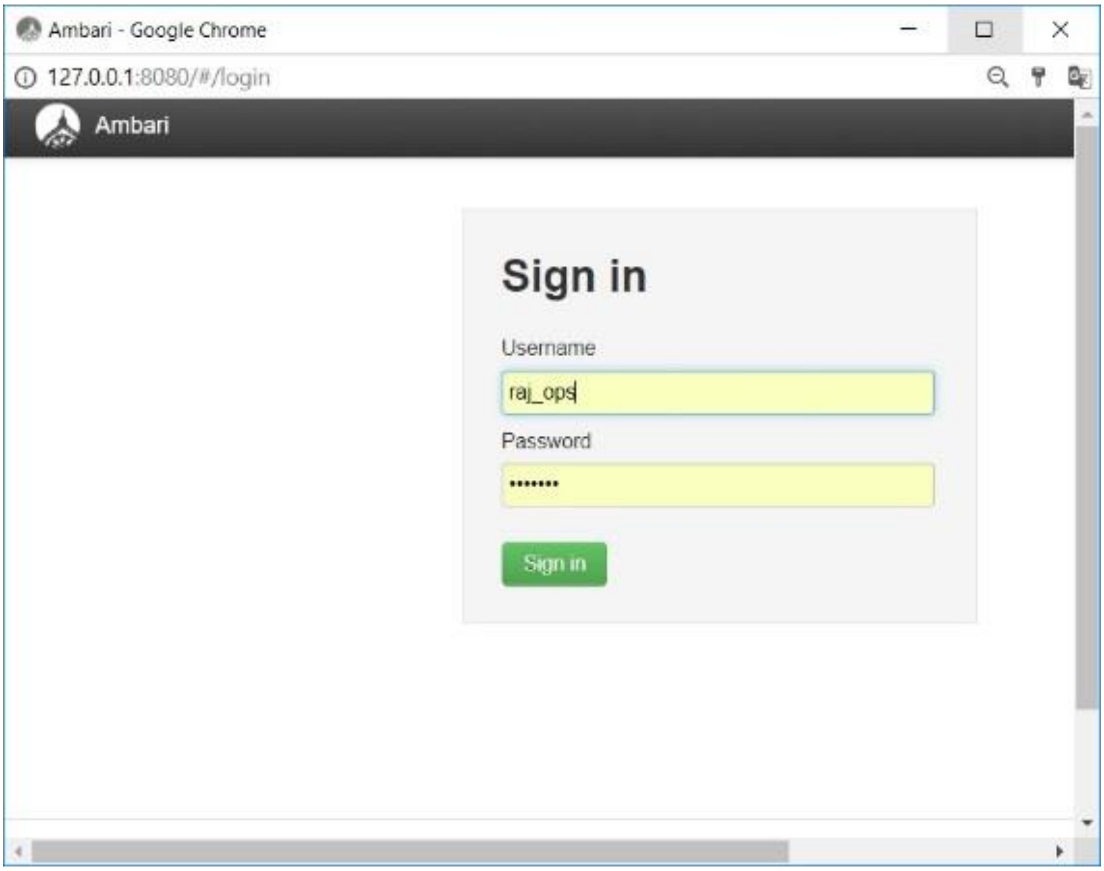
8.5 Hortonworks

For the experiment on this BDA, the virtual appliance with the latest version (2.6.1) of Hortonworks Data Platform has been downloaded and imported into VirtualBox, the process is standard and almost excludes advanced and additional settings.

8.5.1 Cluster Manager

The platform already has some accounts created to admin and use the cluster manager (Ambari), it was decided to use an admin account with the following credentials:

raj_ops/raj_ops. It is possible to access the platform remotely by SSH – Secure Shell protocol or simply by the browser in the URL http://127.0.0.1:8888, as seen in Figure 23.



Username

raj_ops

Password

•••••••

Figure 23 – Ambari user login

The Ambari is also an Apache project developed to enable simple management of HDP which includes tools for provisioning, management, and monitoring of HDP clusters. Its interface is easy to use, intuitive and Web UI (User Interface) backed by its RESTful[14] APIs.

It is possible to analyze the performance of the cluster, workloads, logs, and queries executions.

8.5.2 Data Acquisition

As previously mentioned, the dataset used in this experiment is a CSV, to place the file in HDFS, we chose to use the **Files View** module (see. Figure 24). Next, a folder was created in the user folder and then uploaded the file **Consumer_Complaints.csv**.

[14] Representational state transfer - web services that provides interoperability between computer systems on the Internet.

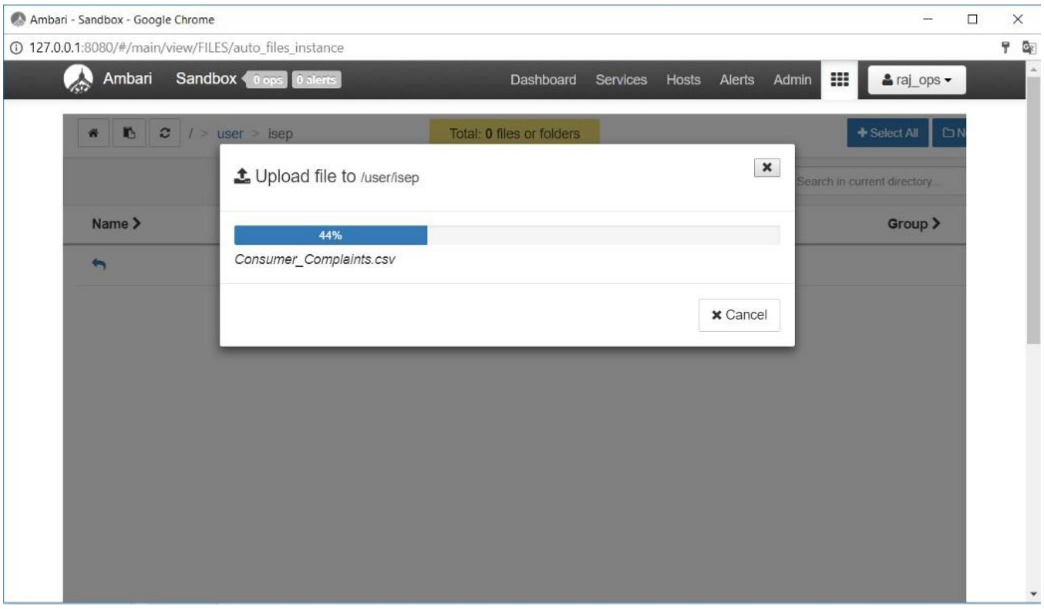
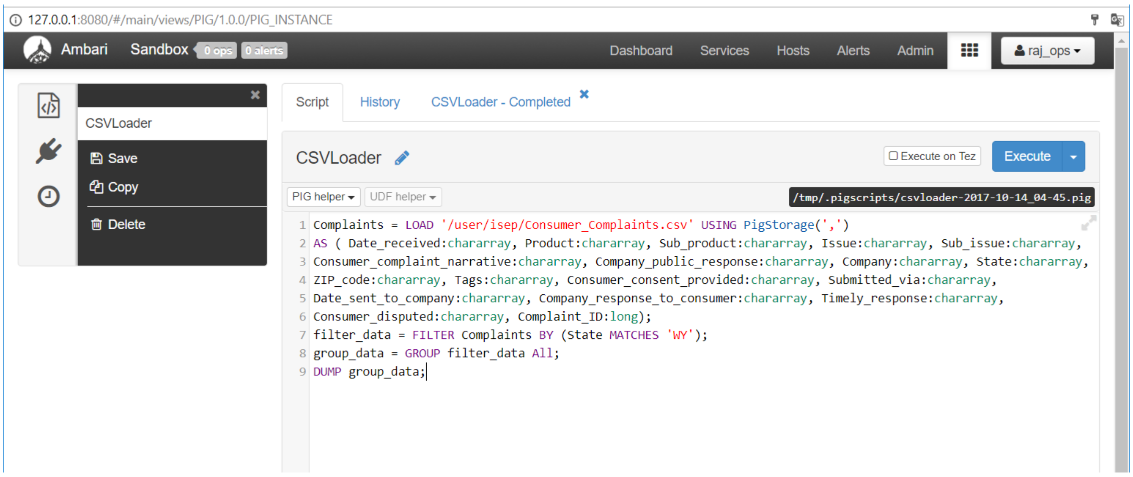

Ambari - Sandbox - Google Chrome
127.0.0.1:8080/#/main/view/FILES/auto_files_instance
Ambari
Sandbox
0 ops
0 alerts
Dashboard
Services
Hosts
Alerts
Admin
raj_ops
user
isep
Total: 0 files or folders
Select All
Search in current directory...
Name
Group
Upload file to /user/isep
44%
Consumer_Complaints.csv
Cancel

Figure 24 – Ambari Files View

8.5.3 Data Integration/Representation

To use CSV as the data object the recommended modules are Pig and Hive. The main difference between the Pig and Hive is that in Pig all objects are declared and operated in the script, and after the execution of the script all objects are deleted unless they are saved. On the other hand in Hive, any table, query, the copied data persists of query to query, thus operating in Apache Hadoop data store.

Testing the file present in HDFS directory **/user/isep/** on Pig, as shown below in Figure 25.



```
Complaints = LOAD '/user/isep/Consumer_Complaints.csv' USING PigStorage(',')
AS ( Date_received:chararray, Product:chararray, Sub_product:chararray, Issue:chararray, Sub_issue:chararray,
Consumer_complaint_narrative:chararray, Company_public_response:chararray, Company:chararray, State:chararray,
ZIP_code:chararray, Tags:chararray, Consumer_consent_provided:chararray, Submitted_via:chararray,
Date_sent_to_company:chararray, Company_response_to_consumer:chararray, Timely_response:chararray,
Consumer_disputed:chararray, Complaint_ID:long);
filter_data = FILTER Complaints BY (State MATCHES 'WY');
group_data = GROUP filter_data All;
DUMP group_data;
```

Figure 25 – Pig script example

For this experience, Hive seemed more appropriate due to its persistence, but also to the fact that it is more intuitive, uses the Hive query language (HiveQL) similar to SQL and with visual representation of data and process.

In Hive, it is necessary to create a table to hold the data. The query in HiveQL typed into the Query Editor to hold the data is the follow:

```
Create Table temp_complaints (col_value STRING);
```

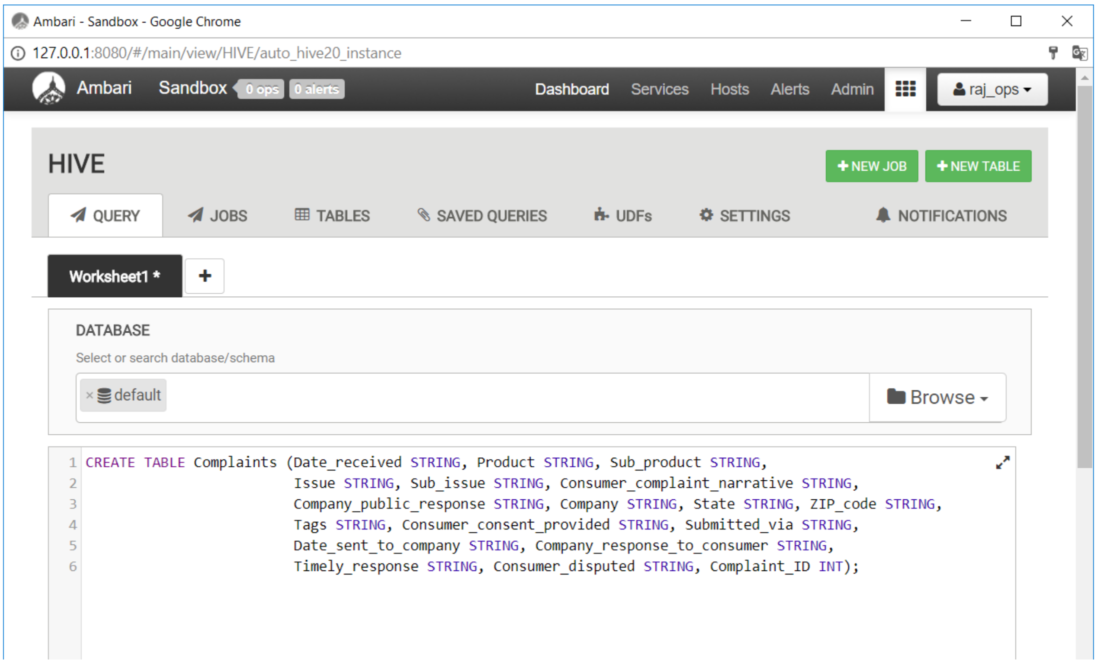
Code 1 – Create Table in HiveQL

After creating the temporary table with just one column, it is necessary to load the CSV file into the **temp_complaints** table, the following code is executed:

```
LOAD DATA INPATH ‘/user/isep/Consumer_Complaints.csv’
        OVERWRITE INTO TABLE temp_complaints;
```

Code 2 – Load CSV file to table

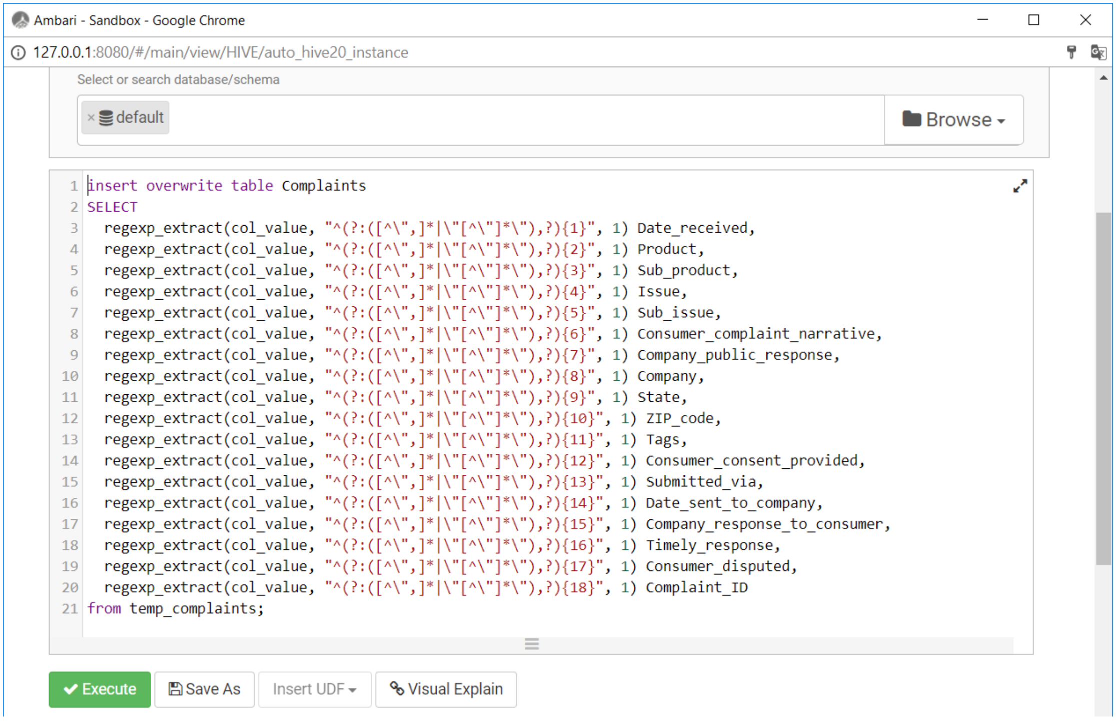
After loading the file, the table **temp_compaints** was populated with data from the CSV file and the file was also consumed from HDFS. Next, the definitive table was created with the desired columns according to the data fields found in the file, as seen in Figure 26.



```
CREATE TABLE Complaints (Date_received STRING, Product STRING, Sub_product STRING,
                         Issue STRING, Sub_issue STRING, Consumer_complaint_narrative STRING,
                         Company_public_response STRING, Company STRING, State STRING, ZIP_code STRING,
                         Tags STRING, Consumer_consent_provided STRING, Submitted_via STRING,
                         Date_sent_to_company STRING, Company_response_to_consumer STRING,
                         Timely_response STRING, Consumer_disputed STRING, Complaint_ID INT);
```

Figure 26 – Structure of the table Complaints in HiveQL

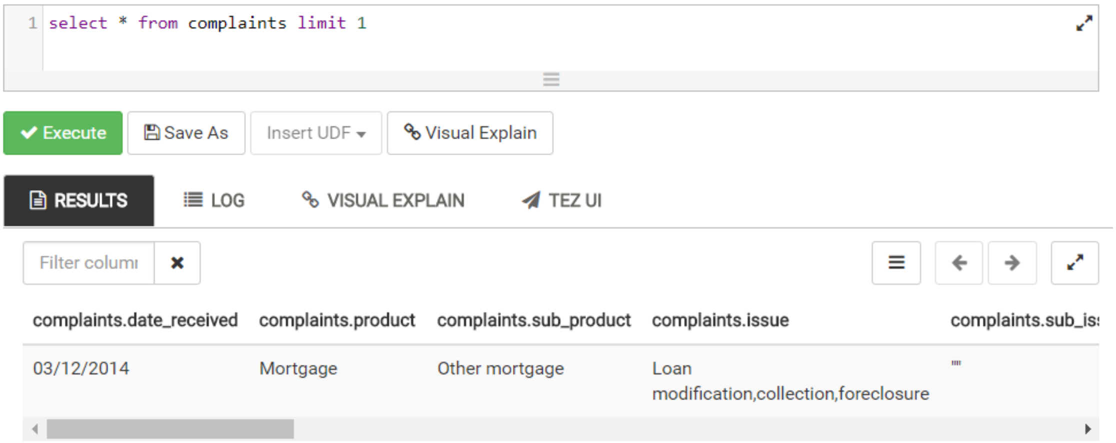
To extract the data from table **temp_complaints** and copy it into table **complaints**, it was used regular expressions, as seen in Figure 27.


Ambari - Sandbox - Google Chrome
127.0.0.1:8080/#/main/view/HIVE/auto_hive20_instance
Select or search database/schema
default
Browse
Execute
Save As
Insert UDF
Visual Explain

```
insert overwrite table Complaints
SELECT
  regexp_extract(col_value, "^(?:([^\",]*|\"[^\"]*\"),?){1}", 1) Date_received,
  regexp_extract(col_value, "^(?:([^\",]*|\"[^\"]*\"),?){2}", 1) Product,
  regexp_extract(col_value, "^(?:([^\",]*|\"[^\"]*\"),?){3}", 1) Sub_product,
  regexp_extract(col_value, "^(?:([^\",]*|\"[^\"]*\"),?){4}", 1) Issue,
  regexp_extract(col_value, "^(?:([^\",]*|\"[^\"]*\"),?){5}", 1) Sub_issue,
  regexp_extract(col_value, "^(?:([^\",]*|\"[^\"]*\"),?){6}", 1) Consumer_complaint_narrative,
  regexp_extract(col_value, "^(?:([^\",]*|\"[^\"]*\"),?){7}", 1) Company_public_response,
  regexp_extract(col_value, "^(?:([^\",]*|\"[^\"]*\"),?){8}", 1) Company,
  regexp_extract(col_value, "^(?:([^\",]*|\"[^\"]*\"),?){9}", 1) State,
  regexp_extract(col_value, "^(?:([^\",]*|\"[^\"]*\"),?){10}", 1) ZIP_code,
  regexp_extract(col_value, "^(?:([^\",]*|\"[^\"]*\"),?){11}", 1) Tags,
  regexp_extract(col_value, "^(?:([^\",]*|\"[^\"]*\"),?){12}", 1) Consumer_consent_provided,
  regexp_extract(col_value, "^(?:([^\",]*|\"[^\"]*\"),?){13}", 1) Submitted_via,
  regexp_extract(col_value, "^(?:([^\",]*|\"[^\"]*\"),?){14}", 1) Date_sent_to_company,
  regexp_extract(col_value, "^(?:([^\",]*|\"[^\"]*\"),?){15}", 1) Company_response_to_consumer,
  regexp_extract(col_value, "^(?:([^\",]*|\"[^\"]*\"),?){16}", 1) Timely_response,
  regexp_extract(col_value, "^(?:([^\",]*|\"[^\"]*\"),?){17}", 1) Consumer_disputed,
  regexp_extract(col_value, "^(?:([^\",]*|\"[^\"]*\"),?){18}", 1) Complaint_ID
from temp_complaints;
```

Figure 27 – Load data from temporary table into complaints

Next, it was possible to query the table complaints (see. Figure 28 with the first row of the table complaints).



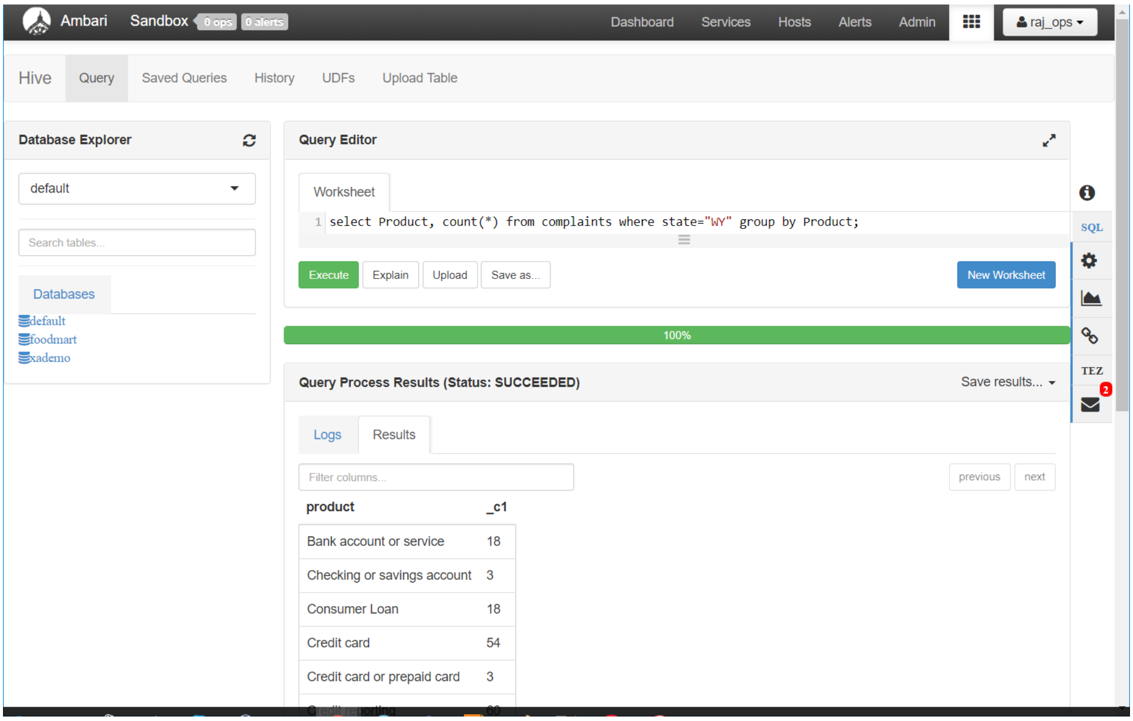
```
select * from complaints limit 1
```

complaints.date_received	complaints.product	complaints.sub_product	complaints.issue	complaints.sub_is:
03/12/2014	Mortgage	Other mortgage	Loan modification,collection,foreclosure	""

Figure 28 – The First row of the table complaints

8.5.4 Analysis and Visual Representation

At this point, it is possible to filter the data to have results from the dataset with the complaints filed by US citizens to US government about financial products and services. For this experiment we executed a query, to know the number of complaints by-product in the state of Wyoming. In the Figure 29 it can be seen the result in a tabular form.



```
select Product, count(*) from complaints where state="WY" group by Product;
```

Query Process Results (Status: SUCCEEDED)

product	_c1
Bank account or service	18
Checking or savings account	3
Consumer Loan	18
Credit card	54
Credit card or prepaid card	3
Credit reporting	60

Figure 29 – Complaints in Wyoming by-product

It is possible to view the data as a simple chart (see. Figure 30), such as point chart, area chart, bar chart, line chart and tick chart. By visualizing the data it is clear that Debt collection is the product that has more complaints.

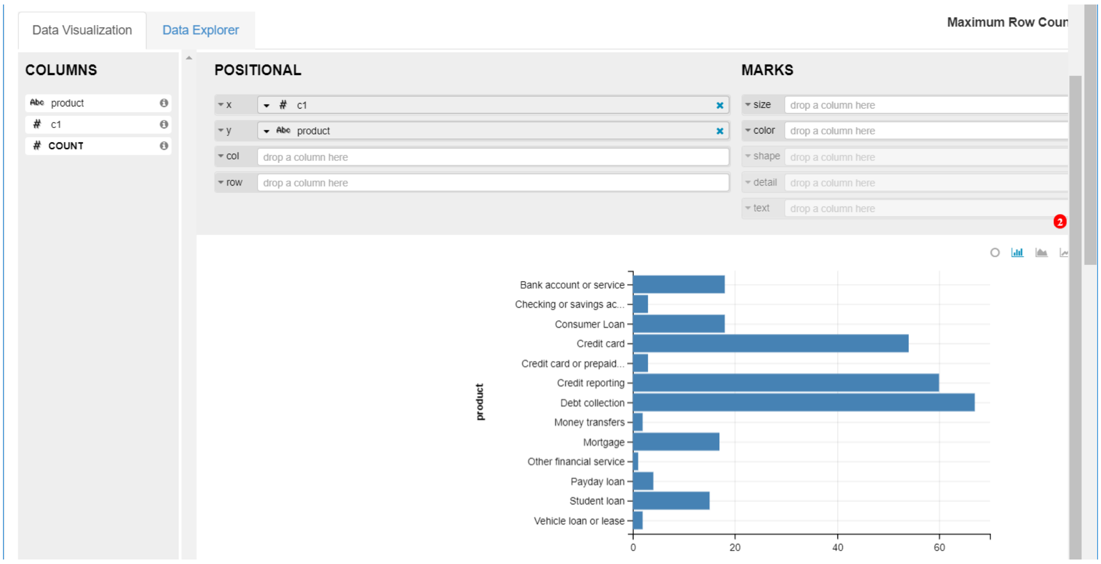


Figure 30 – Data Visualization in Hive

8.6 HPCC

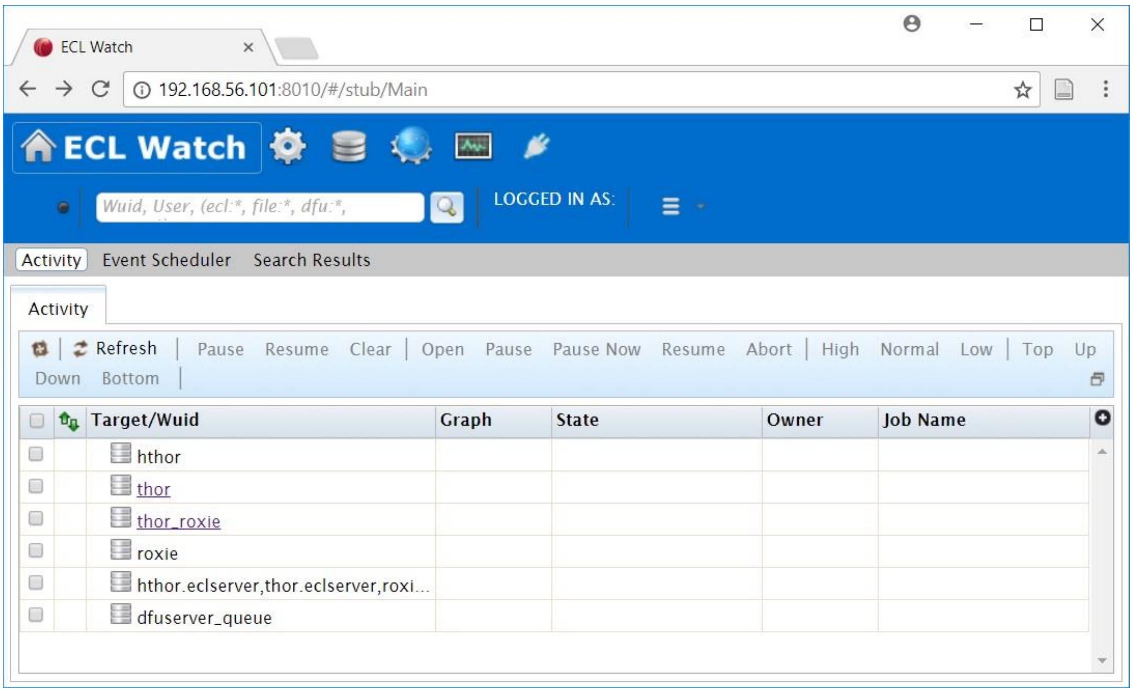
For the experiment on HPCC, the virtual appliance with the latest version (6.4.2) of HPCC Systems platform has been downloaded and imported into VirtualBox; the process is standard, just follow the virtual assistant and almost excludes advanced and additional settings.

8.6.1 Cluster Manager

There are several interfaces to manage the HPCC platform, such as ECL IDE, Eclipse, Command line ECL, ECL Watch, DFU Plus and others ("HPCC Systems Platform," 2016). All of these interfaces run on the Enterprise Services Platform (ESP) and have the option of LDAP authentication, an interesting option for companies that have LDAP. ECL IDE and HPCC Client Tools is also an interesting tool for end users because it has a version to run on MS Windows and designed to run ECL code.

In our experiment, we chose the ECL Watch middleware that comes configured in the virtual appliance and runs in the browser, and there is no need to install.

ECL Watch provides a simple and user-friendly interface (see. Figure 31) allowing users to view node information and check if the other nodes are running as expected, e.g., check processes, examine system end-to-end, monitor the status of jobs and files, and view logs.

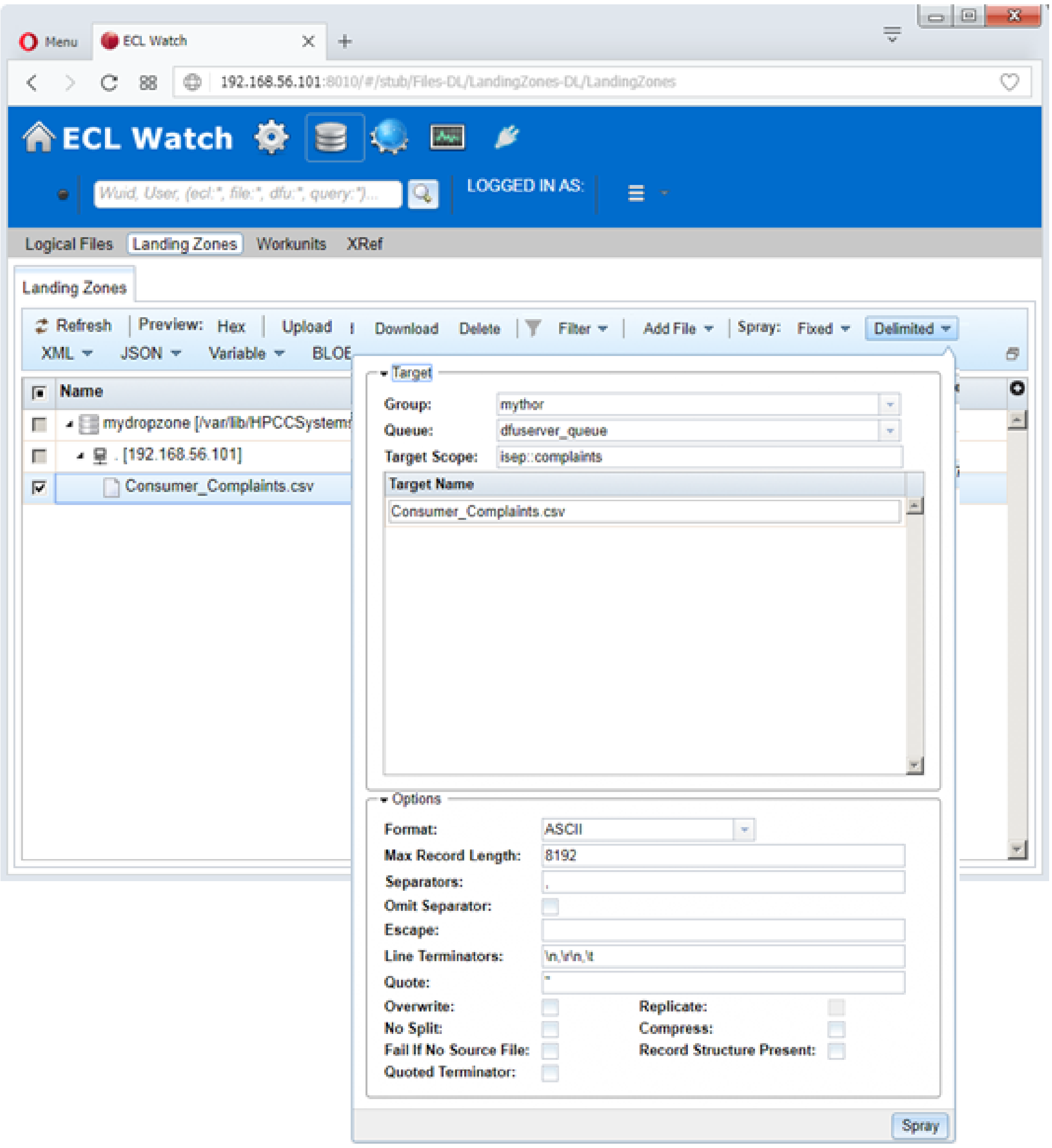


	Target/Wuid	Graph	State	Owner	Job Name
□	hthor				
□	thor				
□	thor_roxie				
□	roxie				
□	hthor.eclserver,thor.eclserver,roxi...				
□	dfuserver_queue				

Figure 31 – ECL Watch start page

8.6.2 Data Acquisition

In the HPCC environment, the physical storage location defined in the HPCC environment is called the Landing Zone or Drop Zone. The dataset was placed in the Landing Zone **mydropzone** via the "*Upload*" button, and then we just selected the file (Consumer_Complaints.csv) on our disk. Next, we needed to load the file into Data Refinery, this operation is called spray in HPCC environment alluding to the spread of data across the nodes. Because our dataset was a CSV file, we had to select the file in Dropzone and click the *"Delimited"* button, as seen in Figure 32.



Group: mythor
Queue: dfuserver_queue
Target Scope: isep::complaints

Target Name
Consumer_Complaints.csv

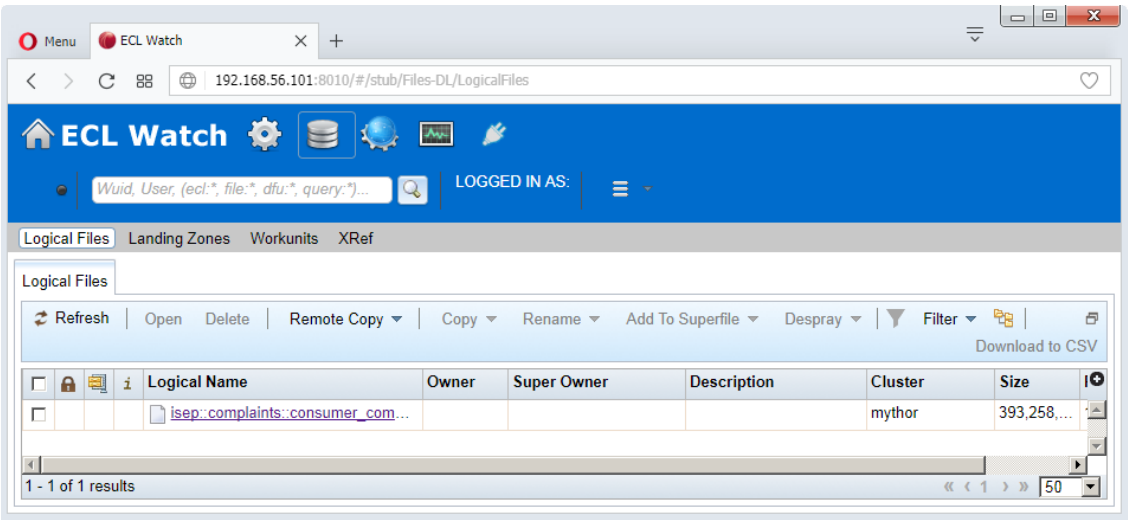
Format: ASCII
Max Record Length: 8192
Separators: ,
Omit Separator: □
Escape:
Line Terminators: \n,\r\n,\t
Quote: "
Overwrite: □
Replicate: □
No Split: □
Compress: □
Fail If No Source File: □
Record Structure Present: □
Quoted Terminator: □

Figure 32 – Spray the Data File to your THOR Cluster

This operation is done with the help of an assistant; it is at this stage that we define the name and target scope by which our dataset will be identified in the ECL as a logical file.

8.6.3 Data Integration/Representation

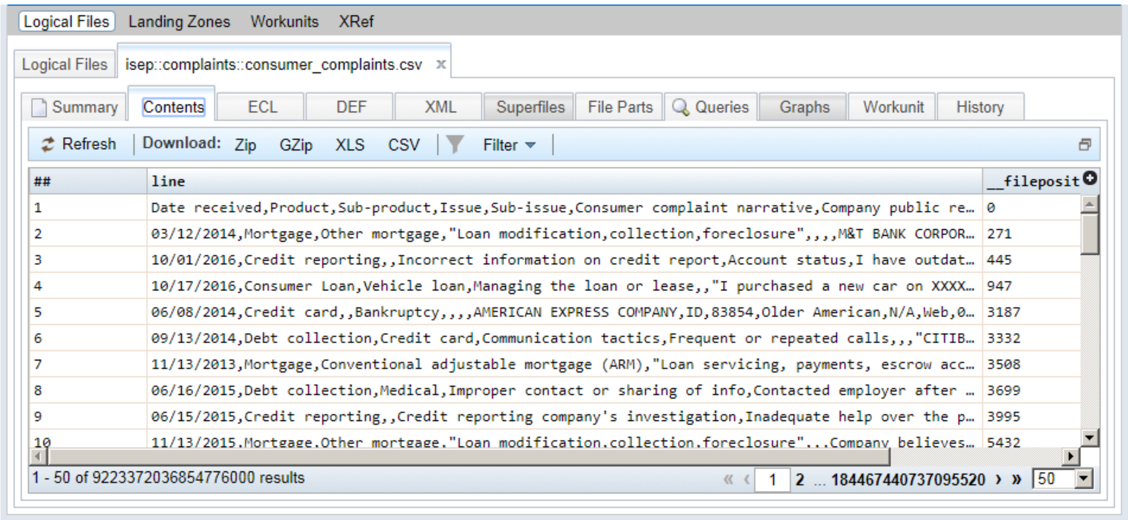
After the file spray process is completed, for this file takes about 21 seconds. Next, it was possible to see the logical file (see. Figure 33), its contents (see. Figure 34) and the structure that the ECL is automatically identified.



□			i	Logical Name	Owner	Super Owner	Description	Cluster	Size
□				isep::complaints::consumer_com...				mythor	393,258,...

1 - 1 of 1 results

Figure 33 – Logical File in HPCC



##	line	__fileposit
1	Date received,Product,Sub-product,Issue,Sub-issue,Consumer complaint narrative,Company public re...	0
2	03/12/2014,Mortgage,Other mortgage,"Loan modification,collection,foreclosure",,,,M&T BANK CORPOR...	271
3	10/01/2016,Credit reporting,,Incorrect information on credit report,Account status,I have outdat...	445
4	10/17/2016,Consumer Loan,Vehicle loan,Managing the loan or lease,,"I purchased a new car on XXXX...	947
5	06/08/2014,Credit card,,Bankruptcy,,,,AMERICAN EXPRESS COMPANY,ID,83854,Older American,N/A,Web,0...	3187
6	09/13/2014,Debt collection,Credit card,Communication tactics,Frequent or repeated calls,,,"CITIB...	3332
7	11/13/2013,Mortgage,Conventional adjustable mortgage (ARM),"Loan servicing, payments, escrow acc...	3508
8	06/16/2015,Debt collection,Medical,Improper contact or sharing of info,Contacted employer after ...	3699
9	06/15/2015,Credit reporting,,Credit reporting company's investigation,Inadequate help over the p...	3995
10	11/13/2015,Mortgage,Other mortgage,"Loan modification,collection,foreclosure",,,Company believes...	5432

1 - 50 of 9223372036854776000 results

1 2 ... 18446744073709552O › » 50

Figure 34 – Logical File contents

8.6.4 Analysis and Visual Representation

To filter and query the data we had to use the **ECL playground**.

For our experience, we first had to define the layout of the records, this definition can be done directly in the ECL code or pre-create the layout and then export it. Then every time we need to query that layout, we just need to reference it. We have always chosen to define the layout. Thus the structure of the dataset is always visible, which helps in queries.

The layout defined was as follows:

```
Layout_Complaint := RECORD
    STRING Date_received;
    STRING Product;
    STRING Sub_product;
    STRING Issue;
    STRING Sub_issue;
    STRING Consumer_complaint_narrative;
    STRING Company_public_response;
    STRING Company;
    STRING State;
    STRING ZIP_code;
    STRING Tags;
    STRING Consumer_consent_provided;
    STRING Submitted_via;
    STRING Date_sent_to_company;
    STRING Company_response_to_consumer;
    STRING Timely_response;
    STRING Consumer_disputed;
    UNSIGNED3 Complaint_ID;
END;
```

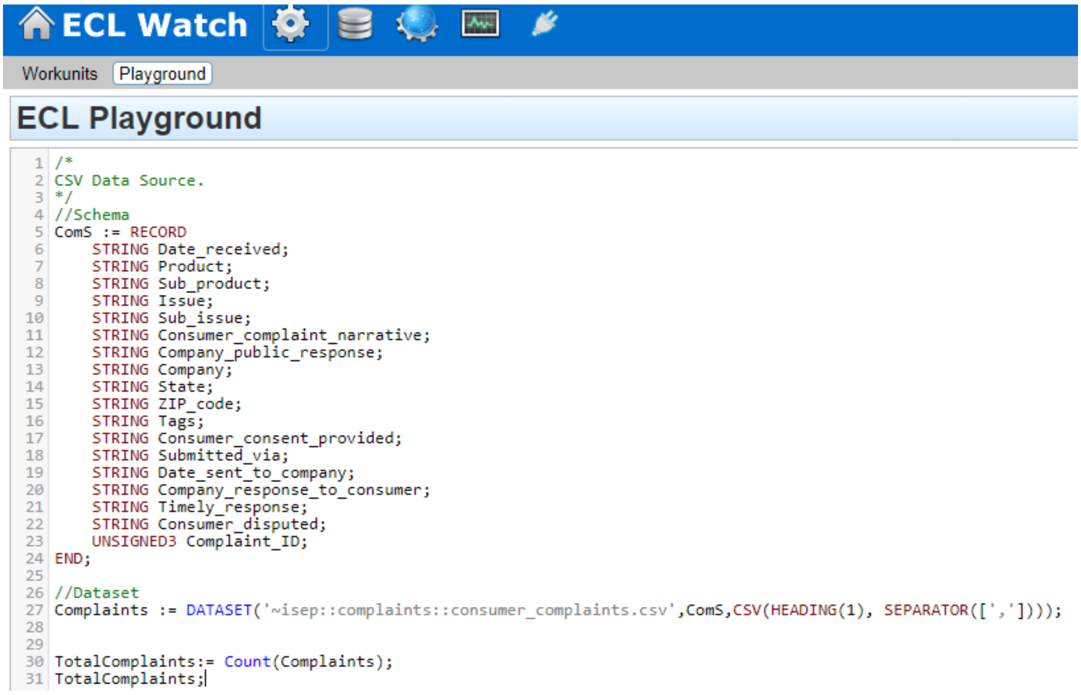
Code 3 – Layout of the record in ECL

After defining the registry layout, the name (Complaints) of the attribute to be used as the dataset is defined, the first argument is the constant string with the name of the logical file, and the second argument the type of file that in our case is a CSV using the number of columns of the file and the field delimiter selected in the spray process. By defining the name of the DATASET is useful for later use in other definitions. The dataset declaration was as follows:

```
Complaints := DATASET('~isep::complaints::consumer_complaints.csv',
ComS,CSV(HEADING(1), SEPARATOR([','])));
```

Code 4 – Dataset declaration

In Figure 35 we can observe the code in ECL Playground.



```
/*
CSV Data Source.
*/
//Schema
ComS  := RECORD
     STRING Date_received;
     STRING Product;
     STRING Sub_product;
     STRING Issue;
     STRING Sub_issue;
     STRING Consumer_complaint_narrative;
     STRING Company_public_response;
     STRING Company;
     STRING State;
     STRING ZIP_code;
     STRING Tags;
     STRING Consumer_consent_provided;
     STRING Submitted_via;
     STRING Date_sent_to_company;
     STRING Company_response_to_consumer;
     STRING Timely_response;
     STRING Consumer_disputed;
     UNSIGNED3 Complaint_ID;
END;

//Dataset
Complaints := DATASET('~isep::complaints::consumer_complaints.csv',ComS,CSV(HEADING(1), SEPARATOR([','])));


TotalComplaints:= Count(Complaints);
TotalComplaints;
```

Figure 35 – ECL Playground

The ECL Playground after executing the ECL and the job end with success than displays the results and also a graph (see. Figure 36) is generated, this can be useful for troubleshooting queries or node problems.

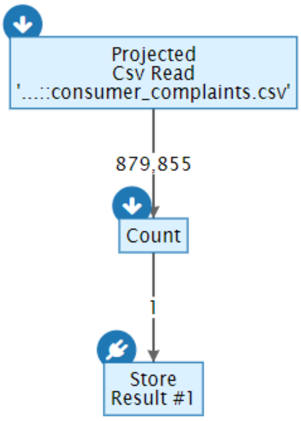


Figure 36 – Activities graph

In ECL Playground the results are displayed in a tabular representation, it is possible to export the results to a compressed file, spreadsheet or CSV. Visualizing ECL results of queries is possible and uncomplicated, this add-on offers a variety of visual representations such as pie chart, line chart, area chart, step chart, scatter chart, bubble chart, word cloud, Maps (see. Figure 37), and others.

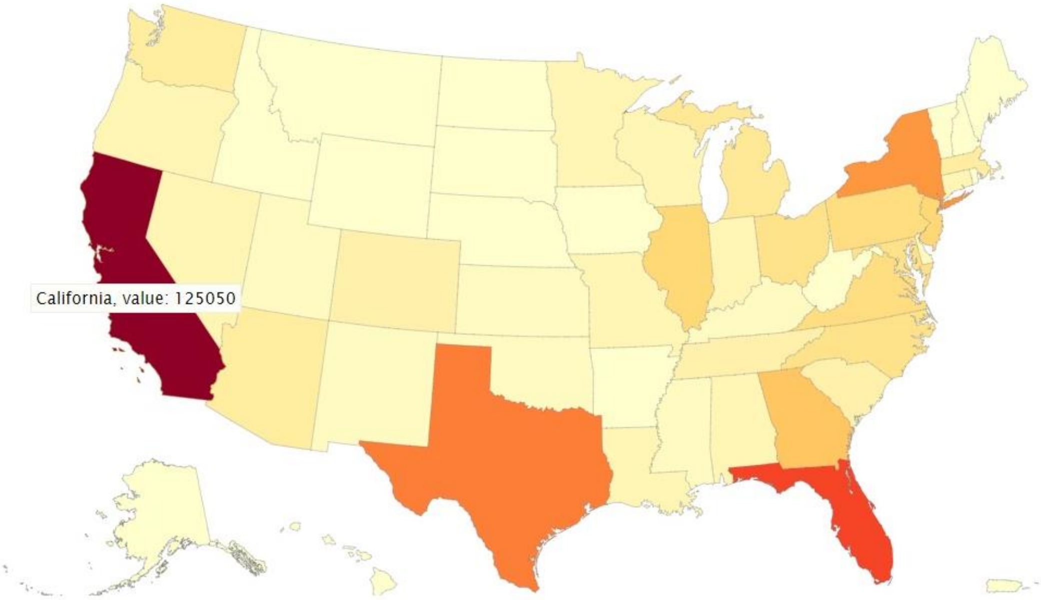


Figure 37 – US financial products and services complaints by State

8.7 Experimental Results and Discussion

The installation and configuration of HDP is relatively simple, however, the configuration and operation of the cluster through SSH or console has a higher level of complexity. The user experience in Apache Ambari is intuitive and quite manageable, the modules (e.g., Hive, Pig, and others) that have a visual interface have all the link in the **Views icon** on the top bar.
Although Pig and Hive do the same operations, there is no doubt that Hive by having its SQL like query language is a positive point. It is familiar to users who have experience using SQL to query data.

The data visualization in Hive it is very simple, other and advanced visualizations like heat maps are not available, this kind of representation would be interesting considering that there are data from all the US states.

The installation of the virtual appliance of HPCC it is really uncomplicated and fast, it is only necessary to set up a second network adapter.

In HPCC the cluster manager used was the ECL Watch, which is a useful, and easy learning tool, on the main page of ECL Watch, are present in the top bar all the essential modules such as ECL Playground, Files, Publish Queries, Operations and search bar. The search bar allows you to search a diversity of items and supports wildcards, can be searched users, files, workunits, and ECL.

To test the queries and define dataset was used the ECL Playground, without a doubt that is an ideal tool for this purpose. It already has some samples of ECL code available which facilitates the learning of the ECL programming language. After the execution of each query, it was possible to see the results of the DAG, and also to visualize the results in a graphical representation.

The analysis of the workunits is also notable; we can go back to consulting the ECL, the DAG, timers, system variables at that moment, and even see the results again in table or chart.

Also, the variety of available chart types is a plus for the HPCC; it is possible to generate charts like bubble chart, word cloud and maps of the USA and the world without make use of external tools.

According with Hortonworks (2016), Apache Hive is best suited for both interactive batch queries and to the petabyte scale.

All the queries were executed in Hive and on the Apache Tez, because according to the literature the Apache Tez improves the MapReduce paradigm in speed and at the same time maintains the ability to scale petabytes of data ("HDP," 2016).

Table 18 shows the time of each query in seconds, the Q1 and Q2 take less time than the others and Apache Tez does not show the Directed Acyclic Graph (DAG) of this type of simple queries. However, this times are shown in Hive jobs but rounded to zero decimal places.

Table 18 – HDP queries times in seconds

	1st Run	2nd Run	3rd Run	4th Run	5th Run	AVG
Q1	2	1	1	1	1	1.200
Q2	1	1	1	1	1	1.000
Q3	69.417	57.122	52.386	36.554	44.220	51.940
Q4	71.604	63.860	74.226	57.506	56.905	64.820
Q5	83.293	85.101	77.255	79.721	78.449	80.764
Q6	93.977	80.253	69.369	78.647	106.809	85.811
Q7	76.470	51.186	37.952	37.688	68.538	54.367
Q8	52.957	44.103	82.551	41.131	70.392	58.227
Q9	46.970	63.884	43.616	39.001	38.329	46.360
Q10	45.509	50.389	43.035	40.130	46.310	45.075

The queries trends of Hortonworks Data Platform are shown in Figure 38, it is verified that the times of each query improve in each interaction.

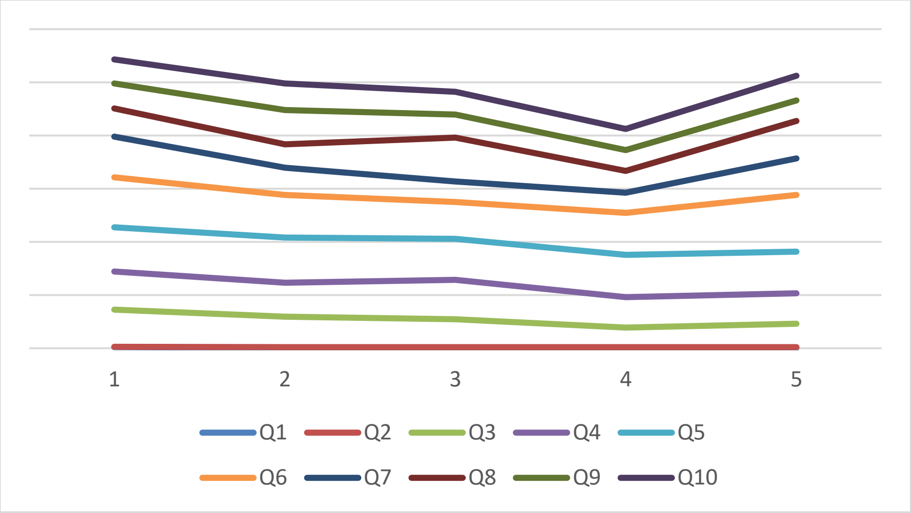


Figure 38 – HDP Queries Trends

For these tests in HPCC, we used the ECL Playground component that is present in the ECL Watch. This is an ideal tool for users who do not have much experience programming in ECL and want to submit some code and see the results (HPCC Systems, 2017). HPCC provides three types of clusters, Roxie, Thor, and hThor. The hThor was the selected and used as the target cluster. It is suitable for testing because hThor emulates the Roxie operation, queries and directly accesses the data disks on a Thor cluster without interfering with the operations of that cluster.

Table 19 shows the time of each query in seconds, the query (Q1) take more time and memory, the default value of the option *"outputLimit"* is 10MB, and 10MB in HPCC are not sufficient to output the results, to perform this query it is necessary to add the option *"outputLimit"* and set it to **500** at the beginning of the ECL code.

Table 19 – HPCC queries times in seconds

	1st Run	2nd Run	3rd Run	4th Run	5th Run	AVG
Q1	13.469	9.211	10.048	9.032	7.673	9.887
Q2	4.612	4.721	4.913	4.771	4.500	4.703
Q3	4.308	4.421	4.507	4.529	4.614	4.476
Q4	4.327	4.718	4.724	4.713	4.546	4.606
Q5	4.420	4.706	4.626	4.645	4.678	4.615
Q6	4.473	4.481	4.653	4.392	4.396	4.479
Q7	4.378	4.687	4.799	4.593	4.547	4.601
Q8	4.404	4.576	4.585	4.636	4.680	4.576
Q9	5.437	4.348	4.348	4.886	4.764	4.757
Q10	4.633	4.963	5.047	4.915	4.954	4.902

The queries trends are shown in Figure 39, it is possible to show query time gain in all the queries during all the runs with exception of the 3rd run of each query during the test.

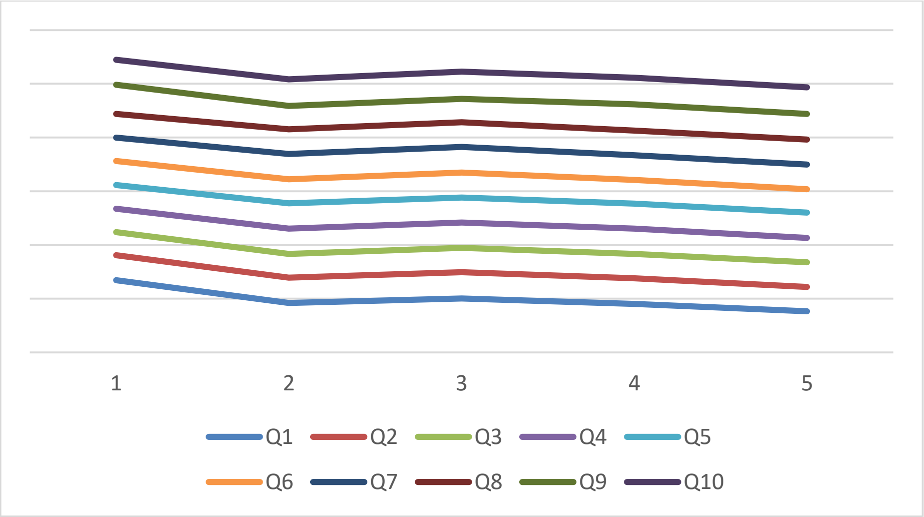


Figure 39 – HPCC Queries Trends

Table 20 shows the average times of each query in HDP and HPCC, absolute slowdown and relative slowdown, the absolute difference (2) and the relative difference (3) as the following equation:

$$AbsoluteDifference = AvgQueryTimeHDP - AvgQueryTimeHPCC \tag{2}$$

$$RelativeDifference = \frac{AbsoluteDifference}{AvgQueryTimeHDP} \times 100 \tag{3}$$

Table 20 – OVERHEAD HDP vs. HPCC

Query #	**HDP (secs)**	**HPCC (secs)**	**Abs difference (secs)**	**Rel. difference (%)**
Q1	1.200	9.887	-8.687	-87.862%
Q2	1.000	4.703	-3.703	-78.739
Q33	51.940	4.476	47.464	1060.458
Q4	64.820	4.606	60.215	1307.421
Q5	80.764	4.615	76.149	1650.028
Q6	85.811	4.479	81.332	1815.852
Q7	54.367	4.601	49.766	1081.681
Q8	58.227	4.576	53.651	1172.383
Q9	46.360	4.757	41.603	874.646
Q10	45.075	4.902	40.172	819.439
TOTAL	489.563	51.601	437.962	9615.309

IT is evident in this tests that HDP has better performance in Q1, Q2 tests, that perform a simple query which includes only selecting all columns and filter by a value, and has no aggregate functions or using sorts. HPCC performance is affected when the result returns many lines as is the case with Q1 that returns 879855 lines.

It is noticed that in the HDP when query fewer columns using only one condition (state="WY") and using sorts the performance improves as is the case of Q7.

However, the Q3, Q4, Q5, Q6, Q7, Q8, Q9, Q10 tests had better results in HPCC, when queries use aggregation functions and sorts. In the individual tests, it was verified in the times of the two platforms that the times of each query improve each interaction.

As noted in the table all the queries in Hortonworks Data Platform take a total of 489.563 seconds, and the HPCC take 51.601 seconds, and the difference between the two platforms is of 437.962 seconds (more than 7 minutes).

8.8 Summary

Using the testing method outlined in chapter 6, we have conducted an experiment to empirically analyze some functionalities and queries performance of the two selected platforms HDP and HPCC. The main goal of this test and experiment was to compare the two BDA platforms implementations and indicate possible drawbacks and advantages.

For this end-to-end experiment with virtual machines (VM) was performed, using the official and last virtual appliances from each platform, without any particular configuration or optimization. For the dataset, for the data used in the test we chose a real dataset from the US government (Consumer Financial Protection Bureau), this dataset contains real records from complaints filed by US citizens from all the USA states about financial products.

In the tests performed, each query was run 5 times, and each test results were the average time taken as seen in Table 20.

When we compare the queries executed on both platforms, we find very different results, Hortonworks Data Platform has 2 in 10 better query times and the total of 489.563 seconds, and the HPCC had better times 8 in 10 making a total of 51.601 seconds average times).

9 Conclusions

Big Data and Big Data Analytics has a direct relationship with the generation of knowledge since it is a fundamental and necessary element for the decision-making within an organization, where information has been acquired.

In this thesis, the whole chapter 4 presents concepts related with Big Data and challenges within the Big Data Analytics context, in chapter 5 explained features and tools of open source platforms as a basis for comparing those platforms with their most outstanding advantages, features and functionalities.

As exposed in chapter 5, the open source platform analysed Hadoop is the most used and serves as basis for some other mention platforms, maybe the better suited for all contexts are HPCC Systems Platform, particularly in the Big Data approach, for integration with existing traditional data managements systems is Hortonworks Data Platform it has its own data integration modules that allows better support for other systems in an approach in terms of processes, analysis, and manipulation of various data sources.

In chapter 7 we evaluated four of the nine platforms described in this research work, focusing on their maturity and functionalities. These aspects are described considering the concepts of the BDA platforms for data analytics, their features, and components. In the future, for such evaluation and selection, the weighting factors of functionality criteria would be more accurate if they were based on questionnaires anonymous to SMEs to know their priorities.

Both platforms are very similar in their cluster manager, components, and functionality, but unlike the HDP, HPC does not use SQL-based interface, but an add-on can be added in HPCC.

When comparing two BDA platforms, HPCC Systems Platform is found to be more efficient and reliable than Hortonworks Data Platform,

There are many possible future performance comparison such as test both the platforms with more nodes to confirm the fault tolerance and scalability.

Without a doubt, several projects and developments offer possibilities for adoption, cost reduction, profit growth and structural for Small and Medium-sized Enterprises (SMEs).

In particular, Portuguese SMEs should consider for BDA platforms an opportunity to obtain competitive advantage and improve their processes and consequently define an IT and business strategy.

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Appendix

Appendix I - Big Data Analytics: A Preliminary Study of Open Source Platforms

Big Data Analytics: A Preliminary Study of Open Source Platforms

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Keywords: Big Data Analytics, BI, Open Source Big Data Platforms.

Abstract: Nowadays organizations look for Big Data as an opportunity to manage and explore their data with the objective to support decisions within its different operational areas. Therefore, it is necessary to analyse several concepts about Big Data Analytics, including definitions, features, advantages and disadvantages. By investigating today's big data platforms, current industrial practices and related trends in the research world, it is possible to understand the impact of Big Data Analytics on smaller organizations. This paper analyses the following five open source platforms for Big Data Analytics: Apache Hadoop, Cloudera, Spark, Hortonworks, and HPCC.

1 INTRODUCTION

Nowadays we observe huge volumes of data in constant growth, due to the evolution of technology together with the massive exchange of information. Therefore it is essential to make use of sophisticated platforms to deal with this massive quantity of data.

There are two types of platforms available for handling Big Data - Open Source and Proprietary Software - which are used by organizations to manage their information. However, many of the organizations do not know the benefits, advantages, and disadvantages that these platforms offer in cost, operation, and information management.

In recent times all types of organizations are present on the Internet, and this channel has a great impact on their business, taking care of what customers want and also serving as a guide for new products and what is offered. This process also highlights the huge deal of information on what has to do with products and services for sale.

This is the main reason why this research work is carried out to analyse in particular the Open Source platforms for analytics that best fit in Small and Medium-sized Enterprises (SMEs) and Non-governmental organizations (NGO).

Currently, organizations and companies have opted for the adoption of open source and proprietary software platforms oriented to Big Data to solve problems of handling, management, storage, and analysis of information.

In order to justify this work, an analysis will be carried out between the open source platforms that can be adopted by SMEs and that cannot or do not wish to acquire proprietary platforms.The objective is to discover what kind of platforms and tools would be most suitable for their environment.

This paper analyses the following open source platforms for Big Data Analytics: Apache Hadoop, Cloudera, Spark, Hortonworks, and HPCC.

The rest of this paper is structured as follows. Section 2 presents the related work, and section 3 describes Big Data and Analytics. In section 4 we describe the analysed platforms for Big Data Analytics. Section 5 presents a comparision of the main features of the analysed platforms. Finally, conclusions and future work are summarized in Section 6.

2 RELATED WORK

Multiple research works have been done to compare and evaluate existing Big Data platforms with some research focused on a specific capability, technology or purpose (Lapa et al., 2014), (Bernardino, 2011/ 2015), (Neves and Bernardino, 2015).

Almeida and Bernardino (2015) focus on the capability of mining data, and in a mix of technical parameters and features that are suitable for Small and Medium Enterprise environments.

Nereu, J., Almeida, A. and Bernardino, J.
Big Data Analytics: A Preliminary Study of Open Source Platforms .
DOI: 10.5220/0006470104350440
In *Proceedings of the 12th International Conference on Software Technologies (ICSOFT 2017)*, pages 435-440
ISBN: 978-989-758-262-2

On the other hand, Morshed et al. (2016) focused their work on platforms addressing distributed real-time data analytics and concluded that the platforms analysed do not cover all the features that are required for distributed computation in real-time.

Miller et al. (2016) works on platforms written in SCALA programming language that supports both the object-oriented and functional programming paradigms built on top of JAVA.

Landset et al. (2015) presented a comprehensive survey of open source tools for machine learning with big data in the Hadoop ecosystem to researchers or professionals in machine learning but is inexperienced with big data.

(Sagiroglu and Sinanc (2013) provides an overview of big data such as samples, methods, advantages and challenges. They compare Hadoop and HPCC by their architectures, primary languages, and indexes in a Distributed File System, data warehouse abilities and performance tests where HPCC shows the best results.

Another recent paper describes an experiment with 40-node using Hadoop Platforms (Hortonworks, Cloudera or Apache), Spark for streaming data processing, HBase and OpenTSDB to store time series sensor data. The authors present the characteristics, requirements, and configurations of Hadoop platforms (Liu et al., 2016).

Consequently, there exist few works which do an evaluation based on specific capability, technology or purpose. Our work contributes to the identification of the Big Data platforms for analytics that may be suitable for SMEs in their operations.

3 BIG DATA AND ANALYTICS

Organizations find it difficult to perform a detailed analysis and provide new advantages and opportunities to their stakeholders. Some collected data which ranges from customers' names, addresses, available products, purchases as well as the employees recruited, has become very important for daily operations ("Ventana Research," 2014).

With this data, it is even more evident that technology is imperative in data storage and its recovery. Technological developments contribute to an increase in capabilities to store more data as well as more methods of collecting this data. Additionally, huge amounts of data have been made easily accessible (Inoubli et al., 2016).

Presently, organizations explore large data volumes that are highly detailed to discover the facts that they were not aware of initially.

Big Data provides government and business organizations new ways to combine miscellaneous digital data sets and after that, use statistics and other data mining techniques to extract from them both occult information and astonishing correlations (Rubinstein, 2012). In short, Big Data is described as an enormous volume of structured, semi-structured and unstructured data that is so big that it is difficult or impossible to process using traditional database systems and software techniques.

3.1 Big Data Analytics

Big Data Analytics is becoming a trending practice that many companies are adopting to build valuable information (Sivarajah et al., 2017). The main objective of Big Data Analytics is to become an asset for making business decisions as well as for data scientists and other analytics professionals to analyse enormous volumes of transaction data.

Platforms oriented to Big Data Analytics are the greatest promoters of the paradigm shift of Big Data. These platforms manage large volumes of data and also work as an application of various analytical techniques for large volumes of data (Miller et al., 2016). To extract useful information from large data volume tools, it is appropriate to collect, store and process data from various analytical perspectives (Prasad and Agarwal, 2016).

3.2 Big Data Ecosystems

The ecosystem of big data includes several aspects such as data, the lifecycle models of big data, and finally the infrastructure that is used for support (Murthy and Bowman, 2014).The maturity of big data and predictive analysis leads to more open source contributors to the technologies used to empower the solutions. Presently, all types and sizes of vendors are making use of open sources for big data processing and the predictive analytics process (Pääkkönen and Pakkala, 2015). In some cases, the cloud, as well as open sources for storage and computing, are the technological catapults that enable start-ups and the emergence of small companies to compete with the more established ones (Sen et al., 2016). Big Data open source platforms are divided into several categories, which are data storage and access, development tools, and platforms for analytics and reporting (Miller et al., 2016).

In the next section, we will analyse five of the most popular open source big data platforms.

4 BIG DATA PLATFORMS

A Big Data platform should be a solution that is specifically designed to meet the needs of one organization (Chandrasekhar et al., 2013).

The next section describes the characteristics of five most popular platforms for Big Data (Landset et al., 2015): Apache Hadoop, Cloudera, Spark, Hortonworks, and HPCC.

4.1 Apache Hadoop

The Apache Hadoop is a free software project of the Apache foundation that implements the MapReduce paradigm and the Hadoop Distributed File System (HDFS). This open source platform allows distributed processing of large data sets across clusters of servers using simple programming models, where one cluster is designated as the master node and other as a slave node (Prasad and Agarwal, 2016). This platform has been projected to scale from one server to thousands of servers where each has its own local processing and storage ("Apache^{TM} Hadoop®," 2016).

The two most important functions that characterize the platform are MapReduce and HDFS, where MapReduce supports analysis of data and HDFS supports storage of data (Saraladevi et al., 2015). HDFS is at the base of the architecture as shown in Figure 1.

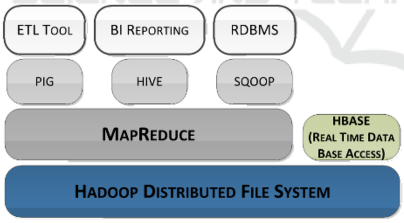

ETL Tool
BI Reporting
RDBMS
PIG
HIVE
SQOOP
MapReduce
HBASE (Real Time Data Base Access)
Hadoop Distributed File System

Figure 1: Hadoop Architecture (Saraladevi et al., 2015).

MapReduce main advantage is the accomplishment of parallelization and failover by splitting the work into multiple units (Chandrasekhar et al., 2013; Miller et al., 2016). Another significant advantage of Hadoop MapReduce pointed by authors is that it permits non-expert users an easy way to run analytical jobs over Big Data.

The platform uses Hadoop Distributed File System (HDFS), which is based on the distributed Google File System – GFS. It supports a scalable distributed file system that stores huge files in various and distributed machines in a reliable and efficient way (Inoubli et al., 2016).

The HDFS automatically replicates data across various nodes for fault tolerance (Inukollu et al., 2014). There are two types of nodes in a cluster. The first is the name-node (master) and the second is the data-node (slave). The name-node manages files, blocks, and mapping in a formation of the data-nodes, the data-node is responsible for storing data from a block unit into a number of locations separately. HDFS files are also replicated in multiples in order to provide parallel processing of large amounts of data (Khan et al., 2014).

4.2 Cloudera

Cloudera is the most well-known platform based on Apache Hadoop, which offers an effective platform that empowers organizations to gain insights from all their data (structured or unstructured) (Chandrasekhar et al., 2013). Cloudera is on the front line of the data management. Furthermore, Cloudera is the most innovative and contributes most for the open source Apache Hadoop platform (Sabapathi and Yadav, 2016). Cloudera is the leader in Hadoop-based platforms (Chandrasekhar et al., 2013) and has the same methods, functions, and main properties present in Hadoop, but it includes other efficient tools for social media (Murthy and Bowman, 2014). Cloudera maximizes the capabilities of Hadoop in storage, retrieval, and analysis (Murthy and Bowman, 2014) and enables enterprises to take advantage of its features of SQL tools to achieve real-time analytics (Prasad and Agarwal, 2016).

Where this platform stands out from the original Hadoop system is that it offers big data processing at faster speeds (Prasad and Agarwal, 2016), and with its user-friendly interface with many features and useful tools like Cloudera Impala. We can see the Cloudera Impala status in the Hadoop Stack in Figure 2.

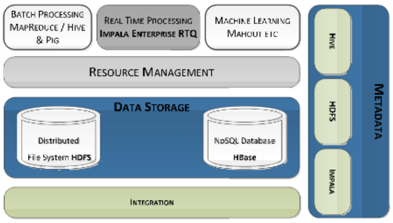

Batch Processing MapReduce / Hive & Pig
Real Time Processing Impala Enterprise RTQ
Machine Learning Mahout etc
Resource Management
Data Storage
Distributed File System HDFS
NoSQL Database HBase
Integration
Hive
HDFS
Impala
Metadata

Figure 2: Cloudera Impala Status in Hadoop Stack analytics (Prasad and Agarwal, 2016).

Impala is a real-time, parallelized processing engine with an SQL-based interface that queries the storage (HDFS and HBASE). Impala is seen as the fastest querying engine present in the Hadoop-based platforms. Moreover, is not just the Impala that stands out from the other platforms; the Cloudera Manager is more stable and complete in features than the Ambari (HDP) and resource manager (Hadoop) (Azarmi, 2015).

4.3 Spark

Spark is an open source framework that was originally developed at UC Berkley in 2009 (Inoubli et al., 2016). This platform stands out for running programs faster than Hadoop MapReduce on disk or memory. Spark API supports Java, Scala, Python and R to develop applications quickly, and can be integrated to work with other platforms or standalone ("Apache Spark^{TM}," 2016).

Apache Spark is particularly appropriate and efficient for the analytics of heterogeneous data (Inoubli et al., 2016) and for stateful computations when precisely a delivery is useful indifferent whether it takes too long or not. Spark supports real-time distributed features, and integrates a complete SQL interface (Spark-SQL). It uses Hive for standard query languages, and also Domain Specific Language – DSL for query structured data (Morshed et al., 2016). It is similar to Impala in features and performance (Azarmi, 2015).

Spark uses a resilient distributed dataset (RDD) as a basic abstraction for a distributed dataset. The core operations (map, reduce and groupByKey) can be accomplished on the elements of the RDD and any one of those operations is evaluated lazily (transformations) or eagerly (actions). The distinct property of RDD is that they are unchangeable; operations on the RDDs create new RDDs (Miller et al., 2016).

Apache Spark is best suitable for near real-time data processing, and not for real-time processing because Spark uses mini batches that are not suitable for event level processing. The attractive feature of Spark is the capability to manage Machine Learning (ML) efficiently, due to its memory caching capacity that is impressive. Almost all of the popular streaming data sources can be easily integrated into the Spark API (Morshed et al., 2016).

4.4 Hortonworks

Hortonworks Data Platform (HDP) is based on Apache Hadoop. It offers its free and open source version of Hadoop along with services and training (Dinsmore, 2016). HDP agglutinates the stable components instead of distributing the latest version of the Hadoop project (Azarmi, 2015). Contrasting with Cloudera, HDP is 100% open source and totally free. It is an excellent choice for organizations that need the capability and cost-effectiveness of Apache Hadoop, with ready business tools (Chandrasekhar et al., 2013; "HDP," 2016).

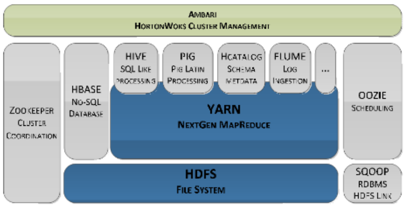


Figure 3: Hortonworks distribution (Azarmi, 2015).

As seen in Figure 3, HDP contains an integrated solution comprised of open source solutions such as Hadoop, Pig, Hive, Yarn, etc. (Khalifa et al., 2016). The components of Hadoop core stack are represented in blue, the components of the Hadoop Ecosystem project are in grey, and the specific component from HDP is represented in green (Azarmi, 2015). To deal with the performance issues, the HDP promotes Apache Tez as a performance optimizer (Dinsmore, 2016). This platform does not view the Hadoop as an alternative to traditional data management platforms and thus focuses on offering integration components for traditional data management platforms ("HDP," 2016). HDP looks for Hadoop as a tool to complement the existing data platforms, a similar vision with the Proprietary Software vendors.

4.5 HPPC System

The High-Performance Computing Cluster (HPCC) Systems Big Data is an open source framework that is used for manipulating, querying, transforming, as well as data warehousing. This framework is typically used as a choice instead of the Hadoop-based platforms, and there are two versions of the platform, one paid and one free (Chandrasekhar et al., 2013).

The HPCC uses the Linux operating system to support the layers of custom-built middleware components, thus providing an environment for running and supporting the distributed file system for data-intensive computing. It makes use of Thor data refinery that is identical to the Hadoop-MapReduce combination, with its functions and capabilities, however, with similar configurations, it offers a much better performance (Furht and Villanustre, 2016). The HPPC data delivery engine Rapid Online XML Inquiry Engine (Roxie) as the name suggests is an online high performance structured query and analysis tool that supports parallel data access processing requests per node per second with sub-seconds response times (Furht and Villanustre, 2016) and the ECL – Enterprise Control Language. This Easy-to-learn and consistent programming language (ECL) was designed specifically for big data processing. There is another version called the community edition, which is a free HPCC version and is also supported by active developers and enthusiasts' community through online forums of discussion. The HPCC Systems platform has the same core technology that LexisNexis has used for years to analyse enormous data sets for its customers in industry, law enforcement, government, and science ("HPCC Systems Platform," 2016).

Due to the high-performance and cost-effectiveness of its implementation, the HPCC has been adopted by several government agencies, companies and research laboratories (Furht and Villanustre, 2016).

5 PLATFORMS COMPARISON

This work aimed at analysing five of the most popular open source big data platforms describing some of the more significant qualities, characteristics, capabilities, and functionalities of each platform. Table 1 shows a succinct description and the key features, contributing to the identification of the Big Data platforms for analytics that may be suitable for SMEs in their day-to-day business operations.

6 CONCLUSIONS AND FUTURE WORK

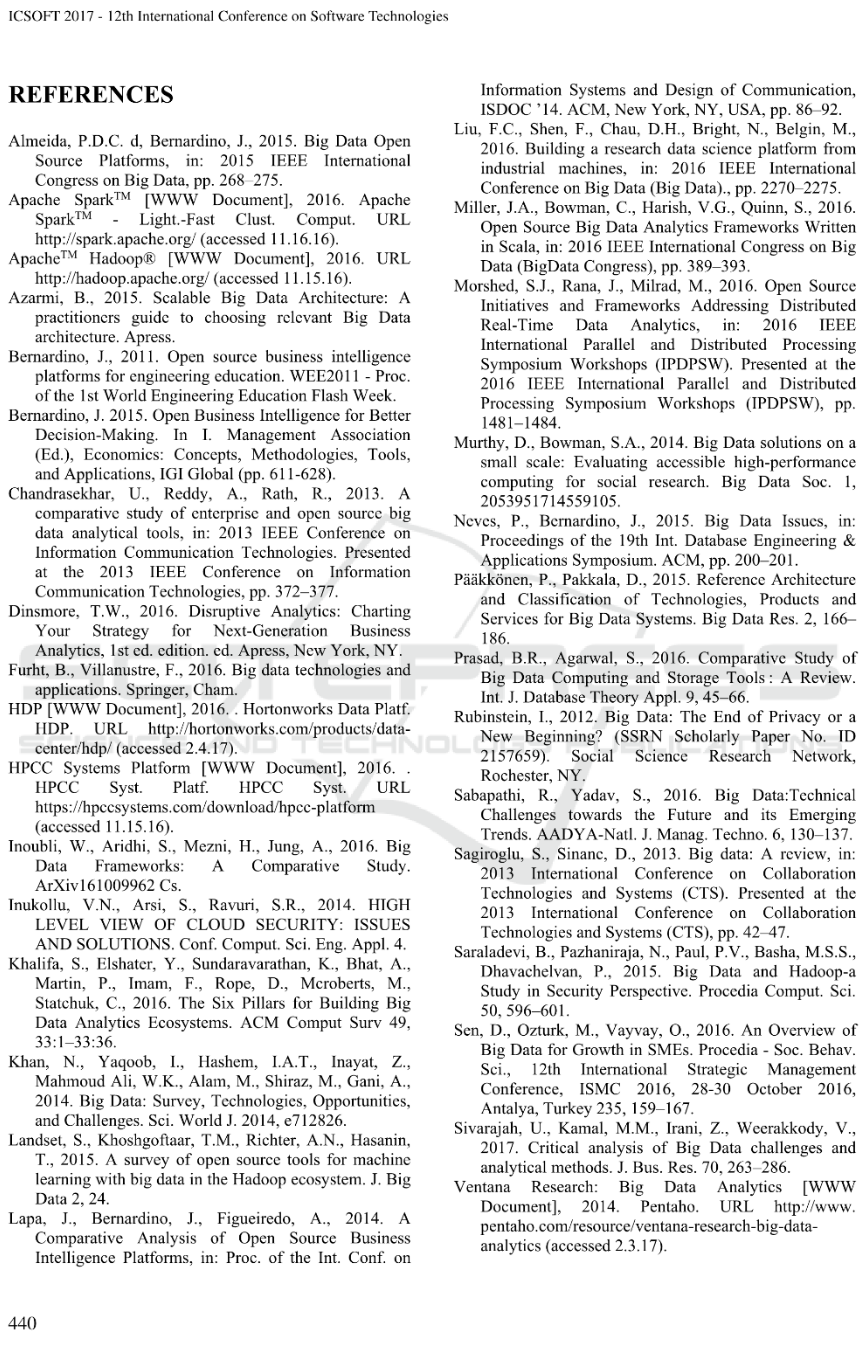
Big Data and Big Data Analytics have a direct relationship with the generation of knowledge since it is a fundamental and necessary element for decision-making within an organization, where information has been acquired.

In the open source platforms analysed Hadoop is the most used and serves as base for some other platforms. We suggest that the Cloudera is better suited for all contexts, particularly when users intend to deal and interact with large data sets in real-time. However, for integration with existing traditional data management systems we propose Hortonworks Data Platform because it has its own data integration modules that allows better support for other systems in an approach in terms of processes, analysis, and manipulation of various data sources.

As future work we propose to test in more detail the platforms characteristics, capabilities and functionalities in Big Data Analytics. We intend to experiment and explore the platforms in a real business environment.

Table 1: Big Data Platforms – comparative table.

	Description	Strong Points
Apache Hadoop	The most popular platform that implements the MapReduce paradigm and uses the HDFS.	-Largest community -Popularity -Forefront
Cloudera	The most well-known Hadoop-based platform. Same methods, functions, main properties as Hadoop, but more efficient in storage, retrieval, and analysis.	-Innovative -Efficient tools for social media -SQL tools for real-time analytics -User-friendly interface -Stability -Training & Support
Apache Spark	This platform runs programs faster than MapReduce on disk or memory and can be integrated to work with others platforms.	-Supports several programming languages -Integration with other platforms -Efficient analytics -Memory caching capacity -Complete SQL interface
Hortonworks	This platform is also Hadoop-based but only uses the stable components. Promotes the Apache Tez to deal with performance issues and the Apache Ambari as the cluster manager.	-Training & Support -Stability -Ready business tools -Low complexity for integration into an IT infrastructure -Windows support
HPCC	Typically chosen as alternative to Hadoop-based platforms, uses Thor data refinery as a distributed file system and for processing data across several nodes.	-High-performance -Consistent programming language (ECL) -Experienced -Robust solution



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Appendix II: Value Analysis Questionnaire

Q1: Numa fase inicial de um processo de negócio e de inovação, baseado no modelo de Peter Koen:
Identifique e explicite, de acordo com o seu tema de projeto, os 5 elementos chave do modelo "the new concept development model" (NCD).
Identifique métodos/técnicas e/ou ferramentas para analisar cada elemento chave.

R1: O conceito de desenvolvimento neste trabalho é sistemático, é um estudo cooperativo e espera ser uma aplicação de inovação. A inovação consiste em novas ideias, conceitos, doutrinas, etc. O *the new concept development model* é importante para este e qualquer trabalho porque possibilita e potencia conceitos alternativos.

Os cinco elementos-chave do modelo "the new concept development model"(Koen et al., 2001) são:

a) *Opportunity Identification*: É neste momento que organização identifica uma oportunidade para obter uma vantagem competitiva, responder a uma ameaça ou resolver um problema. Este elemento é normalmente motivado pelos objetivos do negócio. Nesta etapa podem-se usar técnicas de criatividade, resolução de problemas, *brainstorming*. E utilizadas como ferramentas o diagrama de espinha de peixe (Ishikawa), mapas mentais e mapeamento de processos.
b) *Opportunity Analysis*: Aqui é onde se considera que a oportunidade deve ser avaliada e estabelecida uma prioridade à mesma. Uma boa análise da oportunidade irá determinar o tempo e esforço despendido, o tempo de desenvolvimento, o ajuste com a estratégia e cultura da empresa, e os possíveis riscos. Nesta etapa podem-se usar técnicas de grupos de discussão, pesquisa de mercado, análise de tendências e estudo de cenários. Para esta fase podem-se usar ferramentas como o diagrama de espinha de peixe (Ishikawa), mapas mentais e mapeamento de processos.
c) *Idea genesis*: É neste elemento onde a oportunidade é formulada e transformada em novas ideias de produto. Sendo um processo evolutivo as ideias sugeridas, estas podem ser eliminadas, unidas, ajustadas, alteradas e atualizadas, até surgir uma solução que vá de encontro à necessidade do cliente, e à capacidade produtiva ou comercial. Nesta etapa podem-se usar técnicas de contato direto com os clientes e utilizadores, parcerias com outras equipas transversais, colaboração com outras organizações ou instituições, *brainstorming*, e etnografia. E utilizadas como ferramentas um banco de ideias, folhas de cálculo, *software* e sistemas de informação e comunicação.
d) *Idea selection*: Depois de ter as ideias formadas, é neste passo onde a melhor ideia é escolhida ou várias ideias para o desenvolvimento do conceito. Nesta etapa podem-se usar técnicas de determinação de sucesso probabilístico, probabilidade de sucesso comercial, retorno, encaixe estratégico e processos de seleção de ideias com *feedback* dos criadores das ideias. E utilizadas como ferramentas um *software* especifico.
e) *Concept & Technology Development*: É onde se seleciona os conceitos da ideia com o objetivo de alocação de recursos e se inicia o processo de desenvolvimento de novos

produtos. Nesta etapa podem-se usar técnicas de desenho de experiencias, otimização matemática, teste do conceito e *brainstorming*. E como ferramentas *software* (exemplo: planeamento e de analise de viabilidade).

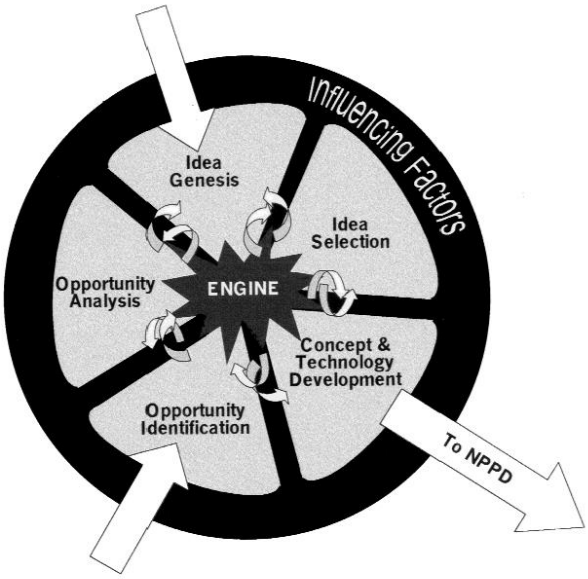


Figura 1 - The NCD model of front end of innovation (Koen et al., 2001)

Q2: Baseado nos conceitos “value”, “value for the customer” e “perceived value”, e de acordo com o tema da sua tese, qual o valor (benefícios/sacrifícios) para o cliente? Justifique convenientemente a sua resposta enquadrando os vários benefícios /sacrifícios numa perspetiva longitudinal de valor.

R2: O cliente pode obter benefícios ao implementar uma plataforma *open source* para análise de Big Data enquanto ao mesmo tempo sacrifica algum tempo e custos. Como não existe um custo de aquisição do *software* pode haver um valor percebido diferente e não totalmente quantificável, ou seja, resulta do custo-benefício que o cliente reconhece, por exemplo se o cliente após a implementação reconhecer uma vantagem competitiva e produtiva, o valor percebido será que foi uma boa aposta e de grande valor, e caso não tenha sucesso, o investimento foi residual.

Q3: Enuncie a proposta de valor do seu Produto/Serviço.

R3: ver 2.2 acima (Value Proposition)

Q4: Apresente o modelo de negócio de Canvas para descrever a sua ideia de negócio.

R4: ver 2.2 acima (Canvas Model)

Q5: "People naturally network as they work so why not model itself as network" (V.Allee). Baseado nesta afirmação, de que forma podemos contruir e analisar o valor? Explique de que forma poderia utilizar o modelo de Verna Allee ou a cadeia de valor de Porter para analisar o valor de negócio.

R5: Segundo Verna Allee o valor de negócio é melhor desenvolvido através de uma rede de valor e criado através da cadeia de valor. Os dois tipos de valor que identifica são os tangíveis e os intangíveis. Assim, o valor não se limita aos produtos e serviços (valores tangíveis), mas também se cria valor intangível, como o conhecimento, *know-how* técnico, etc.

Q6: De uma forma geral, um problema que envolva a necessidade de optar por uma decisão que envolva critérios e alternativas com graus de importância diferentes ou pesos variáveis para o decisor é necessário o uso de métodos multicritério. A variação desses pesos para cada critério pode ter diferentes motivos, podendo por exemplo, numa análise de valor de negócio depender de valor para cliente, da perceção do cliente, dos processos existentes, ou mesmo de outras opções com carácter subjetivo. Através de um exemplo real ou ilustrativo do seu trabalho, indique de que forma utilizaria o método AHP. Apresente os cálculos necessários à elaboração do método.

R6: O *Analytical Hierachy Process* (AHP) é um processo usado para o processo de decisão. E que acrescenta valor na gestão de um trabalho, porque estabelece prioridades, parâmetros ótimos e de seleção de alternativas(Grandzol, 2005). Assim, o método AHP pode simplificar e organizar de forma racional os critérios necessários para a realização deste trabalho de estudo e facilitar a análise e gestão da execução do trabalho.

Por exemplo uma PME quer uma plataforma *open source* para BDA, terá que escolher uma que preencha aos requisitos mínimos exigidos por uma PME e que garanta a continuidade dos negócios fundamentais na área do BI.

Para este exemplo os critérios utilizados são os seguintes:

- Plataforma Open Source para BDA
    - Custo com Hardware
    - Formação
    - Integração
- Critérios de qualidade de *software* (ISO/IEC 9126)
    - Funcionalidade
    - Manutenibilidade
    - Confiabilidade

- Usabilidade
- Eficiência
- Portabilidade

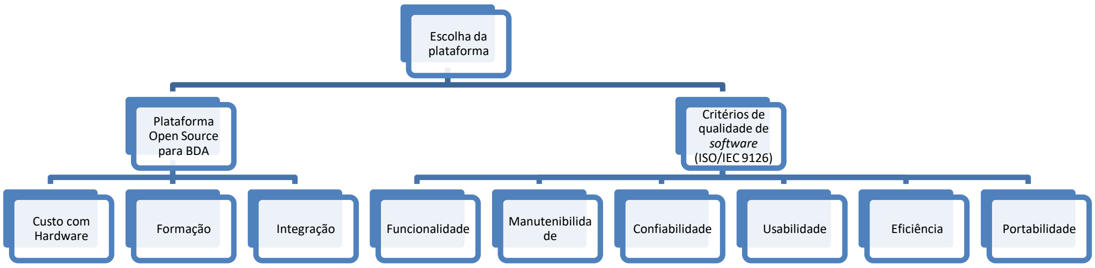


Figura 2 - Estrutura Hierárquica da escolha da plataforma

A importância dos critérios e respetiva matriz de comparação é a seguinte:

Tabela 1 - Matriz de comparação de critérios e respetiva matriz normalizada

Critérios	Plataforma OS para BDA	Qualidade
Plataforma OS para BDA	1	3
Qualidade	1/3	1
SOMA	4/3	4/1

Critérios	Plataforma OS para BDA	Qualidade	Prioridade Relativa
Plataforma OS para BDA	3/4	3/4	0,75
Qualidade	1/4	1/4	0,25

Observa-se que na matriz de comparação, o critério Plataforma OS para BDA têm 3 em relação ao critério da Qualidade, assim é mais importante.

No próximo passo é calcular a Razão de Consistência (RC).

$$Aw = \lambda_{max} \times w$$

Λmax = Média(1,5/0,75;0,50/0,25) = 2,00

Uma vez calculado Λmax, deve-se calcular o Índice de Consistência (IC) para logo calcular a Razão de Consistência (RC).

O índice de consistência é determinado de acordo com a fórmula abaixo, em que n é o número de critérios:

$$IC = \frac{\lambda_{max} - n}{n - 1}$$

IC=(2,0-2) / (2-1) = 0

Após feita a comparação dos critérios principais, fez-se uma comparação entre os subcritérios estabelecidos para um dos critérios.

Tabela 2 - Matriz de comparação de subcritérios de qualidade

Subcritérios	Funcionalidade	Manutenibilidade	Confiabilidade	Usabilidade	Eficiência	Portabilidade
Funcionalidade	1	3	3	2	3	3
Manutenibilidade	1/3	1	2	1/3	1/2	2
Confiabilidade	1/3	1/2	1	1/3	1/2	1/2
Usabilidade	1/2	3	3	1	3	4
Eficiência	1/3	2	2	1/3	1	3
Portabilidade	1/3	1/2	2	1/4	1/3	1

Tabela 3 - Matriz de comparação de critérios plataformas BDA

Subcritérios	Custo com hardware	Formação	Integração
Custo com hardware	1	3	2
Formação	1/3	1	2
Integração	1/2	1/2	1
SOMA	11/6	9/2	5/1

Subcritérios	Custo com hardware	Formação	Integração	Prioridade Relativa
Custo com hardware	6/11	2/3	2/5	0,537
Formação	2/11	2/9	2/5	0,268
Integração	3/11	1/9	1/5	0,195

Observa-se que nos subcritérios de qualidade a Funcionalidade e Usabilidade foram os critérios com maior peso.

A comparação das alternativas (plataformas) é apresentada na seguinte tabela.

Tabela 4 - Comparação de alternativas

Funcionalidade	Plataforma A	Plataforma B	Plataforma C
Plataforma A	1	1/4	1/2
Plataforma B	4	1	2
Plataforma C	2	1/2	1

Manutenibilidade	Plataforma A	Plataforma B	Plataforma C
Plataforma A	1	3,00	1/3
Plataforma B	1/3	1	1/2
Plataforma C	3	2	1

Confiabilidade	Plataforma A	Plataforma B	Plataforma C
Plataforma A	1	1/4	1/2
Plataforma B	4	1	2
Plataforma C	2	1/2	1

Eficiência	Plataforma A	Plataforma B	Plataforma C
Plataforma A	1	1/4	1/2
Plataforma B	4	1	2
Plataforma C	2	1/2	1

Usabilidade	Plataforma A	Plataforma B	Plataforma C
Plataforma A	1	2	1/2
Plataforma B	1/2	1	1/2
Plataforma C	1/2	2	1

Portabilidade	Plataforma A	Plataforma B	Plataforma C
Plataforma A	1	5	1/4
Plataforma B	1/5	1	1/5
Plataforma C	4	5	1

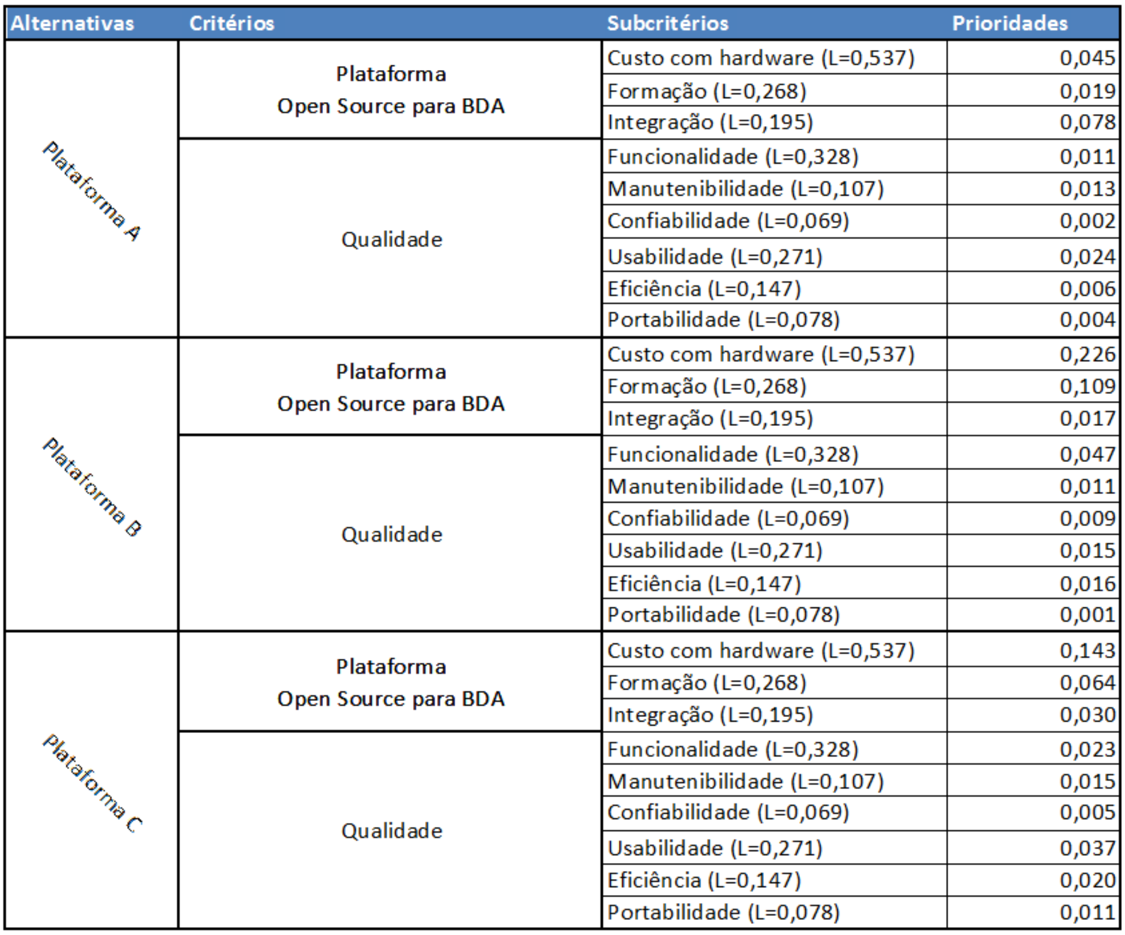
Custo com hardware	Plataforma A	Plataforma B	Plataforma C
Plataforma A	1	1/4	1/4
Plataforma B	4	1	2
Plataforma C	4	1/2	1

Formação	Plataforma A	Plataforma B	Plataforma C
Plataforma A	1	1/5	1/4
Plataforma B	5	1	2
Plataforma C	4	1/2	1

Integração	Plataforma A	Plataforma B	Plataforma C
Plataforma A	1	4	3
Plataforma B	1/4	1	1/2
Plataforma C	1/3	2	1

Na seguinte tabela apresentam-se os resultados das prioridades normalizadas obtidas com base nos julgamentos realizados.

Tabela 5 - Prioridades



Alternativas	Critérios	Subcritérios	Prioridades
Plataforma A	Plataforma Open Source para BDA	Custo com hardware (L=0,537)	0,045
		Formação (L=0,268)	0,019
		Integração (L=0,195)	0,078
	Qualidade	Funcionalidade (L=0,328)	0,011
		Manutenibilidade (L=0,107)	0,013
		Confiabilidade (L=0,069)	0,002
		Usabilidade (L=0,271)	0,024
		Eficiência (L=0,147)	0,006
		Portabilidade (L=0,078)	0,004
Plataforma B	Plataforma Open Source para BDA	Custo com hardware (L=0,537)	0,226
		Formação (L=0,268)	0,109
		Integração (L=0,195)	0,017
	Qualidade	Funcionalidade (L=0,328)	0,047
		Manutenibilidade (L=0,107)	0,011
		Confiabilidade (L=0,069)	0,009
		Usabilidade (L=0,271)	0,015
		Eficiência (L=0,147)	0,016
		Portabilidade (L=0,078)	0,001
Plataforma C	Plataforma Open Source para BDA	Custo com hardware (L=0,537)	0,143
		Formação (L=0,268)	0,064
		Integração (L=0,195)	0,030
	Qualidade	Funcionalidade (L=0,328)	0,023
		Manutenibilidade (L=0,107)	0,015
		Confiabilidade (L=0,069)	0,005
		Usabilidade (L=0,271)	0,037
		Eficiência (L=0,147)	0,020
		Portabilidade (L=0,078)	0,011

Tal como referido anteriormente, pode-se concluir que os critérios para a Plataforma Open Source para BDA (L=0,750) tem prioridade em relação aos critérios da Qualidade (L=0,250).

Assim determina-se a prioridade global para cada alternativa:

- Plataforma A: [0,045+0,019+0,078+0,011+0,013+0,002+0,024+0,006+0,004] ≅ 0,202
- Plataforma B: [0,226+0,109+0,017+0,047+0,011+0,009+0,015+0,016+0,001] ≅ **0,450**
- Plataforma C: [0,143+0,064+0,030+0,023+0,015+0,005+0,037+0,020+0,011] ≅ 0,348

A plataforma mais viável é a plataforma B.

Appendix III - Tests and Evaluation Questionnaire

Questão #1

Descrição clara e sucinta do problema e objetivos

R1: Muitas organizações possuem acesso a dados, e essa informação a retirar pode ter potencial de alterar significativamente o seu comportamento e sua dinâmica organizacional. Mas, estas organizações não conseguem tirar partido deste potencial, pois estes dados por vezes são demasiados e difíceis de processar, armazenados nas mais diversas formas e com características diferentes. Toda esta necessidade de analisar dados para retirar valor e produzir novos produtos/serviços traz consigo grandes desafios, que podem ser ultrapassados pela adoção de uma plataforma de código aberto para análise *Big Data* adequada. Portanto, é indispensável o enquadramento conceptual e tecnológico da temática da *Big Data Analytics*, incluindo a análise de plataforma de código aberto para análise *Big Data* já existentes, de modo a identificar as suas características e limitações.

Questão #2

Que grandezas vai utilizar para avaliar o seu trabalho (e.g. tempo, memória, accuracy, satisfação do utilizador, …)? Justifique.

R2: Neste trabalho de pesquisa vou analisar tempos médios de resposta a *queries* e user-defined functions. Serão feitas *n* execuções e será calculada uma média aritmética simples por teste. Os testes serão em número ímpar. Como os dados (data sets) serão de repositórios (exemplo: Common Crawl[15]), não será fácil aferir a precisão e número de resultados.

Questão #3

Que hipótese ou hipóteses pretende testar para suportar os resultados do seu trabalho?

R3:Não irão ser feitos testes de hipótese, o número de testes serão impar e não há tempos esperados nem de referência, como serão testadas duas plataformas, uma delas irá ter melhor resultado.

[15] http://commoncrawl.org/

Questão #4

Qual a metodologia de avaliação (e.g. grupos de controlo/teste, usar crossvalidation, resultados inquérito de satisfação, …)? Justifique.

R4: O Método de Avaliação será com base no resultado dos testes que correspondem a critérios (ex: aggregation query) a soma dos testes determinará a classificação de cada plataforma.

Questão #5

Como pretende testar essas hipóteses (que teste estatístico vai usar)? Justifique.

R5: Não é aplicável.

Appendix IV – Queries used in tests

HPCC: ECL – Enterprise Control Language

Q1

```
#option('outputLimit',500);

ComS := RECORD
   STRING Date_received;
   STRING Product;
   STRING Sub_product;
   STRING Issue;
   STRING Sub_issue;
   STRING Consumer_complaint_narrative;
   STRING Company_public_response;
   STRING Company;
   STRING State;
   STRING ZIP_code;
   STRING Tags;
   STRING Consumer_consent_provided;
   STRING Submitted_via;
   STRING Date_sent_to_company;
   STRING Company_response_to_consumer;
   STRING Timely_response;
   STRING Consumer_disputed;
   UNSIGNED3 Complaint_ID;
END;

//Data
Complaints :=
DATASET('~isep::complaints::consumer_complaints.csv',ComS,CSV(HEADING(1),
SEPARATOR([','])));
Complaints;
```

Q2

```
#option('outputLimit',500);

ComS := RECORD
   STRING Date_received;
   STRING Product;
   STRING Sub_product;
   STRING Issue;
   STRING Sub_issue;
   STRING Consumer_complaint_narrative;
   STRING Company_public_response;
   STRING Company;
   STRING State;
   STRING ZIP_code;
   STRING Tags;
   STRING Consumer_consent_provided;
   STRING Submitted_via;
   STRING Date_sent_to_company;
   STRING Company_response_to_consumer;
   STRING Timely_response;
   STRING Consumer_disputed;
   UNSIGNED3 Complaint_ID;
END;

//Data
Complaints :=
DATASET('~isep::complaints::consumer_complaints.csv',ComS,CSV(HEADING(1),
SEPARATOR([','])));
WyomingComplaints:= Complaints(State='WY');
WyomingComplaints;
```

Q3

```
#option('outputLimit',500);

ComS := RECORD
   STRING Date_received;
   STRING Product;
   STRING Sub_product;
   STRING Issue;
   STRING Sub_issue;
   STRING Consumer_complaint_narrative;
   STRING Company_public_response;
   STRING Company;
   STRING State;
   STRING ZIP_code;
   STRING Tags;
   STRING Consumer_consent_provided;
   STRING Submitted_via;
   STRING Date_sent_to_company;
   STRING Company_response_to_consumer;
   STRING Timely_response;
   STRING Consumer_disputed;
   UNSIGNED3 Complaint_ID;
END;

//Data
Complaints :=
DATASET('~isep::complaints::consumer_complaints.csv',ComS,CSV(HEADING(1),
SEPARATOR([','])));
WyomingComplaints:= Count(Complaints(State='WY'));
WyomingComplaints;
```

Q4

```
#option('outputLimit',500);

ComS := RECORD
   STRING Date_received;
   STRING Product;
   STRING Sub_product;
   STRING Issue;
   STRING Sub_issue;
   STRING Consumer_complaint_narrative;
   STRING Company_public_response;
   STRING Company;
   STRING State;
   STRING ZIP_code;
   STRING Tags;
   STRING Consumer_consent_provided;
   STRING Submitted_via;
   STRING Date_sent_to_company;
   STRING Company_response_to_consumer;
   STRING Timely_response;
   STRING Consumer_disputed;
   UNSIGNED3 Complaint_ID;
END;

//Data
Complaints :=
DATASET('~isep::complaints::consumer_complaints.csv',ComS,CSV(HEADING(1),
SEPARATOR([','])));
NewYorkComplaints:= Count(Complaints(State='NY'));
NewYorkComplaints;
```

Q5

```
#option('outputLimit',500);

ComS := RECORD
   STRING Date_received;
   STRING Product;
   STRING Sub_product;
   STRING Issue;
   STRING Sub_issue;
   STRING Consumer_complaint_narrative;
   STRING Company_public_response;
   STRING Company;
   STRING State;
   STRING ZIP_code;
   STRING Tags;
   STRING Consumer_consent_provided;
   STRING Submitted_via;
   STRING Date_sent_to_company;
   STRING Company_response_to_consumer;
   STRING Timely_response;
   STRING Consumer_disputed;
   UNSIGNED3 Complaint_ID;
END;

//Data
Complaints :=
DATASET('~isep::complaints::consumer_complaints.csv',ComS,CSV(HEADING(1),
SEPARATOR([','])));
WYComplaints:= SORT(Complaints(State='WY'),Complaint_ID);
WYComplaints;
```

Q6

```
#option('outputLimit',500);

ComS := RECORD
   STRING Date_received;
   STRING Product;
   STRING Sub_product;
   STRING Issue;
   STRING Sub_issue;
   STRING Consumer_complaint_narrative;
   STRING Company_public_response;
   STRING Company;
   STRING State;
   STRING ZIP_code;
   STRING Tags;
   STRING Consumer_consent_provided;
   STRING Submitted_via;
   STRING Date_sent_to_company;
   STRING Company_response_to_consumer;
   STRING Timely_response;
   STRING Consumer_disputed;
   UNSIGNED3 Complaint_ID;
END;
//Data
Complaints :=
DATASET('~isep::complaints::consumer_complaints.csv',ComS,CSV(HEADING(1),
SEPARATOR([','])));
WyomingComplaints:=Complaints(State='WY');
GroupWyomingComplaints:=RECORD
         WyomingComplaints.Complaint_ID;
END;

```

```
WYComplaints:= TABLE(WyomingComplaints,GroupWyomingComplaints,
Complaint_ID);
WYComplaints;
```

Q7

```
#option('outputLimit',500);

ComS := RECORD
   STRING Date_received;
   STRING Product;
   STRING Sub_product;
   STRING Issue;
   STRING Sub_issue;
   STRING Consumer_complaint_narrative;
   STRING Company_public_response;
   STRING Company;
   STRING State;
   STRING ZIP_code;
   STRING Tags;
   STRING Consumer_consent_provided;
   STRING Submitted_via;
   STRING Date_sent_to_company;
   STRING Company_response_to_consumer;
   STRING Timely_response;
   STRING Consumer_disputed;
   UNSIGNED3 Complaint_ID;
END;
//Data
Complaints :=
DATASET('~isep::complaints::consumer_complaints.csv',ComS,CSV(HEADING(1),
SEPARATOR([','])));
WyomingComplaints:=Complaints(State='WY');
GroupWyomingComplaints:=RECORD
            WyomingComplaints.Complaint_ID;
            WyomingComplaints.Date_received;
            WyomingComplaints.Issue;
            WyomingComplaints.Company;
            WyomingComplaints.State;
END;

WYComplaints:= SORT(TABLE(WyomingComplaints,GroupWyomingComplaints,
Complaint_ID),Complaint_ID);
WYComplaints;
```

Q8

```
ComS := RECORD
   STRING Date_received;
   STRING Product;
   STRING Sub_product;
   STRING Issue;
   STRING Sub_issue;
   STRING Consumer_complaint_narrative;
   STRING Company_public_response;
   STRING Company;
   STRING State;
   STRING ZIP_code;
   STRING Tags;
   STRING Consumer_consent_provided;
   STRING Submitted_via;
   STRING Date_sent_to_company;
   STRING Company_response_to_consumer;
   STRING Timely_response;
   STRING Consumer_disputed;
   UNSIGNED3 Complaint_ID;
END;

Complaints :=
DATASET('~isep::complaints::consumer_complaints.csv',ComS,CSV(HEADING(1),
SEPARATOR([','])));
WyomingComplaints:=Complaints(State='WY');
GroupWyomingComplaints:=RECORD
           WyomingComplaints.Product;
           Total:=COUNT(GROUP);
END;

WYComplaints:= TABLE(WyomingComplaints,GroupWyomingComplaints, Product);
WYComplaints;
```

Q9

```
ComS := RECORD
   STRING Date_received;
   STRING Product;
   STRING Sub_product;
   STRING Issue;
   STRING Sub_issue;
   STRING Consumer_complaint_narrative;
   STRING Company_public_response;
   STRING Company;
   STRING State;
   STRING ZIP_code;
   STRING Tags;
   STRING Consumer_consent_provided;
   STRING Submitted_via;
   STRING Date_sent_to_company;
   STRING Company_response_to_consumer;
   STRING Timely_response;
   STRING Consumer_disputed;
   UNSIGNED3 Complaint_ID;
END;

Complaints :=
DATASET('~isep::complaints::consumer_complaints.csv',ComS,CSV(HEADING(1),
SEPARATOR([','])));
WyomingComplaints:=Complaints(State='WY' AND Product='Mortgage');
GroupWyomingComplaints:=RECORD
        WyomingComplaints.Sub_product;
        Total:=COUNT(GROUP);
END;

WYComplaints:= TABLE(WyomingComplaints,GroupWyomingComplaints,
Sub_product);
WYComplaints;
```

Q10

```
#option('outputLimit',500);
ComS := RECORD
   STRING Date_received;
   STRING Product;
   STRING Sub_product;
   STRING Issue;
   STRING Sub_issue;
   STRING Consumer_complaint_narrative;
   STRING Company_public_response;
   STRING Company;
   STRING State;
   STRING ZIP_code;
   STRING Tags;
   STRING Consumer_consent_provided;
   STRING Submitted_via;
   STRING Date_sent_to_company;
   STRING Company_response_to_consumer;
   STRING Timely_response;
   STRING Consumer_disputed;
   UNSIGNED3 Complaint_ID;
END;

Complaints :=
DATASET('~isep::complaints::consumer_complaints.csv',ComS,CSV(HEADING(1),
SEPARATOR([','])));
USAComplaints:=Complaints;
GroupUSAComplaints:=RECORD
        USAComplaints.Product;
        Total:=COUNT(GROUP);
END;

```

```
AllComplaints:= TABLE(USAComplaints,GroupUSAComplaints, Product);
AllComplaints;
```

HDP: HiveQL - Hive query language

Q1

```
select * from complaints
```

Q2

```
select * from complaints where state="WY"
```

Q3

```
select count(*) from complaints where state="WY"
```

Q4

```
select count(*) from complaints where state="NY"
```

Q5

```
select * from complaints
where state = "WY" order by Complaint_ID
```

Q6

```
select Count(*) from (select count(*) from complaints where state="WY" group by
Complaint_ID) as table_1;
```

Q7

```
select distinct Complaint_ID, Date_received, Issue, Company, State  from complaints
where state="WY" order by Complaint_ID
```

Q8

```
select Product, count(*) from complaints where state="WY" group by Product
```

Q9

```
select Sub_product, count(*) from complaints where state="WY" and
Product="Mortgage" group by Sub_product
```

Q10

```
select Product, count(*) from complaints group by Product;
```