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Evaluating Hadoop Distributions: Towards an Enterprise Guide

Bachelor Thesis

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Abstract

Big Data and Cloud Computing are some of today's most respected business trends. Hadoop, a framework providing scalable, distributed computing on commodity hardware, has become the de facto standard for IT. Thus many companies are planning to implement Hadoop in their IT landscape. A whole industry developed around it, providing services, improvements and easier maintenance for the Hadoop framework. However, it is difficult to decide which preconfigured Hadoop distribution like Cloudera, Hortonworks or MapR should be chosen. In this thesis, I investigate the decision factors to compare Hadoop Distributions, focusing on establishing a decision support process using a simple decision matrix.

Contents

Acronyms

AHP	Analytic hierarchy process
CDH	Cloudera Distribution Including Apache Hadoop
CEO	Chief Executive Officer
CRWAD	Create, Read, Write, Append, and Delete
DAG	Directed Acyclic Graph
EDW	Enterprise Data Warehouse
ETL	Extract Transform Load
GB	Gigabytes
GFS	Google File System
GUI	graphical user interface
HA	High Availability
HDFS	Hadoop File System
HDP	Hortonworks Data Platform
JSON	JavaScript Object Notation
MB	Megabytes
MPP	Massively Parallel Processing
PAM	Pluggable Authentication Modules
PB	Petabytes
PMI	Project Management Institute
ROI	Return on Invest
SAN	Storage Area Network
SNMP	Simple Network Management Protocol
SPOF	Single Point of Failure
SWOT	Strengths, Weaknesses, Opportunities and Threats
TB	Terabytes
TCO	Total Cost of Ownership
USP	unique selling proposition
VM	Virtual Machine
ZB	Zettabytes

1. Introduction

Supporting statement, description of my hypothesis, paper context –> allow the reader to understand the reasoning behind my work:

Brief explanation why Big Data, Hadoop, etc. is being hyped.

> Forrester expects the market for big data Hadoop solutions to sky-rocket during the next few years.

[YG12]

Questions:

- What kind of Hadoop Distribution is the right Distribution for my company?
- What are the similarities, what are the differences?
- Could I use a pure open source Hadoop without a distribution?

Hypothesis

Just about every organization is seeking ways to profit from Big Data, and Hadoop is increasingly serving as the most capable conduit to unlock its inherent value. This means that Hadoop is likely to have a major role to play in the enterprise business. Given this probability, one should carefully consider the choice of Hadoop implementation, and pay particular attention to its performance / scalability, manageability, TCO,..., dependability, and ease of data access.

It depends on the use cases and financial opportunities.

- Open-Source => Hortonworks
- Real-Time NoSQL => MapR
- Upgrading => Cloudera or MapR (because of Rolling Updates)
- Disaster Recovery => MapR
- Volume Support => MapR
- Costs Cloudera: $2600 / Node / Anno
- Costs MapR: $4000 / Node / Anno
- Costs Hortonworks: Free (Open Source License)

2. Foundation

2.1. The Rise of Big Data

"You can't manage what you don't measure." - W. Edwards Deming

Deming clearly understood how important metrics are, and it clarifies the data generation and usage burst, managers can learn more about their business by collecting and analyzing data, and thus make informed decisions. Such decisions are often called *data-driven decisions*. The topic of *Big data analytics* evolved during the last years because with the help of big data companies are not trying to confirm their current business model or operational business, but they are "trying to discover new business facts that no one in the enterprise knew before" [R+11]. Basically, the enterprise need to analyze big data is a consequence of the ongoing data growth. Prof. Vossen analyzed in 2014 the drivers leading to big data, and extracted one of the major reasons for it to be the transition from Web 1.0 to Web 2.0. This transition has been possible because of "three parallel streams of development" [Vos14], described in the previous work of Vossen and Hagemann (2010) [VH10]: *the applications stream, the technology stream, and the user participation and contribution stream*. The *applications stream* is described as the platform on which the users access, share and generate information. The *technology stream* is the underlying foundation, enabling the Web through hard- and software. Finally, the *user participation and contribution stream* is the transition of the users from simple information consumers to information producers. Knowing a transition is in progress, the figures we are talking about are impressive: humankind is producing data like never before, for example did Google process 20 Petabytes (PB) of data per day in 2007 [36] and Facebook's data warehouse stores around 300 PB with an incoming rate of roughly 600 Terabytes (TB) per day (April 2014) [41]. If one compares today's humankind's data with the ancient Library of Alexandria, which was in charge of collecting all the world's knowledge, it would be possible "to give every person alive 320 times as much of it as historians think was stored in Alexandria's entire collection - an estimated 1,200 exabytes' worth." [CMS].

Doug Laney (with Gartner) defined big data as four dimensional, including *Volume* (amount/scale of data), *Velocity* (analysis of streaming data, speed of data in and out), *Variety* (different forms of data, like range of data types and sources), and *Veracity* (uncertainty of data) [BL12].

This four dimensional view is sometimes criticized to be [more coming!]

Furthermore is big data itself being criticized, Microsoft Research showed in the article that most of the putative problems, solved by big data computations (jobs), are usually "less than 100 GB of input" [AGN+13].

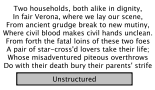

Figure 2.1.: Visualization of unstructured data.

An IBM research, analyzing sources of McKinsey, CISCO, Gartner, EMC, and others gives additional information on the *4 V's* of big data. Regarding *Volume*, by 2020 40 Zettabytes (ZB) of data will be created (see Table A.1 for a comparison of data sizes). *Velocity*, sensors in modern cars monitor fuel level and tire pressure in real time (roughly 100 sensors per car). The *Variety* of different forms is great: on Facebook every month around 30 billion pieces of content are shared and on Twitter 400 million tweets are sent per day. Uncertainty of data, *Veracity*, like poor data quality is expensive, $3.1 trillion a year (for the US economy) [29]. These information show, how the impact of big data is rising and why the industry cares this much about it. In the following chapter big data issues, the Hadoop ecosystem and basics of IT decision processes, used to compare different software frameworks, are explained.

Coming back to the example of Bosch from the introductory of The Rise of Big Data, one may asks how it is possible to store and process such a vast amount of data. The following section will deal with this and other questions, providing an overview of big data computing.

However, storing and working on the data does not provide business insides, thus a major topic of big data is the data exploration, because most enterprise have data stored but no idea what the data can be used for because the data is unstructured and not explored. Such data is often called *dumb data* [32]. Unstructured data can be text, images or audio files, see Figure 2.1, everything that's not machine readable because of missing context or form, e.g. *What is the meaning of Shakespeare's Romeo and Juliet?* is not a question a machine can answer even if the raw data, the poem, is accessible. Structured data is often visualized as some kind of table or cluster, see Figure 2.2, as it is possible for machines to query it, e.g. *What is the value of column 1, row 2?*. The first step of data exploration is information gathering sometimes called getting an *Bird's Eye View*. In this step data from each system and silo, inside and outside the enterprise has to be visualized to understand what is available. Afterwards the data has to be made accessible, to support the enterprise decision making and business operations. Finally the data can be used to discover insights, establish dynamic contextual views of relevant content and reduce uncertainty [28].

The topic of data exploration is way broader than the above introduction. Data exploration is only possible if the enterprise's data is stored digitally and connected. Many companies established data warehouse systems in the last 10 to 15 years, to store their data and to extract reports. During the rise of big data solutions the question came up, whether the approaches are

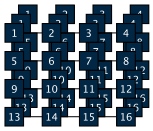

Figure 2.2.: Visualization of tructured data.

adaptive or superseding. Because data warehouses are very different to big data solutions. Bill Inmon, recognized as “the father of the data warehouse”, states, the difficulty of comparing big data solutions to data warehousing is that data warehousing is an information system architecture, whereas a big data solution is a technology. Inmon considers “reliable, believable and accessible data” is only possible to provide with a data warehouse architecture, and additional big data solutions are only supportive systems [11]. In the Chapter Integration with Existing Systems I will answer if and how it is possible to use data warehouses and big data solutions in symbioses and where the main differences rely in.

2.2. Big Data Problems and their Solutions

2.2.1. Scalable, Distributed Computing

Distributed computing exists since the early 90s but in the last two decades different system models developed. Four classifications can have been made by Hwang et al. [HDF13]: *Computer Clusters*, *Peer-to-Peer Networks*, *Data/C omputational Grids*, and *Cloud Platforms*. The differentiation has to be made regarding their architecture, resource management, and type of applications running on top of the cluster. Look at Table 2.1 to get an overview about the differentiation of distributed computing systems.

Hadoop literally represents distributed computing but not directly as grid because Hadoop is not directly centralized and especially not intended to do super-computing or to solve global problems, thus it is better classified as computer cluster.

Talking about scalable and distributed systems one company’s name pops up immediately: *Google*. Even though Google did not invent distributed-computing it applied the techniques on massive scale and on commodity hardware, and because today’s big data solutions, like Hadoop, are built to run on commodity hardware as well and furthermore nearly every solution is building upon the basis of Google’s work with the Google File System (GFS), Bigtable, and MapReduce it is worth explaining that work briefly.

The GFS [GGL03] has been developed to meet the fast expanding need of Google to process it’s data in a reasonable amount of time. An important part of it’s design is fault tolerance, because the GFS consists of many thousands of storage machines, each suffering “from problems caused by application

Table 2.1.: Differentiation of distributed computing systems [HDF13].

Functionality, Applications	**Computer Clusters**	**Peer-to-Peer Networks**	**Data / Computational Grids**	**Cloud Platforms**
Architecture, Network Connectivity, and Size	Network of compute nodes interconnected by SAN, LAN or WAN hierachically	Flexible network of client machines logically connected by an overlay network	Heterogenous clusters interconnected by high-speed network links over selected resource sites	Virtualized cluster of servers over data centers via SLA
Control and Resource Management	Homogenous nodes with distributed control, running, distributed control, running UNIX or Linux	Atonomous client nodes, free in and out, with self-organization	Centralized control, server-oriented with authenticated security	Dynamic resource provisioning of servers, storage and networks
Applications and Network-centric Services	High-performance computing, search engines, and web services etc.	Most appealing to business file sharing, content delivery, and social networking	Distributed supercomputing, global problem solving, and data center services	Upgraded web search, utility computing, and outsourced computing services
Representative Operational Systems	Google Search Engine, SunBlade, IBM Road Runner, Cray XT4, etc.	Gnutella, eMule, BitTorrent, Napster, Kaza, Skype, JXTA	TeraGrid, GriPhyN, UK EGEE, D-Grid, ChinaGrid, etc.	Google App Engine, IBM Bluecloud, AWS, and Microsoft Azure

bugs, operating system bugs, human errors, and the failures of disks, memory, connectors, networking, and power supplies", thus a wide variety of issues requires fault tolerance, build in monitoring, error detection and automatic recovery. Google's research indicates, the most used file operation is *appending*, therefore the file system has to be tuned to support this operation at best. As a result of a cluster file system, including thousands of nodes, the append operation has to be able to process multiple clients, writing concurrently to a file without extra synchronization. GFS made this possible. The file system used by Hadoop the Hadoop File System (HDFS) is an open source implementation of GFS and will be briefly explained in the Chapter The Hadoop Ecosystem. A distributed file system is not enough, some data is better be stored in a database, thus Google developed Bigtable [CDG+08]. Bigtable was build between 2004 and 2006, and is a distributed storage system for managing petabytes of structured data and uses the GFS for log data and file storage. It is a multi-purpose database, including the possibility to store a vast amount of data types, "from URLs to web pages to satellite imagery". The data model used by BigTable is called a *sparse, distributed, persistent multidimensional sorted map*. Such a map is indexed by a row key, column key, and a timestamp. As an example, see Figure 2.3, showing a table, called *Webtable*, for Google's website parsing table. URLs (reversed) are used as row keys, various aspects of web pages as column names, and the contents of the web pages is stored in the *contents* column under the timestamps when they were fetched. Additionally, the anchor column family contains the text of any anchors that reference the page. E.g. CNN's home page is referenced by two other pages the Sports Illustrated and the MY-look home page, hence the row contains columns named `anchor:cnnsi.com` and `anchor:my.look.ca`. Furthermore, each anchor cell has one version; the contents column has three versions, at timestamps t_3, t_5, and t_6 (this is the example of the Google Paper [CDG+08]). The Hadoop counterpart is HBase an open source, non-relational, distributed database modeled after Google's BigTable, briefly explained in the Chapter The Hadoop Ecosystem.

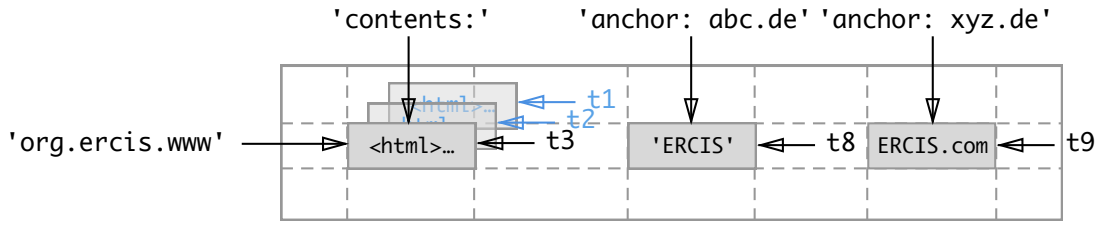

Figure 2.3.: Exemplary slice of a BigTable table that stores Web pages.

Subsequent, after data storage the data usage and processing will be discussed in the following chapter Data Processing on Large Clusters.

2.2.2. Data Processing on Large Clusters

We discovered some of the fundamentals of distributed computing, especially the data storage because this is mandatory for every big data solution. Next, I will provide an overview about how the data is being processed.

MapReduce

MapReduce is a programming model for processing and generating large data sets [DG08]. The model borrows from functional programming, a user implements two functions against two interfaces, a `map` and a `reduce` function, see Listing 2.1 and MapReduce automatically parallelizes, executes, and schedules the job on a large cluster of nodes. Image we would like to parallelize the famous word-count: the map function emits an intermediate result each word plus a count of occurrences (e.g. 1 for each finding). The reduce function sums together all counts, Listing 2.2. Even if modern database systems have built in functions to express the type of computations supported by MapReduce, they are not comparable [DG10].

Listing 2.1: Map and Reduce Interfaces.

```
map (in_key, in_value) -> (inter_key, inter_value) list
reduce (inter_key, inter_value) -> (out_key, out_value) list
```

Listing 2.2: Map and Reduce Sample.

```
map (key, value) ->
  for word in value:
        intermediate(word, 1)
reduce (key, values) ->
  // key: a word; values: a list of counts
  result = 0
  for count in values:
    result += count
  emit(result)
```

For a better understanding look at Fig. 2.4, the data is give to multiple workers of the same map-task. Intermediate results are temporarily stored and handed over to the reduce-task (again multiple workers are possible). The output of the single reduce partition is appended an output file. Since Hadoop Version 0.23 the MapReduce implementation got a successor called MapReduce 2.0 (MRv2) or YARN. I will discuss it briefly in Chapter The Hadoop Ecosystem. Concluding, the main difficulties to overcome for big data are data storage and data processing.

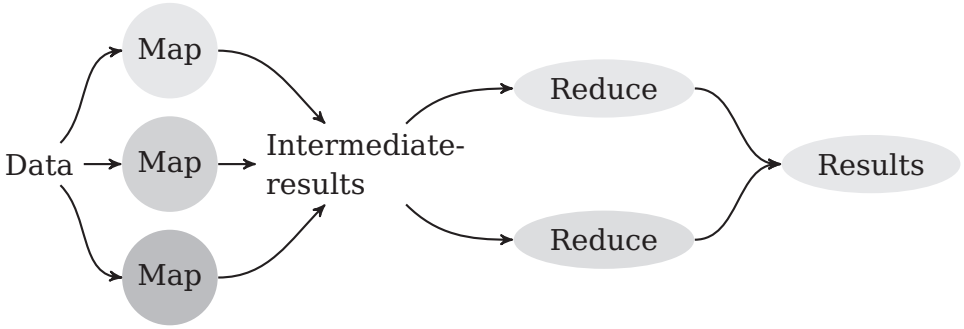

Figure 2.4.: MapReduce Data Flow.

2.3. The Hadoop Ecosystem

Essentially, data storage and data processing on a large scale is what most people mean by big data. Apache Hadoop is a technological solution to conquer these two difficult tasks. Strictly speaking, Hadoop is a set of solutions, like a distributed file-system, a job scheduler etc. One could also say it is some kind of framework "that allows for the distributed processing of large data sets across clusters of computers using simple programming models" [44].

Hadoop is not the only project, solving data storage and processing. Microsoft initiated the *Dryad* project [IBY+07b, IBY+07a], it had the objective to investigate "programming models for writing parallel and distributed programs to scale from a small cluster to a large data-center". Unfortunately, the project has been dropped by Microsoft, which now focuses on Hadoop, thus is not actively maintained anymore [38, 37]. Another, very different but interesting approach has been developed by Joyent, called *SmartDataCenter* (SDC) and *Manta Storage Service*. SDC is a container-based IaaS, cross data-center management platform [33] and Manta is an object storage [CP14] including computing and map-reduce functionality running on top of the SDC [10]. Additionally, a project named Disco has been started in 2009 by Nokia Research and has reached the alpha version 0.5.4 in October 2014 [20]. Dryad is not maintained anymore, SDC and Manta, as well as Disco are very young and not broadly used, Hadoop on the other hand is widely used, established and an economy has been built around it, time will show whether SDC-Manta or Disco are going to replace Hadoop for some use cases but at the moment Hadoop is still the biggest open source big data solution.

Subsequent, I will describe the most important solutions inside Hadoop, followed by some concrete big data challenges, and an introduction of three major Hadoop distributions.

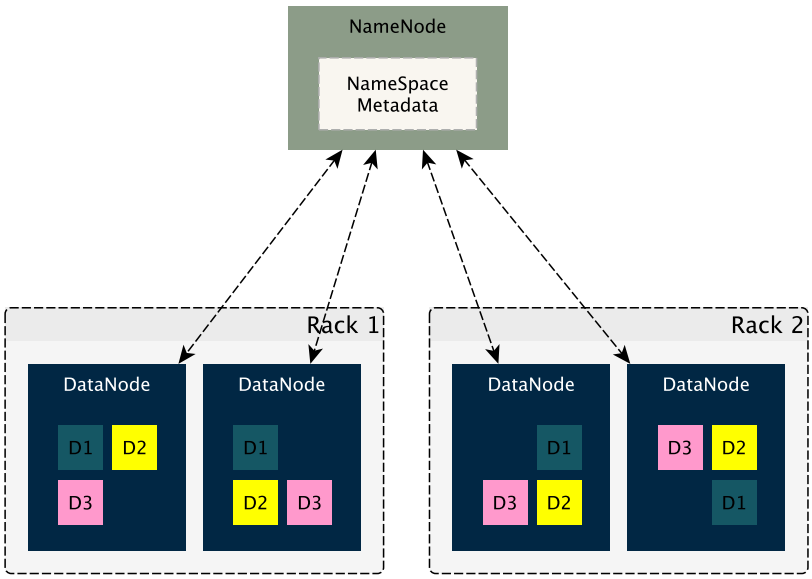

Figure 2.5.: Hadoop HDFS Architecture.

2.3.1. Hadoop Related Open Source Projects

Hadoop File System: HDFS

HDFS is an open source implementation of the GFS but with some changes made. One of the biggest change is the *single writer, no reads allowed during writing* implementation. It was made to have a strong consistency but comes with major drawbacks which I am discussing later, and furthermore how MapR is solving this issue. HDFS does support parallel reading and processing, as well as Create, Read, Write, Append, and Delete (CRWAD) but no random writing. Similar to GFS, HDFS is optimized to read, write and process large files (some Gigabytes (GB) to TB per file) but it can handle small files as well. HDFS is built to be used with a cluster of servers, called nodes. Each cluster has got one node called the NameNode and some thousands DataNodes. Files are stored, chopped into blocks of 64 Megabytes (MB) (recommended by the Apache Hadoop Documentation, different resources talk about 128 MB or 256 MB configurations [6]) chunks, inside the DateNodes and replicated over the nodes, if possible, each chunk will reside on a different DataNode. It has build in disk and node failure detection and recovery, mandatory to run a thousand node cluster of DataNodes.

The HDFS is a Java Application, working on a usual linux file system, like ext3, ext4, or XFS. Thus the DataNodes store blocks on the regular file system and HDFS manages the chopping, replication and fail-over. Have a look at Fig. 2.5 to get an overview of the HDFS architecture.

The Fig. 2.5 shows how a single NameNode is talking to each of the DataNodes, in this example a two rack setup including two DataNodes each. The colored squares `D1`, `D2`, and `D3` are representations of blocks, replicated over

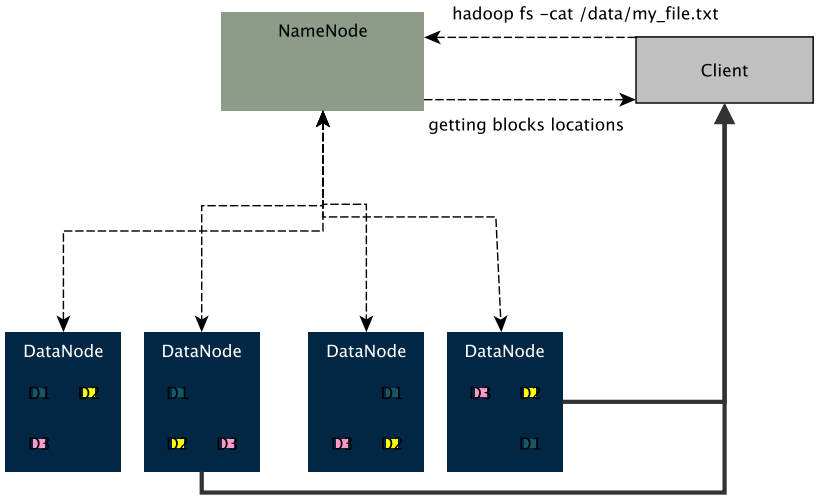

Figure 2.6.: Reading a file from HDFS [7].

the nodes. Reading a file from HDFS is done through an RPC call to the NameNode, asking for the blocks locations followed by the real data consumption from the given DataNodes, see Fig. 2.6. Thus, no block data is ever sent through the name node. As you can see on Fig. 2.5 the NameNode holds NameSpace and Metadata information. The NameSpace is a representation of the directories and files of the file system and a mapping of files to the blocks belonging to them. This data is stored In-Memory to provide a very fast look-up. It is obvious that the NameNode is the clusters Single Point of Failure (SPOF). But since Hadoop Version 2.0 HDFS ships with the so called *High Availability (HA)* feature, which addresses the SPOF problem by "providing the option of running two redundant NameNodes in the same cluster in an active-passive configuration with a hot standby" [4].

HBase

Use Apache HBase when you need random, realtime read/write access to your Big Data. This project's goal is the hosting of very large tables – billions of rows X millions of columns – atop clusters of commodity hardware. Apache HBase is an open-source, distributed, versioned, non-relational database modeled after Google's Bigtable: A Distributed Storage System for Structured Data by Chang et al. Just as Bigtable leverages the distributed data storage provided by the Google File System, Apache HBase provides Bigtable-like capabilities on top of Hadoop and HDFS.

In the last chapters I discussed the most important technical projects and aspects of Apache Hadoop. Following I will provide a short overview about other Hadoop open source projects, which meet special requirements evolved by the enterprise usage of Hadoop.

Hadoop's Data Operating and Workflow Management System: YARN

The MapReduce pattern build into Hadoop is similar to the described pattern in MapReduce. But Hadoop's MapReduce has undergone a complete re-engineering in Hadoop Version 0.23 and got a successor called MapReduce 2.0 (MRv2) or YARN [5]. YARN simplifies two different roles, the ResourceManager (RM) and per-application ApplicationMaster (AM). "An application is either a single job in the classical sense of Map-Reduce jobs or a Directed Acyclic Graph (DAG) [VMZ+10] of jobs" [5]. To put it simple, YARN is a *Data Operating and Workflow Management System*, sometimes described as *Modern Data Operating System*, but because YARN does scheduling and resource management the preceding title is most suitable.

2.3.2. Hadoop Open Source Projects for Special Purposes

Besides the named technologies like HBase, MapReduce and HDFS several others are used inside most of the distributions to provide data access and execution possibilities. Three different but either most used or new and promising components will be described in more detail. *Apache Hive* is a SQL like data warehouse system for Hadoop, enabling developers to store and query data in a relational manner. Additionally, it is possible to plug in MapReduce jobs if necessary. *Apache Pig* is a high-level query language and parallel-processing framework, it lets users write complex MapReduce jobs in the pig-query language. A compiler than builds multiple MapReduce jobs out of the pig-program. *Apache Drill* is a new, but promising Apache top-level project, enabling Business Analysts and Developers to do data discovery, and data analytics across multiple data silos, like offline data warehouses, Hive tables, mobile application click streams log-files, and more. Data warehouses will be discussed later, important to understand is, that Drill is able to analyze structured and semi-structured data regardless of format. For further interest, Table 2.2 provides a brief overview on the other most used components, grouped into five categories: Data Governance and Operations, Data Integration as well as Data Access, Security as well as Access and Execution Engines, see table 4.1 for a detailed category description.

2.3.3. Concrete Big Data Challenges

Big Data does not come without big questions like scalability, performance, availability, security and manageability of the big data platform. CITO Research made a list of five questions one has to ask before choosing an Hadoop distribution and they map very well to mine: "What does it take to make Hadoop enterprise-ready?", "Does the distribution offer scalability, reliability and performance?", "Is the distribution efficient when it comes to TCO and ease of administration?", "What additional workforce expertise does a company need to run Hadoop?" [Res14]. Nearly the same considerations Robert Schneider

brings up in his *Hadoop Buyer's Guide* [Sch13]. Schneider writes about *Performance and Scalability*, *Dependability*, *Manageability* and *Data Access*. As you can see, the challenges of big data and thus of each Hadoop distribution are known. I have collected and researched fifteen considerations for the establishment of a comparison matrix in Chapter Categories for a Distribution Comparison in which I am discussing the relevance of each consideration and in Chapter The Decision Matrix the real distributions are weighted against each other. Furthermore, the following four topics of big data challenges *Scalability and Performance*, *Continuous Availability and Data Security*, *Manageability*, and *Costs* will be briefly discussed.

Scalability and Performance

Regarding performance some factors do count for each big data implementation or distribution. One key factor for performance can be the technology used to build key-components. If key-components are written in technologies *close to the metal*, like C or C++ the performance can increase. Hadoop is written in Java and even the JVM is quite fast [Hun11] it is not as fast as C or C++. Another factor is about the path a big data job has to go to produce an output. For example, Hadoops architecture with the HBase Master, the RegionServer, the JVM and finally the Linux File-System consists of four layers through which a task has to travel. Less numbers of layers result into better performance [Sch13]. Regarding scalability, two main factors are important: does the number of cluster nodes scale unlimited and does the number of files inside the cluster scale unlimited? In The Decision Matrix I am looking into the details of each distribution and MapR's MapReduce engine for example is written in C/C++ and thus it's performance is better for some use-cases, and respecting the number of files in one cluster, MapR scales better as well, because of it's *No-NameNode Architecture*.

Continuous Availability and Data Security

If a big data solution like Hadoop is becoming an enterprises main data source and *data processing engine* it is critical that it can meet the enterprise's dependability expectations. Schneider explains in the *Hadoop Buyer's Guide* that less manual tasks increase the dependability and thus the availability, therefore it is important for a big data solution to provide many axiomatization tools. Another important aspect is the replication of files as well as snapshots and data integrity across the cluster to prevent data loss or corruption caused by node-failures.

Manageability

Traditionally, data came from source like CRM, ERP or SCM systems. This data has been stored in Data Warehouses and used for a strictly defined objective.

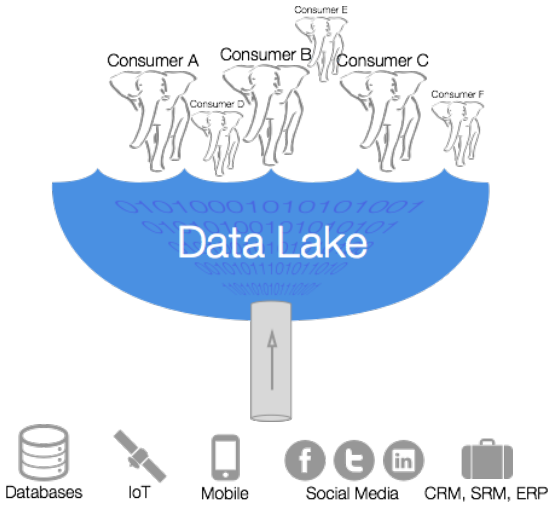

Figure 2.7.: Data Lake.

Integrating a new data source or storage has been expensive, checkout the following chapter Costs, but it existed a clear project goal, for example: *business unit Finance would like to get a report of all financial assets on each Monday*. On the other hand, the data is not being managed and therefore no one feels responsible. Shah, Horne and Capellá state, that most companies are missing a consistent structure, enabling easy access to the existing data [Sha12]. Such a data hub where the data is accessible is often called a *Data Lake*. This term has been created by James Dixon, CTO of Pentaho, who promotes the "Data Lake Architecture" [12]. The Data Lake architecture will be discussed later in greater detail in the Chapter Understanding the Data Lake approach. Furthermore it will be compared with the established Data Warehouse architecture, if one wishes a look ahead, see Figure 2.7. The data lake holds all of the company's data from different sources. Much of the data flows in fast and semi- or unstructured. This differs extremely from data warehouses, see Figure 2.8, where data has to be stored in one structure only and often is not easily accessible.

Costs

The possibility of having access to massive amounts of data comes with the drawbacks of costs for storing it. IT managers made expensive experiences deploying Enterprise Data Warehouse (EDW) and Massively Parallel Processing (MPP), Storage Area Network (SAN), or custom engineered systems, to store and access TB of data. As an alternative, Hadoop "provides storage at 5% of the Costs" [39], see Figure 2.9, for a comparison of traditional data stores with Hadoop. Since the deployment of EDW etc. has been as expensive, managers are looking to achieve *quick wins* on big data solutions, because it shows a " visible contribution to the success of the business" [VBS09] before the company has to make a wide role out.

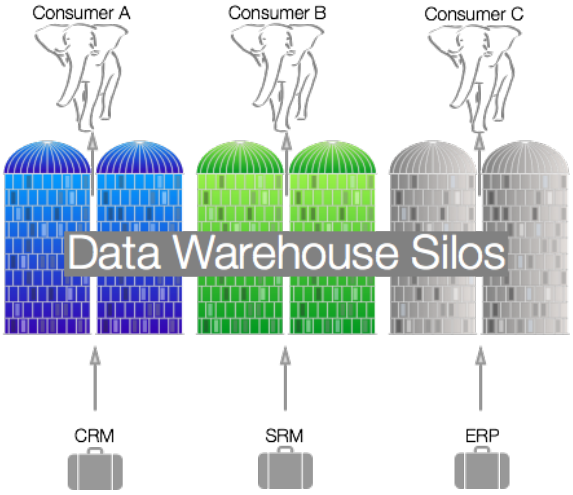

Figure 2.8.: Data Warehouse.

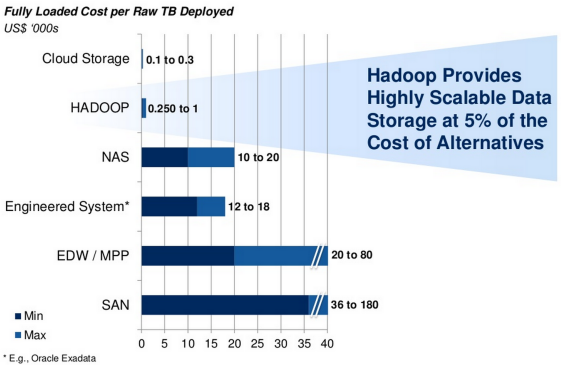

Figure 2.9.: Fully Loaded Cost Per Raw TB of Data, source: Jürgen Urbanski [39].

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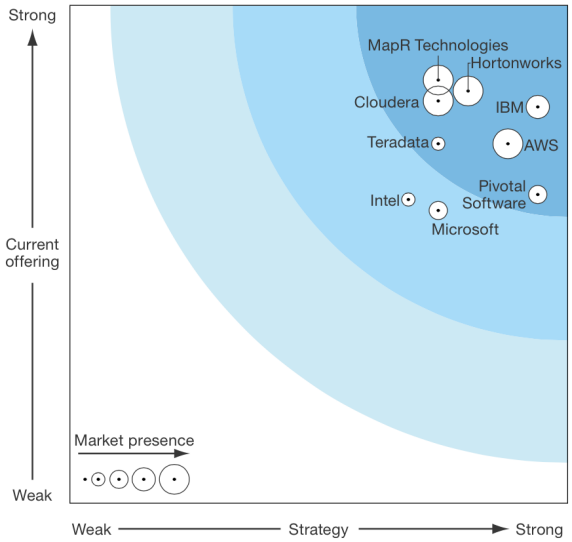

Figure 2.10.: Forrester Wave: Big Data Hadoop Solutions, Q1 2014 [YG12].

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2.3.4. The Hadoop Hype-Cycle and Industry

Hadoop itself is an open source project, but because it is complex as well, a whole industry developed around it. Different vendors of Hadoop distributions appeared during the last years, providing services, improvements and easier maintenance for the Hadoop framework. “Forrester expects the market for big data Hadoop solutions to skyrocket during the next few years” [YG12].

Three major vendors has been chosen to analyze in the Hadoop Distribution Decision Matrix, see chapter Hadoop Distributions Decision Matrix and SWOT Analysis. They have been chosen because of their market share, technologies used and their strategy. Each distribution is a cross-domain solution, thus they do not focus on particular business use-cases. Forrester Research has got a so called “Big Wave” graphic, showing “Big Data Hadoop Solutions, Q1 2014” [YG12], see Fig. 2.10. As the reader can see, the three distributions *Cloudera*, *Hortonworks* and *MapR Technologies* (MapR) are close to each other, are all strong in strategy and current offering and share a similiar market presence. They will be analyzed and the question “how do they compare?” will be asked and answered during the following chapters, but first I will provide an overview of the different solutions.

2.3.5. Hadoop Distributions

Cloudera

Cloudera is the oldest Hadoop service and distribution provider, founded in 2008, closely after the initial open-source Hadoop release. One of Cloudera’s biggest partners is Intel, which recently bought 18% of Cloudera for $740 million [31] in a $900 million funding round, making Cloudera the highest

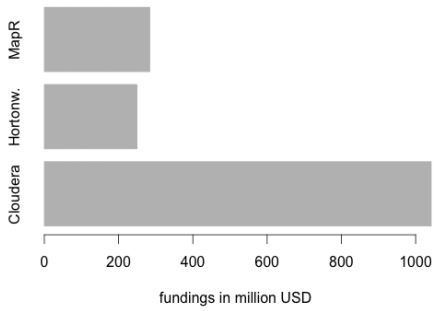


Figure 2.11.: Debs and fundings, sources: [31, 22].

valuated Hadoop company, see Figure 2.11 for a comparison of each vendor and it's capitalization. Cloudera's flagship product for enterprise Hadoop is *Cloudera Enterprise*, including Cloudera Distribution Including Apache Hadoop (CDH) and several further system and data management tools. CDH "is 100% Apache-licensed open source" [15] and can be downloaded and used without any costs. But *Cloudera Enterprise* is not open-source, the *Data Management* and *System Management* components are closed-source and licensed. Cloudera does not have a clear pricing strategy, thus no prices are available on it's website, the distribution price depends on the number of nodes, secondary services etc.

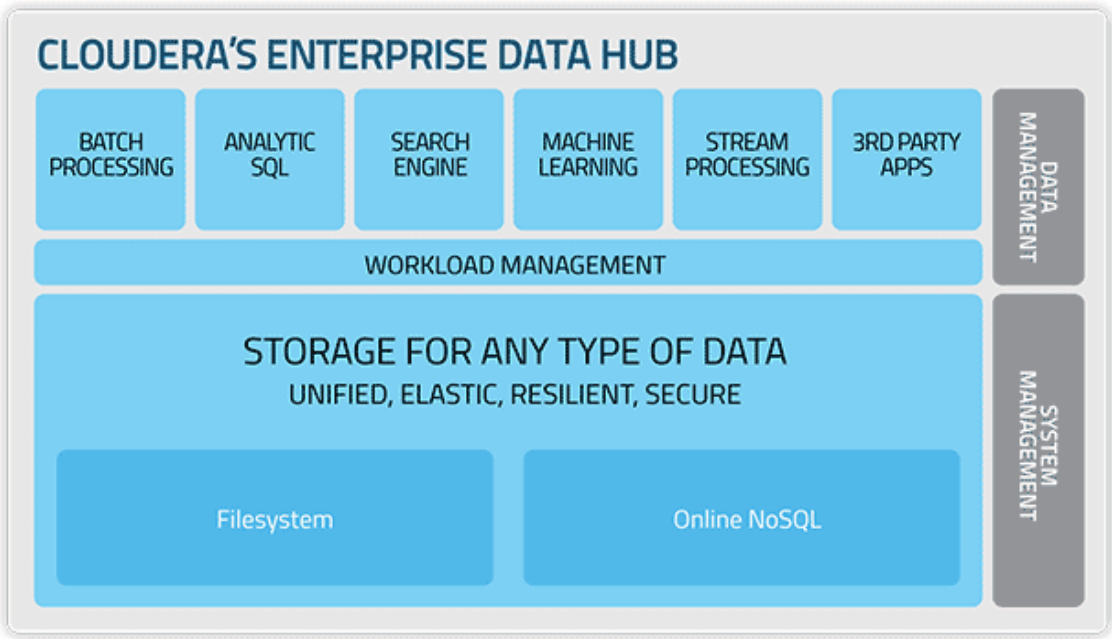


Figure 2.12.: Cloudera's architecture.

Hortonworks

Hortonworks was the biggest open-source contributor to the Hadoop project in 2012 and 2013 and a strong partner of Microsoft and it's Azure Cloud [23]. It was funded by Yahoo! and Benchmark Capital as an independent company in 2011 [22] and with it's CTO Eric Baldeschwieler, one of the Hadoop core inventors, they have got a community known person in it's team [9]. Interestingly, it's enterprise distribution the Hortonworks Data Platform (HDP) is completely free and open-source. Hortonwork's business model is selling services around it's platform not licensing it. While writing this thesis, they offer two editions of services, *Enterprise* and *Enterprise Plus* both editions provide the same response time and support but differentiate in the supported for different components like Storm, Spark and Kafka, but like Cloudera they do not provide any prices on their website, because again it depends on the amount of services needed.

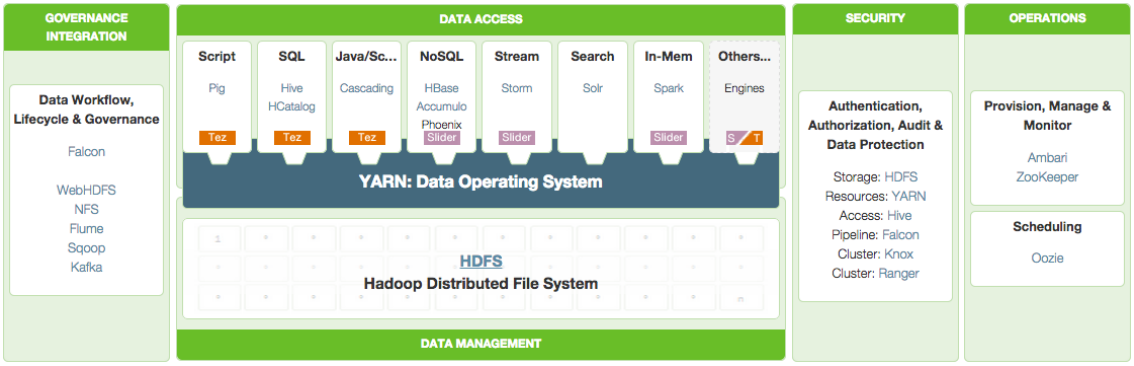


Figure 2.13.: Hortonworks' architecture.

MapR

MapR is not much younger than Cloudera, it is founded in 2009 and has become a strong enterprise Hadoop distributor. The have alliances with EMC, Google, and Amazon. MapR broke the TeraSort World Record in 2012 [34] and the MinuteSort World Record in 2013 [24], both on the Google Compute Engine. They did the TeraSort on regular Google Compute instances in under 54 seconds, spending $9, "compared to the over $5M estimate to run the previous record" [14] it shows how well cloud solutions and such an Hadoop distributions complement each other. From this numbers one can not tell, Whether another distribution would or would not be able to achieve the same results. Just like Cloudera, MapR does not have fixed pricing, the distribution price depends on the number of nodes, secondary services etc.

Each distribution uses some kind of graphical representation, like shown in Figures 2.12, 2.13, and 2.14, to structure it's feature-set. Such representations provide a fast, recognizable absorption but a comparison is difficult because

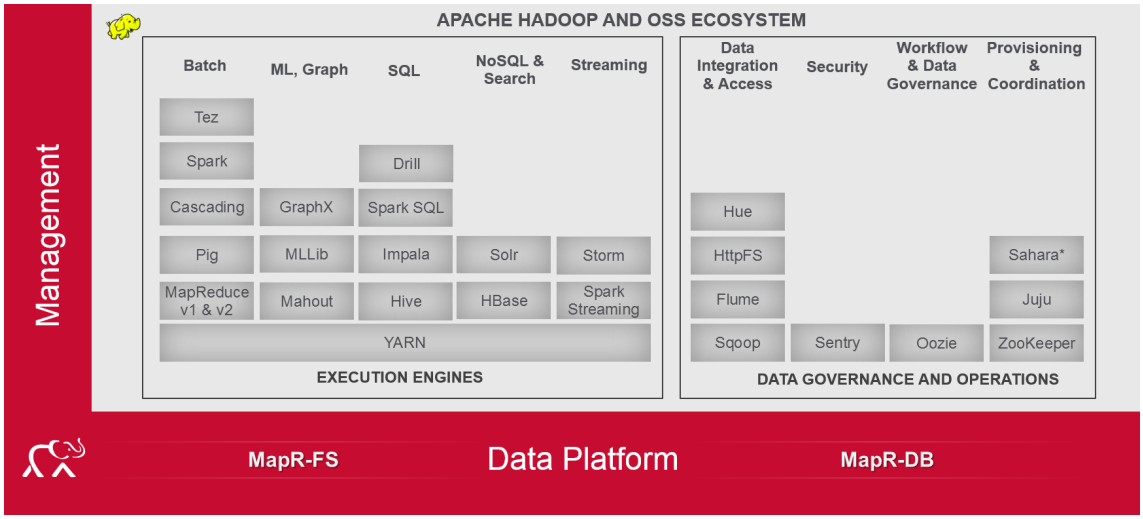


Figure 2.14.: MapR's architecture.

of the different presentation forms. Thus I included a standardized graphical *distribution representation* in chapter The Decision Matrix.

2.4. Basics of IT Decision Processes

Making a sustainable decision in IT management is a very complex task because most of the time uncertainties must be integrated and classified in the evaluation process, in despite of the pure factor of uncertainty. Thus an important aspect is to choose the considerations that are important, to evaluate the different components influencing the decision [Saa90]. Successfully proven decision techniques have been developed such as a SWOT analysis, context analysis and Analytic hierarchy process (AHP), developed by Thomas Saaty in the 1970s, for coordinating and resolving complex decisions, based on "mathematics, philosophy and psychology" [Saa90]. SWOT analysis and AHP will be used by myself in this thesis, therefore a brief explanation follows: The AHP procedure can be summarized in:

1. Modelling the problem, containing *decision goal, alternatives, criteria for evaluation the alternatives*
2. Prioritizing the different criteria by a pairwise comparison
3. Synthesize analyzed priorities into global priorities for each objective/property
4. Control consistency of the prior judgments
5. Making the final decision

AHP is not aiming towards any perfect solution, it simply helps decision makers to discover and to understand the problem in greater detail. "AHP is a useful way to deal with complex decisions that involve dependence and feedback analyzed in the context of benefits, opportunities, costs and risks." [Saa08]

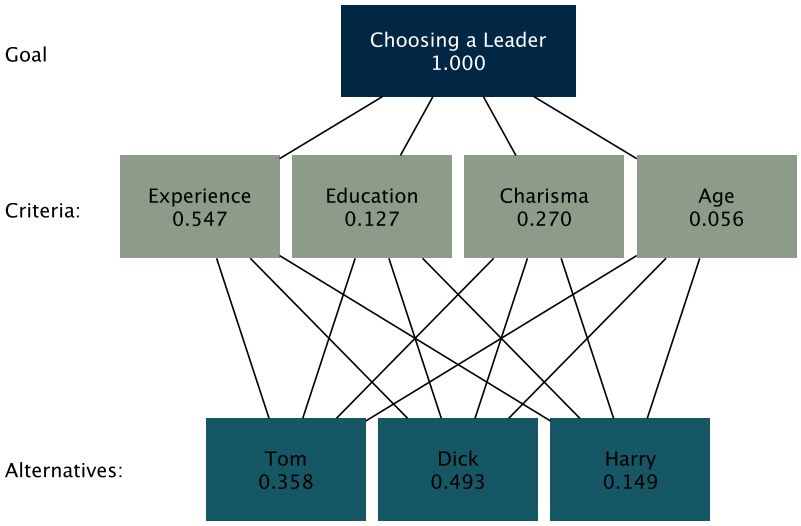


Figure 2.15.: AHP Example: Leader Election.

A key assumption of the AHP is human judgment, not just the underlying information, which has to be used to make right decisions [Saa08].

A regular used example of AHP is the problem of finding an appropriate leader for a company. The problem description can be found in the web-reference [3], a simple understanding of AHP is shown in Fig. 2.15. This figure is the graphical representation of a AHP for a leader election problem.

In my chapter Designing the Decision matrix I am using a simpler abstraction of the AHP to achieve a mathematical and psychological influenced decision for qualitative factors.

The Strengths, Weaknesses, Opportunities and Threats (SWOT) analysis [HW97] is also used in this thesis. This type of analysis is easy to apply, because to put it simple, it is a two dimensional pro-contra list. The pro column is called *helpful* and the contra column is called *harmful*. As mentioned it has two dimensions, the first is *internal factors*, the second *external factors*. Putting everything together makes a 2x2 SWOT matrix 2.16. Such a SWOT analysis will be used to compare intangible factors of the different distributions, see the Chapter SWOT Analysis.

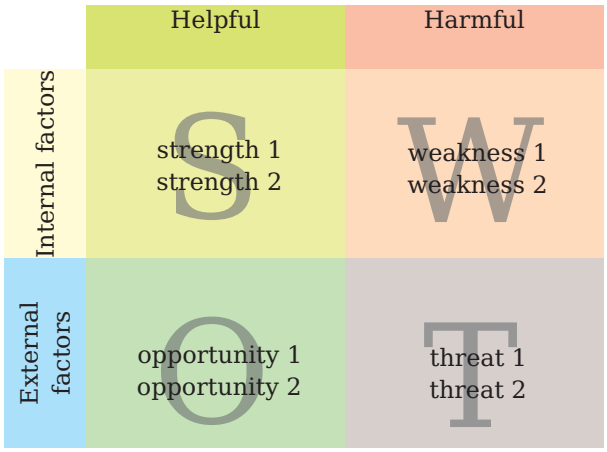


Figure 2.16.: 2x2 SWOT matrix.

Table 2.2.: Hadoop projects for special purposes, structured after the Building Block Concept discussed in 4.1.

Building Block Name	Description
Data Governance	
Falcon	Data processing and management software for Hadoop. Special purpose for coordination of data pipelines, data motion, lifecycle management, and data discovery.
Data Operations	
Ambari	Project objective: making Hadoop management simpler by providing software for provisioning, managing, and monitoring Hadoop clusters.
ZooKeeper	A centralized, distributed service configuration and maintenance system.
Oozie	Workflow scheduler system to manage Apache Hadoop jobs.
Avro	Data serialization system.
Integration & Access	
Hue	A Web interface for exploring, analyzing and querying data with Hadoop. It supports a file and job browser, and query interfaces for many services.
Flume	A distributed service for collecting, aggregating, and moving large amounts of log data (e.g. webserver logs).
Sqoop	A transferring tool to send data between Hadoop and structured datastores like relational databases.
Kafka	A publish-subscribe messaging service.
Security Projects	
Sentry	A role based authorization system for data and metadata stored on an Hadoop cluster.
Knox	A gateway system for interacting with an Hadoop cluster, including authentication, federation/SSO, authorization, and auditing.
Ranger	A central security policy administration system across a whole Hadoop cluster.
Access & Exec. Engines	
Batch, Scripting	
Tez	An application framework, allowing complex directed-acyclic-graph of tasks for processing data, built atop YARN.
Spark	An open-source, general purpose, in-memory, cluster computing framework.
Cascading	A software abstraction layer for Apache Hadoop.
MapReduce, Yarn	see Hadoop's Data Operating and Workflow Management System: YARN
Pig	A high-level language for expressing data analysis programs on Hadoop.
ML, Graphs	
Mahout, MLLib	Machine learning libraries for Hadoop.
SQL	
Drill, SparkSQL	SQL query engines for Hadoop.
Impala	An analytic database for Hadoop.
Hive	Data warehouse infrastructure built on top of Hadoop for providing data sum- marization, query, and analysis.
NoSQL	
Accumulo	A sorted, distributed key/value store, based on Google's BigTable design.
Pheonix	A relational database layer over HBase.
Search	
Solr	A Full-Text search platform.
Stream	
Storm	A streaming, realtime computation system.

3. Problem Description: Entry Barriers to the Big Data-Era

> "Another challenge for businesses is deciding which technology is best for them open source technology (such as Hadoop) or commercial implementations (such as [...] Cloudera, Hortonworks, and MapR)." [KTC14]

Most companies would like to enter the big data sector or would like to enable and use big data solutions inside their business, but because the topic and it's research is quite young, a guide towards installing big data solutions is missing. In this chapter I will provide a small collection of known pitfalls, companies forget about, while deploying big data solutions.

3.1. Process of integrating and using big data solution

Prof. Vossen's research [Vos14] concludes a basic big data adoption strategy, it is a five step procedure starting with information gathering and planning, see Figure 3.1. If the management decides to implement a big data solution, the data sources need to be selected, subsequently an approximation has been made what kind and how much data has to be stored an processed. The third step is called *Detailed Planning* and it involves an examination of different big data solutions, e.g. Hadoop distributions, and this third phase is the driver of this thesis. The later steps will be ignored for the scope of this thesis but nevertheless are important for an enterprise adoption strategy for big data.

An elementary problem of integrating and using big data solutions is the measurement of the Return on Invest (ROI), and for some companies even failing expectations of their big data solution. Prof. Marchand (IMD Lausanne) and Prof. Peppard (ESMT Berlin) [MP13] analyzed 50 international organizations and their finding is, most companies try use the same conventional

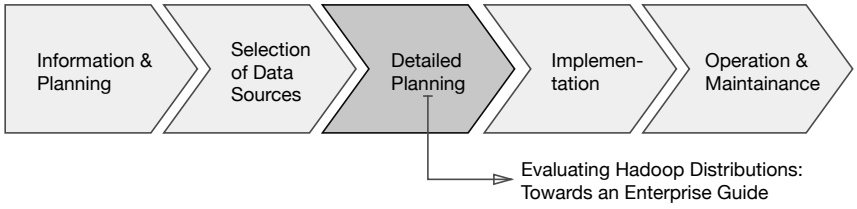


Figure 3.1.: Big data adoption strategy, see [Vos14].

IT-project process for big data projects. But there is a relevant difference between the implementation of a big data solution and an introduction of an ERP- or CRM-system, in fact it differs because usually big data will not change a core competence business process, thus the success is not immediately measureable. Rather the employees have to be encouraged to use and access the newly available data variety to produce new economically meaningful and value-adding solutions. Thus an important feature of the used big data solution has to be a well working data exploration and quickly working data analyzing query interfaces.

3.2. Big data solutions and intelligent information gathering

> Value creation from Big Data could become the major driver of the European digital economy. [25]

Data has got an economical value [SSV13], that's way companies try to leverage it. Nevertheless, the simple existence of data is not the economical value, thus some people call big data *dumb data*. "Big dumb data is the kind of personalization that shows you re-targeted ads from your own employer ("Yes, I have been to my company's website, but I am not interested in buying.")" [32]. Having said that, it is not feasible to simply collect some data, and to fill a data lake. Value creation only starts by collecting the right data plus using it. The conclusion, the collecting and using has to be managed to be profitable. Shah et al. advise executives to manage data like capital or resources and not leave it at the IT-departements competence [Sha12]. Thus every available data source has to be examined and rated, the data has to be stored and afterwards made accessible to the whole company easily. Furthermore, the research of Vossen, Schomm et al. shows how companies are not only using their own data to improve their business value, but moreover, data is becoming a good, traded on data marketplaces [SSV13]. This is an interesting development which could lead into further demand of big data solutions in enterprise. However, these two approaches: collecting and using big data, leads towards the data lake model discussed in the following chapter.

3.3. Understanding the Data Lake approach

Previously, the Figures 2.7, and 2.8 were used to briefly explain the comparison between traditional data warehouses and *data lakes*, a term created by James Dixon, CTO of Pentaho, [12]. Dixon says, that the enterprise data has to be stored in a single data reservoir, accessible by every application, if necessary. Shah et al. underline Dixon's findings by arguing, that most companies are missing a consistent structure, enabling easy access to it [Sha12]. Following I

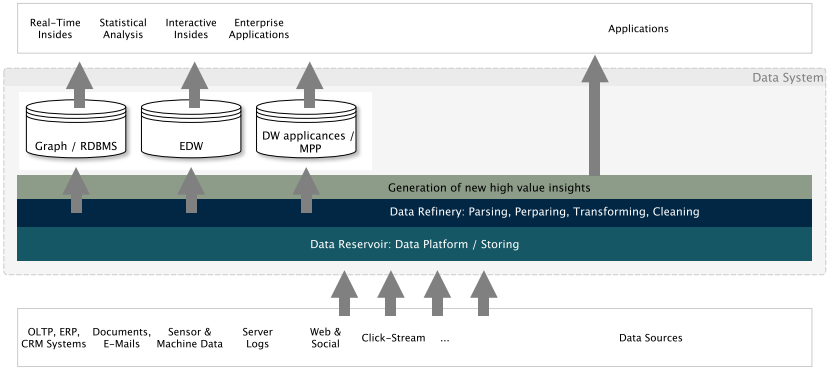


Figure 3.2.: The Data Lake Architecture.

will describe the data lake in greater detail, comparing it with traditional data warehouses and emerging the differences.

Capgemini together with Pivotal analyzed four “enterprise data warehouse pain points” [45] companies encounter with traditional data warehouse systems and emerging business needs. “Reconcilling conflicting data needs” is the first challenge described, meaning, business units need specialized data, but the organization doesn’t need this data globally. Thus EDW “implementations mandate the creation of a single consistent view” which conflicts with the business units requirements. Another objection is “real-time access”, “because today’s business decisioning systems need access to real-time information in addition to historical information to enable optimum decisions” [45]. Thirdly, today’s multi-channel business strategies providing and gather data from multiple resources. Thus, such data has to be stored in one system to enable data scientists to work on the whole available data. Lastly, next to “regular operational reporting, enterprises need the ability to run ad hoc analysis” [45].

These challenges include greater technical objectives like data integration, analysis of data in motion, analysis of structured and unstructured data, exploration of un-modeled multi-structure data, graph analysis, the acceleration of Extract Transform Load (ETL) processing, and storing, and reprocessing of archived data warehouse data, to name just a view. The following graphic, Fig. 3.2, is a combination of multiple proposals of data lake representations. An important part in the new design is data availability and cost reduction. Going back to Fig. 2.9, one main cost driver for EDW is ETL processing [Fer14]. The *Data Reservoir* and *Data Refinery* are the essential parts of an enterprise data lake and actually they can be viewed as “managed and governed Hadoop environment“ [Fer14].

4. Hadoop Distributions Decision Matrix and SWOT Analysis

4.1. Structural Process for the Decision Making

The decision making matrix, designed and evaluated later in this main chapter has been created in a clear and structured process, described in the following subchapters.

4.1.1. Approach

The approach is an elementary element, it had to be defined before the matrix creation to achieve an objective result. The process can be structured into four main parts. First, the Hadoop distribution choosing, followed by defining the requirements. These two steps had to be completed, before the process could continue. These both steps where followed by a quantitative ranking of the requirements, mapped to the distributions and completed by a qualitative ranking.

1. *Hadoop Solutions*: I have chosen the three major distributions, likely to be deployed in enterprise companies [YG12]
2. *Requirements*: I gathered requirements in 15 different categories, described in Categories for a Distribution Comparison
3. *Quantitative Ranking – using a scoring model*: Subsequently the categories and the detailed requirements were weighted and based on the findings the rating of each solution was made. The end result is the product of these two factors (Weight & Rating). This approach is similar but not equally to the above, briefly explained AHP in Basics of IT Decision Processes
4. *Qualitative Ranking – using a SWOT analysis*: All other intangible factors have been captured in a SWOT Analysis which has to also play an important role in the overall evaluation

The following comparison as heavily based on third party documentation, websites, company whitepapers and benchmarks. The assumption has been made, that the published results are not massively incorrect or knowingly distorted. To stay within the scope of this thesis no Hadoop cluster has been setup, thus judgments could vary in a field study or analysis.

4.1.2. Categories for a Distribution Comparison

Fifteen different requirements have been researched by analyzing papers and white-papers, blog posts, buyer guides and news related to Hadoop distributions. The following requirements have been distilled.

1. Performance and Scalability
2. Availability and Dependability
3. Manageability and Usability
4. Integration with Existing Systems
5. Security
6. Data Access
7. Flexibility, Customizability
8. Total Cost of Ownership and other additional Workforce Expertise
9. Customer Support
10. Community Support
11. Documentation
12. Risk of Vendor-Lock-In Effect
13. Time to Market (Time to Installation)
14. Upgrade, Release Cycles
15. Vendor's future viability

Subsequent to a brief explanation of each category, an objective comparison of each distribution compared to each category will follow, leading towards the decision matrix.

Performance and Scalability

Hadoop has been built for fast, scalable, and distributed computing on commodity hardware, thus each distribution has to compete against each other in this topic. Because they slightly differ I searched for comparisons and benchmarks. Benchmarks for TeraSort, MinuteSort, PageRank and the famous Word Count have been found and analyzed. Furthermore the technical differences between each distribution came into account. These differences are the technology in which important parts of the architecture are implemented, and the manner how components are orchestrated, used and connected.

Availability and Dependability

Applying the data lake approach with an Hadoop distribution makes the data platform to a component in your enterprise architecture with the highest ratio of required availability and dependability. Thus a failure and major outage is not allowed to happen. Again the distributions differ from each other because of their implementations of disaster recovery, failover strategies, rollbacks and snapshots.

Manageability and Usability

Previously discussed, *dumb data* does not generated value. The distribution has to be easily manageable to grant employees the access needed. This access should be possible in a usable manner to engage the platform acceptance. This has been previously discussed in Problem Description: Entry Barriers to the Big Data-Era referencing the research of Prof. Marchand, and Prof. Peppard [MP13], as well as the Shah et al. research [Sha12].

Integration with Existing Systems

In previous chapters I have sliced a difference between old IT architectures like the Data Warehouse and the new big data solutions, regarding data storage, like the *Data Lake*. Inmon, as quoted in **??**, has the opinion, that reliable data sources are only possible by data warehouses. And he is right, if one looks at single data sources inside the data lake. But if one looks at the description of the *Data Lake* architecture from Understanding the Data Lake approach it gets clear, that such raw stored data has to be crummy. This chapter analyses how good the different distributions can access old data warehouse architectures and established IT systems.

Security

Securing Hadoop and the big data solution is indispensable for an enterprise grade distribution. Three main targets have been discovered: *Comprehensive Security*, *Central Administration*, *Consistent Integration*. *Comprehensive Security* is the security of all distribution's components including authentication, authorization, as well as data and audit protection. *Central Administration* is the possibility to view and manage policies in one single place. Finally, *Consistent Integration* is the integration with different other identity and security management systems, for compliance with IT policies [19]. Another important aspect of IT security are the provided security guidelines and security best practices for each distribution.

Data Access

Being able to access data within the data storage from other systems is important and should be considered all the time. Thus, features like NFS support and connectors for standard business applications like Microsoft SQL Server or similar are necessary for enterprises.

Flexibility, Customization

Changing default behavior and customize certain aspects of the distribution may be important because not every company is equal, hence easy extendibility and changeability are creditable features.

Total Cost of Ownership and other additional Workforce Expertise

Many projects do have a tight financial plan, even if research done by Standish shows [Cha01] and the work of the Project Management Institute (PMI) underlines this, that many projects significantly overrun their cost estimates. Nevertheless, every project manager aims towards a balanced budget thus it is important to analyze differences in the Total Cost of Ownership (TCO) of each

distribution. TCO can either increase by hidden licenses costs or by additional required workforce experience.

Customer Support

In this area I will highlight the differences between the different vendor's customer support plans. Comparing the Price-Performance ratio of each vendor.

Community Support

A strong community can leverage the own success because of help from, knowledge transfer in and the possibility to find new employees in the community (the *network-effect*). Measurements about a community size and it's value are more a qualitative than a quantitative exploration, because no data is public available and no information about inactive community members are published. Nevertheless, the different vendor communities have been analyzed regarding users in the support forums and the amount of questions asked inside this forums.

Documentation

The documentations of each distribution have been analyzed regarding *technical accuracy*, *consistency*, *task orientation*, *completeness*, *clarity*, *concreteness*, *style*, *organization*, and *visual effectiveness*. These attributes have been taken from the research of Dautovich [Dau11] and the NASA Software Documentation Standard (STD-2100-91) [1].

Risk of Vendor Lock-In Effect

A problem can occur if the chosen distribution has got a specific file-format and data-accessibility API, bound to this specific distribution and therefore a switch towards another distribution would require a complete data and service migration. Such a vendor lock in leads to an heavy dependence on the big data distribution vendor. This vendor lock-in problem and the occurring switching costs and network effects have been researched by Farrell et al. [FK07], this research shows on the one hand the problems but on the other the opportunities because of the network effect: "one agent's adoption of a good benefits other adopters of the good and increases others' incentives to adopt it" [FK07]. Accordingly, a strong and active user base may improve the distribution because of the explained network-effect.

Time to Market (Time to Installation)

Setting up and using a big data solution will never be a job, done within a minute of time. But guided and easy setup-processes encourage an enterprise

to test a distribution. Thus, an easy installation and conversely a fast internal roll-out improve the acceptance of the newly introduced IT system.

Upgrade, Release Cycles

The vendor's release, update and patch cycle tells how fast the development is and whether the distribution supports so called *rolling upgrades*. Rolling upgrades are an important feature for cluster operating systems to upgrade a whole cluster avoiding downtime [Rou01]. Equally important are stable release cycles and partly backwards compatibility.

Vendor's future viability

Especially when dealing with some kind of *vendor lock-In effect*, but as well if big parts of the company's value creation depends on the distribution's further development and availability, the vendor's future viability is very important to the company installing a distribution.

4.1.3. Designing the Decision matrix

Before analyzing and comparing each distribution the rough design and principles behind the decision matrix shall be discussed. A quantitative ranking approach, using a scoring model, close to the AHP principle will be used to compare each analyzed distribution. The matrix has categories, including subcategories. A (sub-)category has two values, the (sub-)category weight and the corresponding total weight:

$$C = CategoryA \begin{array}{c} \\ \end{array} \begin{array}{c} \begin{array}{cc} CategoryWeight & TotalWeight \end{array} \\ \begin{pmatrix} 10\% & \sum STW = 10\% \end{pmatrix} \end{array}$$

$$SubC = \begin{array}{c} \\ SubcategoryB \\ SubcategoryC \end{array} \begin{array}{c} \begin{array}{cc} SubcategoryWeight & SubcategoryTotalWeight \end{array} \\ \begin{pmatrix} 20\% & 2\% \\ 80\% & 8\% \end{pmatrix} \end{array}$$

In the example C is the matrix of a single category A and $SubC$ is the corresponding matrix of each subcategory of A, subcategory B, C. The (sub-)category weight is something the user of the decision matrix can change according to it's needs. For example could a very performance and scalability critical project apply the following values:

$$M = \begin{array}{l} \\ Performance and Scalability \\ Availability and Dependability \\ Manageability and Usability \\ \vdots \\ Vendors Future Viability \end{array} \begin{array}{c} CategoryWeight \\ \begin{pmatrix} 30\% \\ 5\% \\ 5\% \\ \vdots \\ 5\% \end{pmatrix} \end{array}$$

The distributions themselves will be analyzed on each (sub-)category in the following chapter, The Decision Matrix. The scoring-model used to compare each distribution goes from zero to ten, where ten is the highest ratio of category fulfillment and zero indicates no fulfillment at all. For example, if a distribution implements everything non-standardized and conversely a 100% vendor lock-in exists, this distribution would receive a score of 0, because it does not fulfill the category expectations.

4.2. The Decision Matrix

In this chapter I will provide a universal model for Hadoop distributions to make it possible to differentiate them on a more abstract level. Furthermore, I will compare each distribution, Cloudera, Hortonworks, and MapR, using the above explained scoring model for each category, coming back to an initial question "how do they compare?".

Figure 4.1 shows an universal model of a Hadoop distribution. Every analyzed Hadoop distribution has got the same different building blocks named in the model: Data Governance, Data Operations, Data Integration & Access, and Security as stand alone blocks, coupled with the main system structured in three layers Data Access & Execution Engines, Data Operation and Workflow Management System, and a Data Platform. Have a look at the following Table 4.1 for a detailed description what the different building block names mean.

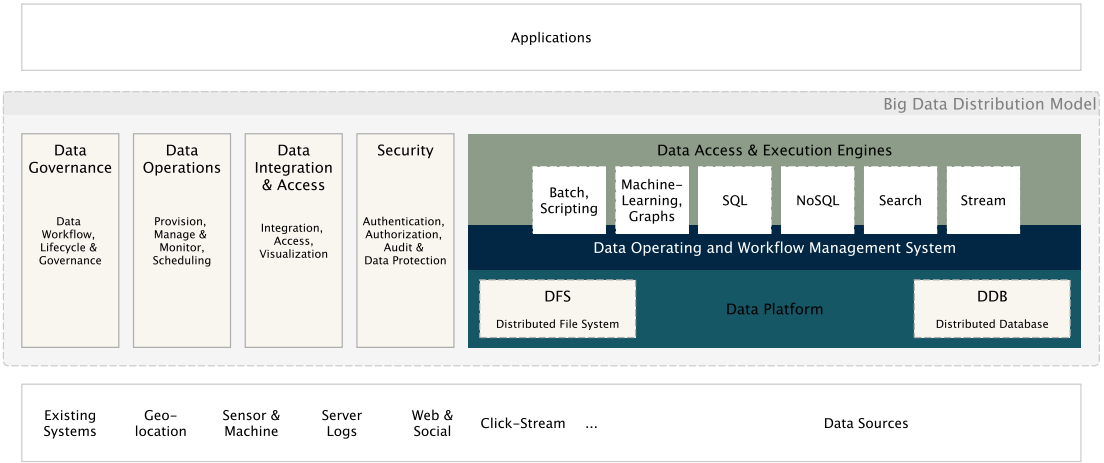


Figure 4.1.: Big Data Distribution Model.

Comparison of Performance and Scalability

The comparison starts with the first category, *Performance and Scalability*, at the core of each distribution, it's *Data Platform*. Cloudera and Hortonworks

Table 4.1.: Building Block Naming and Description.

Building Block Name	Description
Data Governance	Responsible for data quality of incoming data into the system. Administrator should be able to define rules for data quality.
Data Operations	Provisioning, Managing, Configuration, Data Transformations, etc. Everything needed to work with the data.
Data Integration & Access	Collecting, Aggregating, and Moving data across different systems and interfaces. Connecting existing enterprise systems, like date warehouses, CRM and ERP systems.
Security	Authentication, Authorization, Audit & Data Protection.
Data Access & Execution Engines	Different Engines to access and compute on the big data cluster. This can be Batch and Scripting Engines, Machine Learning and Graph-Databse Engines, No-/SQL DBs, Search and Stream Processing Engines.
Data Operating and Workflow Management System	Cluster data operating system.
Data Platform	Distributed data storage.

share the common Apache Hadoop HDFS implementation, and both distributions include HBase directly into the Data Platform. As pointed out in chapter The Hadoop Ecosystem, HDFS does come with drawbacks, especially the NameNode SPOF as well as the 100 million files problem. While it is possible to overcome it by using the HA feature it has to be done by the administrators and is not activated by default. MapR has rewritten its *Data Platform*, the result is MapR-FS and MapR-DB, two opinionated, closed-source implementations, similar to HDFS and HBase. The main parts of MapR's *Data Platform* are written in `C/C++`, whereas the pure Hadoop HDFS parts are written in `Java`. `C/C++` is faster than `Java`, sometimes called *close to iron* languages and especially `C/C++` does not have a *garbage collector* like `Java` and thus no *garbage collector issue* [8] appear. Because of that rewrite, MapR receives ten points in the sub-category: *Key Components written in "close to iron" languages like C/C++*, the opponents only five. Furthermore, a minimal software layer approach is in general beneficial because less moving parts generate less bugs. MapR-DB, is not HBase, but has got the same core API, but without the need of Master and RegionServer. Fig. 4.2 shows how different the standard Hadoop HDFS, HBase implementation differ from MapR's FS and DB implementations. MapR-DB advantages the HBase core API to run existing HBase applications. Again, MapR receives the full ten points in *Minimal Software Layer* and both other distributions, Cloudera and Hortonworks, five. Subsequently, scaling like

TB to PB Scaling and *Scaling towards 100 million files* is the next sub-category analyzed. Both, Cloudera and Hortonworks are able to fulfill the objective, but it has to be configured manually, see the following *Comparison of Availability and Dependability* for more information. Because it has to be done manually for Cloudera and Hortonworks, and MapR because of the No Namenode feature, scales (nearly) without any restrictions, MapR gains two more points each. See Table 4.2.

Comparison of Availability and Dependability

Especially when using the *Data Lake* approach, an available solution is critical for the success. Availability and Dependability are only achieved, if the cluster is accessible and working, but mostly an increasing cluster becomes difficult to manage in case of failures and recovery. For example:

A large cluster, consisting of 10 drives per node, 100 nodes per cluster (1,000 drives). The failure rate of usual hard disks are 3 years, thus drive failure every day are statistically possible. Assuming 2 TB per drive, it takes 7 hours to re-sync at 1,000 MB/s (sync on the same rack), practical if it is in the same data center 200 MB/s apply, and it takes 35 hours. But if you have to re-sync to a geographically separated cluster, over the internet, with a throttled re-sync rate of around 20 MB/s it goes up to 350 hours (or 15 days) to re-sync. This example has been created by M.C. Sriva, CTO of MapR [21], thus it could be opinionated. Nevertheless, the discussed problem of data replication exists, no questions whether a disk fails or not - it will fail - but has the data been synced into another rack or better to a geographically dispersed data center is the big question. This topic is clearly HA, High Availability, and like mentioned above, standard Hadoop does have a feature to provide HA, like in the documentation of Hortonworks described: “ Chapter 8. NameNode High Availability for Hadoop” [16]. The issue here, the replication has to be configured manually and especially geographically dispersed clusters are not easy to manage because the replication is done by the NameNode and so a configured “Hadoop Rack Aware” replication or Apache Falcon has to be used to achieve a reliable multi-rack/cluster replication [2]. MapR uses a different approach for replication, but first recall Fig. 2.6 to have a visual understanding, how standard HDFS does it. The difference is, that MapR chops the data on each node to 1,000s of pieces (called containers) and spreads replicas of each container across the cluster, this is similar to the block-store syncing of HDFS but because of MapR’s No-NameNode architecture, it is faster to re-sync, because no in-between broker has to make any action. Especially it is possible on real commodity hardware, on which you assume more than one drive per node (no RAID possible), no hardware load-balancers between NameNodes and hence no choice but to replicate for reliability. Look at Fig. 4.3, if in a MapR-FS cluster a node fails, all other nodes simple re-sync. Going back to the 100 node cluster it means 99 nodes are sync’ing in parallel. Because of MapR’s better

HA features and as a result, a better dependability they receive 10 points and Hortonworks and Cloudera both 7 points, see Table 4.2.

Comparison of Manageability and Usability

All distributions got a management service, Cloudera has got the Cloudera Manager, Hortonworks has Ambari and MapR has the MapR Control System. Because Cloudera's has the most clear user interface, and Ambari is open-source. But, MapR's Control System has got *Volume Support* and *Data and Job Placement Control* [Sch13]. All distributions support Hue out of the box, an open source UI for Hadoop and its ecosystem components. This enables employees to discover and easily access the data for exploration. Because of the Volume Support and Data and Job Placement Control, MapR receives ten points, Cloudera 9, because of its good user interface, and Hortonworks 8, because Ambari has got a good user interface as well, but less features.

Comparison of Integration with Existing Systems

Discussed earlier, especially in the chapter Understanding the Data Lake approach, the integration with existing systems is essential for big data solutions. Two different areas can be evaluated, the ability to do ETL jobs to use and enhance EDW data, and furthermore the possibility to integrated with your IT landscape like server operating system etc. Again, MapR is the leader, but this time directly followed by Cloudera and Hortonworks. MapR is the sponsor of Apache Drill, a good designed but young technology, supporting real schema flexibility [Gil15]. Additionally, MapR will eventually add a JavaScript Object Notation (JSON) NoSQL document database, modeled on MongoDB. Cloudera is the most used distribution in combination with existing infrastructures, Hortonworks partnered with Microsoft to support a native Microsoft Server integration, thus both vendors earn nine points, MapR one more, see Table 4.2.

Comparison of Security

Apache Hadoop is not famous for being secure, actually it never was designed to be highly secure it was designed with high performance and scalability in mind. Hence, it is lacking in this fundamental area. Hadoop offers Kerberos authentication only, and MapR's distribution added Linux Pluggable Authentication Modules (PAM) which doesn't require additional infrastructure, therefore if an authorization scheme works with the Linux file system, it should work with the MapR distribution. Cloudera developed Apache Sentry to provide a more fine-grained authorization capabilities, and it has been adopted by each distributor. Furthermore, Apache Knox, a REST API Gateway, has been built to enable *end-to-end wire encryption*. Knox is used by Cloudera and Hortonworks, whereas MapR has got a proprietary wire-level security architecture [42], see Table 4.2.

Comparison of Data Access

Data access through a low-level systems like NFS is one way to access the data inside a Hadoop cluster. The other type of access, is through the *Data Access & Execution Engines* layer. This layer is very similar for each distribution and thus MapR will again earn one point more, ten out of ten and Cloudera and Hortonworks will earn 9, see Table 4.2.

Comparison of Flexibility, Customizability

Flexibility and customization are especially important if the IT department needs very special control about the Hadoop cluster. No distribution has go a serious lock-in effect regarding the data. Another aspect which is not directly vendor lock-in but similar, is the possibility to make upgrades of parts of the system whereas leaving other on a known working state. Example: Upgrading the system, but letting the component Hive stay on the old version. Cloudera and Hortonworks have locked versions on components for each major framework release, MapR has got the feature of supporting multiple versions. By now all vendors support rolling upgrades. Thus MapR receives ten points in sub-category *Version Flexibility*. The other sub-category is *Customization*, and because Hortonworks is the only 100% open-source distributor, they will receive ten points, Cloudera with it's partly open-source structure 7 and MapR because of a closed system, but as well with open-source projects will earn 3 Points.

Comparison of Total Cost of Ownership and other additional Workforce Expertise

This is a difficult topic to measure, on the one hand the costs per cluster node should be a mathematically easy determinable value, but it is not because Cloudera and MapR calculating the prices per node customer individually, sources show it is around $ 4,000 per node [43]. But whether this costs are real is difficult to tell, since it highly depends on the additional services, like support, and how many nodes the cluster has. Hortonworks is the only provider giving away it's distribution for free, generating reveneau through support and service. MapR includes a TCO calculator on it's website [1], it must be assumed that the calculations and assumptions are on average chosen to emphasis on MapR. The TCO comparison is attached in the appendix, see Results TCO Calculator. MapR considers less node per cluster usage, because of MapR-FS and MapR-DB, thereby less personnel, software and hardware costs. Workforce Expertise as well is not easy to measure, because this differs highly from team to team and the project objectives. From my research of the documentation provided by each distribution, blog posts including user reviews and the test

[1] MapR TCO Calculator
https://www.mapr.com/resources/hadoop-total-cost-of-ownership-calculator

installation I can not tell whether one distribution exceeds the others by far in reference to workforce expertise, but it is a fact, Hortonworks is the most cost efficient distribution concerning installation costs per node, because it is *zero*. As a result of the uncertainties regarding workforce experience and real costs per node, Hortonworks will earn ten points, Cloudera and MapR both seven, see Table 4.2.

Comparison of Customer Support

All distributions offer a free customer support through moderated user forums and through support tickets. Furthermore do all vendors offer multiple support subscription plans. One can not directly tell which vendor does a better support job without actually using it. The variety of the support plans is a possible factor to differentiate them. Because this big uncertainty, each vendor will receive 0 points, this category is something another user of the decision matrix with deeper knowledge in terms of the different support characteristics could change.
Disclaimer: the following is a note for the reader and has not influenced this thesis. During my research I wrote to each vendor through the possible contact forms, asking for further information and technical clearance. The only vendor really caring and answering all my questions has been MapR Technologies, responding immediately and offering good information, well knowingly I am not interested in buying anything.

Comparison of Community Support

Each vendor established a community support forum, each actively used by the distribution users. Cloudera has got around 9,000 Users, and 11,310 questions have been asked in the community forum. The Hortonworks users are not easy measurable, but rougly 9,800 questions have been asked in their forums. MapR's community differs a lot, data from the questions and answer forum states ca. 164,000 Users exists, but only 2,300 Questions have been asked. Analyzing *Stackoverflow*, a heavily used question and answer platform for IT professionals, MapR generated 63 questions and 10 followers, whereas Hortonworks generated 226 questions and 17 followers and Cloudera 1,255 question and 127 followers (sum of Cloudera, Cloudera Manager and Cloudera CDH topics). It is noticeable that questions regarding MapR are less common at Stackoverflow and as well in the official support forum. MapR's official support forum has only 21.79% the number of questions asked compared to Cloudera and Hortonworks forums, and 8.50% of questions asked on Stackoverflow. Taking this two factors, users and questions, into account, it is fair to split the points for each sub-category. Cloudera and Hortonworks earn 5, respectively 10; MapR will receive 10 and 5 points.

Comparison of Time to Market (Time to Installation)

Each vendor offers a free to use so called *Quick Start* Virtual Machine (VM), pre-configured VM images, one can easily setup to test the distribution on the own computer. Furthermore, there's no need for buying a vendor's distribution, just to test it, each vendor also offers a *Community* or free edition, including many of the features but not all. MapR for example offers the *M3 Community Edition*, which includes every feature from M7 excepts Multi-Tenancy, Consistent Snapshots, HA, and Disaster Recovery. These features are for sure very important but not necessary for an evaluation phase. Cloudera's free offer is called *Cloudera Express*, that combines the open source, free to use *CDH* with *Cloudera Manager*. Cloudera's list of unsupported features in this free edition is a little bit longer, it misses Kerberos Integration, LDAP Integration, Rolling Updates/Restarts, Simple Network Management Protocol (SNMP) Support, a protocol used to monitor network device statuses, Configuration History and Rollbacks, Operational Reports, Scheduled Diagnostics, and Automated Disaster Recovery. Mentioned before, Hortonworks is the only distributor, providing it's enterprise Hadoop distribution free of charge and fully open source. To stay within the scope of this thesis, only the provided VMs have been installed to gain quick insides, no cluster has been actively built and analyzed. Each VM starts fast and no serious setup has to be done. Cloudera's VM has an graphical user interface (GUI) included, it starts in a pre-configured web-browser inside the VM. Hortonwork's and MapR's VMs work differently, these are pure server operating-systems, without an included GUI, one accesses the VM through the own web-browser after starting the VM. MapR, because of the native NFS support even supports mounting volumes easily in it's test VM.

Comparison of Upgrade, Release Cycles

Cloudera and MapR, release regularly and because the systems support *rolling upgrades* the customer do not have to fear major issues because of patches and minor updates. Hortonworks on the contrary has no rolling upgrade support and thus planned downtimes are necessary for releases, therefore it is reasonable, why Hortonworks published only two major versions since 2012. Comparing it with MapR, which released four major releases since 2012 and Cloudera, which released three, it is noticeable that Hortonworks has to be more conservative regarding its release cycle. A detailed release comparison can be found in the Appendix, A.1. Cloudera is the only vendor supporting multiple major versions during the a broad overlapping time period, thus customers can choose to stay on a major version or to upgrade. MapR has a different approach, the major version itself changes, but components, like Hive, can still be used in a deprecated version, mostly two releases behind the actual implemented version. This is a unique feature, because administrators are able to choose versions on a granular level. Because of the best backwards compatibility and the steady release cycles, MapR will earn 10 points, Cloudera

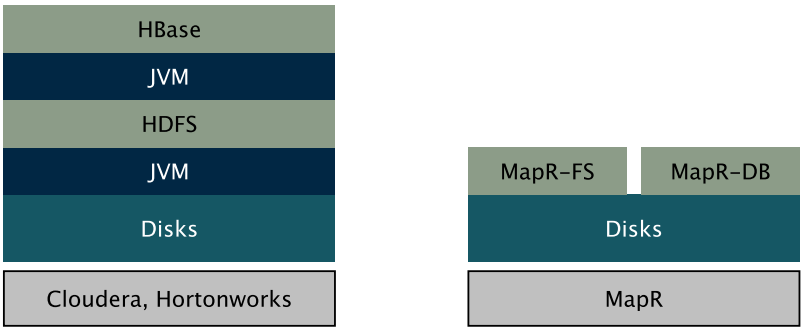


Figure 4.2.: HDFS, HBase vs. MapR-FS, MapR-DB.

9, as a result of the multiple major version support, and Hortonworks 5 points, considering long cycles and only downtime upgrades.

Comparison of Vendor's future viability

The future viability of each vendor is a non-orthogonal, dynamic system, because if one distribution makes a disrupting move, the other distribution could be replaced quite fast. Furthermore different aspects come into account, as seen in Fig. 2.11, Cloudera is the highest fundet company. This implies two different things, the venture capitalists and therefore the market trusts Cloudera will or should become the major player, but postpositive it also states Cloudera is not able to make it without such high fundings. Interestingly is the partner network, Cloudera partnered with Intel, the major funding partner as well. Hortonworks partnered with Microsoft to support Hadoop on the Azure Cloud and it runs natively on Microsoft Server. MapR has alliances with Google, Amazon and EMC.

MapR has over 700 customers [13], the IPO is planned for late 2015, Hortonworks has around 300 customers and had it's IPO in November 2014 [40], whereas Microsoft accounts for more than a third of the revenue, and Cloudera has got around 300 customers [17].

Intel's investment in Cloudera, is aimed to optimize CDH and CDH Enterprise, and the core open-source Hadoop platform, to run on Intel's chip architecture [30]. Naturally, improvements to the core open-source Hadoop platform, improve each Hadoop vendor, especially Hortonworks, since MapR's M5 and M7 distributions include proprietary parts.

Each vendor's future viability is solid, because of Cloudera's great liquidity and greater company size, 500 to 1,000 employees [18] (Hortonworks: 200-500 [27]; MapR: 200-500 [35]) it will earn ten points, MapR because of the strong alliances with EMC, Google, and AWS nine, and Hortonworks eight, as a result of the dependence on Microsoft.

Table 4.2.: Comparison.

			Cloudera		Hortonworks		MapR	
Categories	**CW (%)**	**TW (%)**	**P**	**wp**	**P**	**wp**	**P**	**wp**
Perf. & Scale	**10.00%**	10.00%		0.68		0.68		1
"close to iron"	**20.00%**	2.00%	5	0.1	5	0.1	10	0.2
Min Software	**20.00%**	2.00%	5	0.1	5	0.1	10	0.2
TB to PB	**60.00%**	6.00%	8	0.48	8	0.48	10	0.6
> 10$\hat{6}$ files	**0.00%**	0.00%	8	0	8	0	10	0
HA & Dep.	**20.00%**	20.00%	7	1.4	7	1.4	10	2
Mng.&Ux.	**5.00%**	5.00%	10	0.5	10	0.5	10	0.5
Integration	**5.00%**	5.00%	10	0.5	10	0.5	10	0.5
Security	**10.00%**	10.00%	10	1	10	1	10	1
Data Access	**5.00%**	5.00%	10	0.5	10	0.5	10	0.5
Flex./Cust.	**10.00%**	10.00%	10	1	10	1	10	1
TCO	**5.00%**	5.00%	10	0.5	10	0.5	10	0.5
Cust. Sup.	**5.00%**	5.00%	10	0.5	10	0.5	10	0.5
Com. Sup.	**5.00%**	5.00%		0.005		0.005		0.01
Users	**1.00%**	0.10%	5	0.005	5	0.005	10	0.01
Questions	**5.00%**	0.50%	10	0.05	9	0.045	2	0.01
TTM	**5.00%**	5.00%	10	0.5	10	0.5	10	0.5
Upgr. Cycl.	**10.00%**	10.00%	10	1	10	1	10	1
Vendor V.	**5.00%**	5.00%	10	0.5	10	0.5	10	0.5
Total	100.00%			8.585		8.585		9.51

CW: Category Weight, *TW*: Total Weight *P*: Points, *wp*: weighted points
This is an exemplary Comparison, as one can see, the category weight has been "randomly" chosen. .

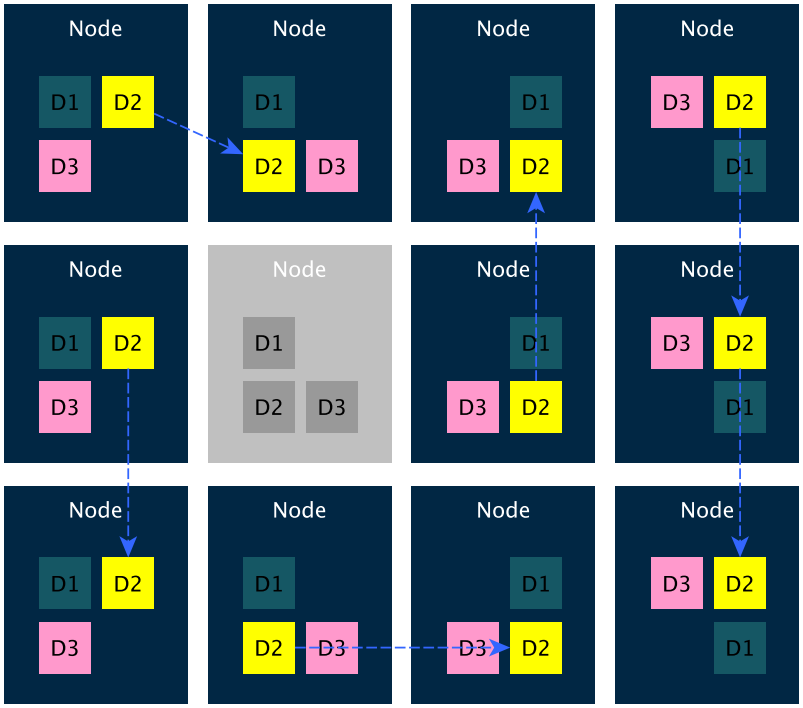


Figure 4.3.: MapR node failure, parallel re-sync example.

4.3. SWOT Analysis

For the SWAT analysis, the *internal factors* differ heavily from company to company. Thus in this chapter I will only provide *opportunities* and *threads*, the external factors which are not directly influenced by internal factors. Kotler's [Phi88] research shows, that an external factor can either be qualified given the probability of a successful enhancement or given the likelihood of a threat, regarding the business or project.

4.3.1. Opportunities

Cloudera

Cloudera is the highest funded company and thus can invest much more than its competitors. Furthermore, the Intel chipset, as you read Intel is the biggest investor and development partner, is most common in data centers, accordingly increasing the performance of Cloudera's Hadoop on the Intel chipset could be relevant.

Hortonworks

Hortonworks works 100% open source and it's HDP is license free, this is because Hortonworks aims for the long run, selling services and nothing else

to help HDP to become the standard Hadoop distribution on the market. The company has done it's IPO in November 2014 and since increased is stock price by 5.44%, its Chief Executive Officer (CEO) Rob Bearden has experience in making most of open source software, "having previously sold JBoss Inc. to Red Hat Inc" [26].

MapR

MapR is trusted by Google, see the funding round in 2014, in which Google Capital invested 100 million US dollar. Because Google itself has probably the most fundamental knowledge and understanding of large scale computing, such an alliance says something about the technological level of MapR. They also have the largest number of customers, 700 and the IPO is planned for late 2015. MapR developed important parts of it's system proprietary, mainly to be faster and to provide additional features (like NFS), but they also may have the opportunity to develop faster, because no open source foundation exerts influence.

4.3.2. Threads

Cloudera

Intel is a strong shareholder, maybe Intel's objectives for Hadoop are not congruent to the Apache Hadoop project objectives and thus open source parts of Clouder are going to be proprietary in the future.

Hortonworks

Maybe Hortonworks misses momentum to head up to Cloudera and MapR, because of lower financial opportunities, even after the IPO in late 2014. Strong shareholders could try to influence the open source strategy, implementing closed source, proprietary components. Furthermore, Hortonworks is financial dependent on Microsoft, because it is the highest paying customer.

MapR

For MapR, no serious threads have been found. One could argue, that the proprietary components do become a weak spot, but that's not true, since MapR supports the core APIs of HDFS, HBase and MapReduce / YARN and thus could probably switch back towards a pure Hadoop if one day this would become a major issue, which in fact is not very likely, hence the re-write of especially the named components is one of MapR's unique selling proposition (USP).

4.4. Web-Application for the Decision Matrix

In this chapter I’ll briefly describe how the implementation from the theoretical decision matrix towards a usable web application was made.

5. Evaluation

5.1. An exemplary Use Case

5.1.1. Use Case Description

5.1.2. Applying the Decision Matrix on to the Use Case

5.1.3. Testing the Output and Hypotheses

5.2. Critical Reflection

6. Conclusion

A. Appendix

A.1. Tables

Table A.1.: Data sizes and comparisons.

Binary Value	Metric	Comparisons for scale
1024^2	`MB megabyte`	A typical English book in plain text format (500 pages × 2000 chars / page).
1024^3	`GB gigabyte`	One hour of SDTV video at 2.2 Mbit/s is approximately 1 GB.
1024^4	`TB terabyte`	One terabyte of audio recorded at CD quality contains approx. 2000 hours of audio.
1024^5	`PB petabyte`	The German Climate Computing Centre (DKRZ) has a storage capacity of 60 petabytes of climate data.
1024^6	`EB exabyte`	According to the Digital Britain Report, 494 exabytes of data was transferred across the globe on June 15, 2009.
1024^7	`ZB zettabyte`	As of 2013, the World Wide Web is estimated to have reached 4 zettabytes.

Vendor Release Cycles

Release Month	Cloudera	Hortonworks	MapR
12 2011			1.2.0
01 2012			
02 2012	3.3.0		1.2.1
03 2012			1.2.3
04 2012			
05 2012	3.4.0		
06 2012	4.0.0		1.2.7
07 2012	4.0.1		1.2.9
08 2012			2.0.0
09 2012		1.1.0	
10 2012	3.5.0, 4.1.0, 4.1.1		
11 2012	4.1.2		2.0.1, 2.1.0
12 2012			2.1.1
01 2013		1.2.0	
02 2013	4.1.3		
03 2013	4.2.0	1.3.0	2.1.2
04 2013	3.6.0, 4.1.4, 4.2.1		
05 2013	4.3.0		2.1.3, 3.0.0
06 2013			
07 2013			2.1.3.2
08 2013	4.1.5, 4.2.2, 4.3.1		
09 2013	4.3.2, 4.4.0		3.0.1
10 2013		2.0.0	3.0.2
11 2013	4.5.0		
12 2013			3.1.0
01 2014			
02 2014	4.6.0		
03 2014	5.0.0		
04 2014			
05 2014	4.7.0, 5.0.1, 5.0.2		
06 2014			3.1.1, 4.0.0
07 2014	5.0.3, 5.1.0		
08 2014	5.0.4, 5.1.2		
09 2014	5.1.3		4.0.1
10 2014	5.1.4, 5.2.0	2.2.0	
11 2014			
12 2014	4.7.1, 5.0.5, 5.2.1, 5.3.0		
01 2015			4.0.2
02 2015	5.2.3		
03 2015			
04 2015			

A.2. Results TCO Calculator

Visualizer Values

Inputs

Storage Assumptions		
File Storage Requirements in TB, Cluster 1		330
File Storage Requirements in TB, Cluster 2		0
File Storage Requirements in TB, Cluster 3		0
Storage Requirements by Number of Files, Cluster 1		110.000.000
Storage Requirements by Number of Files, Cluster 2		0
Storage Requirements by Number of Files, Cluster 3		0
Data Growth and Compression		
Compression Factor For MapR		30%
Compression Factor For Competitor		0%
Annual Data Growth Rate		100%
Node Assumptions		
Size of Drive Per Node		2.000
Number of Drives Per Node (Used For Data)		12
Hardware Cost Per Node		$9.000
Number of Files Supported Per Namenode		100.000.000
Hardware Maintenance Cost		20%
Network Port Assumptions		
Number of Ports Per Node		2
Type of Port	10 GB	
Cost of 1 GB Port		$208,14
Cost of 10 GB Port		$633,23
Watts Per Port for 1 GB Port		88
Watts Per Port for 10 GB Port		240
Software Assumptions		
Per Node License + Support Fee, Per Year		$4.000
Financial Assumptions		
Discount Rate		10%
Staffing Assumptions		
Hadoop Admin Base Salary		$130.000 / yr
Overhead Rate/Benefits		30%
Environmental Assumptions		
Cost of Power Per KW Hour		$0,10
Cooling as a Percentage of Power		100%
U-Height Per Node		2
Rack Height/Usable U		40
Square Feet Per Rack		16
Cost of Raised Floor Space Per Sq. Foot		$100,00 / mo

Ports Per Switch	24
U-Height Per Switch	1
Software Assumptions	
Per Node License + Support Fee, Per Year (competitor)	$4.000
Outputs	
Hardware Summary	
Total Nodes, Year 1	20
Total Nodes, Year 2	39
Total Nodes, Year 3	77
Total Ports, Year 1	40
Total Ports, Year 2	78
Total Ports, Year 3	154
Cluster 1	
Storage Requirements, End of Year 1	462
Storage Requirements, End of Year 2	924
Storage Requirements, End of Year 3	1.848
Nodes Required, End of Year 1	20
Nodes Required, End of Year 2	39
Nodes Required, End of Year 3	77
Ports Required, End of Year 1	40
Ports Required, End of Year 2	78
Ports Required, End of Year 3	154
Cluster 2	
Storage Requirements, End of Year 1	0
Storage Requirements, End of Year 2	0
Storage Requirements, End of Year 3	0
Nodes Required, End of Year 1	0
Nodes Required, End of Year 2	0
Nodes Required, End of Year 3	0
Ports Required, End of Year 1	0
Ports Required, End of Year 2	0
Ports Required, End of Year 3	0
Cluster 3	
Storage Requirements, End of Year 1	0
Storage Requirements, End of Year 2	0
Storage Requirements, End of Year 3	0
Nodes Required, End of Year 1	0
Nodes Required, End of Year 2	0
Nodes Required, End of Year 3	0
Ports Required, End of Year 1	0
Ports Required, End of Year 2	0
Ports Required, End of Year 3	0

Hardware Summary

Total Nodes, Year 1	**37**
Total Nodes, Year 2	**68**
Total Nodes, Year 3	**131**
Total Ports, Year 1	**74**
Total Ports, Year 2	**136**
Total Ports, Year 3	**262**

Cluster 1

Storage Requirements in TB, End of Year 1	**660**
Storage Requirements in TB, End of Year 2	**1.320**
Storage Requirements in TB, End of Year 3	**2.640**
Storage Requirements by Files, End of Year 1	**220.000.000**
Storage Requirements by Files, End of Year 2	**440.000.000**
Storage Requirements by Files, End of Year 3	**880.000.000**
Data Nodes Required, End of Year 1	**28**
Data Nodes Required, End of Year 2	**55**
Data Nodes Required, End of Year 3	**110**
NameNodes and Other Nodes Required, End of Year 1	**9**
NameNodes and Other Nodes Required, End of Year 2	**13**
NameNodes and Other Nodes Required, End of Year 3	**21**
Ports Required, End of Year 1	**74**
Ports Required, End of Year 2	**136**
Ports Required, End of Year 3	**262**

Cluster 2

Storage Requirements in TB, End of Year 1	**0**
Storage Requirements in TB, End of Year 2	**0**
Storage Requirements in TB, End of Year 3	**0**
Storage Requirements by Files, End of Year 1	**0**
Storage Requirements by Files, End of Year 2	**0**
Storage Requirements by Files, End of Year 3	**0**
Data Nodes Required, End of Year 1	**0**
Data Nodes Required, End of Year 2	**0**
Data Nodes Required, End of Year 3	**0**
Main and Other Nodes Required, End of Year 1	**0**
Main and Other Nodes Required, End of Year 2	**0**
Main and Other Nodes Required, End of Year 3	**0**
Ports Required, End of Year 1	**0**
Ports Required, End of Year 2	**0**
Ports Required, End of Year 3	**0**

Cluster 3

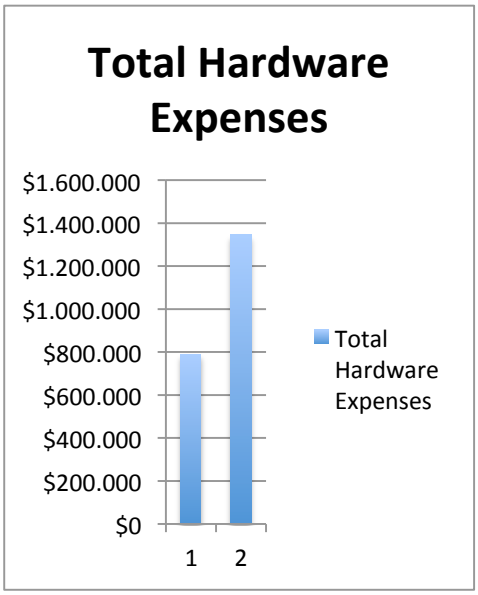
Storage Requirements in TB, End of Year 1	**0**

Storage Requirements in TB, End of Year 2	0	
Storage Requirements in TB, End of Year 3	0	
Storage Requirements by Files, End of Year 1	0	
Storage Requirements by Files, End of Year 2	0	
Storage Requirements by Files, End of Year 3	0	
Data Nodes Required, End of Year 1	0	
Data Nodes Required, End of Year 2	0	
Data Nodes Required, End of Year 3	0	
Main and Other Nodes Required, End of Year 1	0	
Main and Other Nodes Required, End of Year 2	0	
Main and Other Nodes Required, End of Year 3	0	
Ports Required, End of Year 1	0	
Ports Required, End of Year 2	0	
Ports Required, End of Year 3	0	

Scenario Values	***MapR***	***Alternative***	
Inputs			
Hidden 1=Mapr 2=Competitor	1	2	
Staffing Assumptions			
Nodes Managed Per FTE	51	50	
Environmental Assumptions			
Watts Per Node	750	750	
Outputs			
3-Year Total Cost of Ownership (TCO)	$2.185.809	$3.642.264	
Total Capital and Operating Cash Flows, Year 1	$558.654	$890.004	
Total Capital and Operating Cash Flows, Year 2	$723.545	$1.282.581	
Total Capital and Operating Cash Flows, Year 3	$1.437.441	$2.360.108	
Total Hardware Expenses	$790.517	$1.344.906	
Hardware Expense, Year 1	$205.329	$379.859	
Hardware Expense, Year 2	$195.063	$318.260	
Hardware Expense, Year 3	$390.125	$646.787	
Hardware - Total Node Expenses	$693.000	$1.179.000	
Hardware - Node Expense, Year 1	$180.000	$333.000	
Hardware - Node Expense, Year 2	$171.000	$279.000	
Hardware - Node Expense, Year 3	$342.000	$567.000	
Hardware - Total Port Expenses	$97.517	$165.906	
Hardware - Port Expense, Year 1	$25.329	$46.859	
Hardware - Port Expense, Year 2	$24.063	$39.260	
Hardware - Port Expense, Year 3	$48.125	$79.787	
Total Software Expenses	$544.000	$944.000	
Software Expense, Year 1	$80.000	$148.000	
Software Expense, Year 2	$156.000	$272.000	
Software Expense, Year 3	$308.000	$524.000	
Total Hardware Maintenance Expenses	$279.248	$484.577	
Hardware Maintenance Expense, Year 1	$41.066	$75.972	

Hardware Maintenance Expense, Year 2	$80.078	$139.624
Hardware Maintenance Expense, Year 3	$158.103	$268.981
Total Staffing Expenses	$676.000	$1.014.000
Staffing Expense, Year 1	$169.000	$169.000
Staffing Expense, Year 2	$169.000	$338.000
Staffing Expense, Year 3	$338.000	$507.000
Total Power Costs	$293.075	$508.571
Total Power Costs, Year 1	$43.099	$79.734
Total Power Costs, Year 2	$84.043	$146.537
Total Power Costs, Year 3	$165.932	$282.300
Power and Cooling Cost of Nodes, Year 1	$26.280	$48.618
Power and Cooling Cost of Nodes, Year 2	$51.246	$89.352
Power and Cooling Cost of Nodes, Year 3	$101.178	$172.134
Power and Cooling Cost of Ports, Year 1	$16.819	$31.116
Power and Cooling Cost of Ports, Year 2	$32.797	$57.185
Power and Cooling Cost of Ports, Year 3	$64.754	$110.166
Power Consumption, Year 1	131.400	243.090
Power Consumption, Year 2	256.230	446.760
Power Consumption, Year 3	505.890	860.670
Total Floor Space Costs	$136.800	$236.640
Total Floor Space Costs, Year 1	$20.160	$37.440
Total Floor Space Costs, Year 2	$39.360	$68.160
Total Floor Space Costs, Year 3	$77.280	$131.040
Floor Space Cost for Nodes, Year 1	$19.200	$35.520
Floor Space Cost for Nodes, Year 2	$37.440	$65.280
Floor Space Cost for Nodes, Year 3	$73.920	$125.760
Floor Space Cost for Ports, Year 1	$960	$1.920
Floor Space Cost for Ports, Year 2	$1.920	$2.880
Floor Space Cost for Ports, Year 3	$3.360	$5.280
Total Environmental Costs	$429.875	$745.211
Total Environmental Costs, Year 1	$63.259	$117.174
Total Environmental Costs, Year 2	$123.403	$214.697
Total Environmental Costs, Year 3	$243.212	$413.340


3-Year Total Cost of Ownership (TCO)
$4.000.000
$3.500.000
$3.000.000
$2.500.000
$2.000.000
$1.500.000
$1.000.000
$500.000
$0
1
2
3-Year Total Cost of Ownership (TCO)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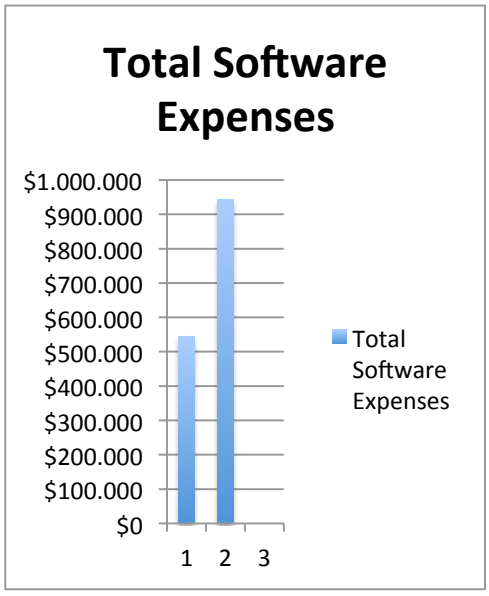
$0
1
2
Total Hardware Expenses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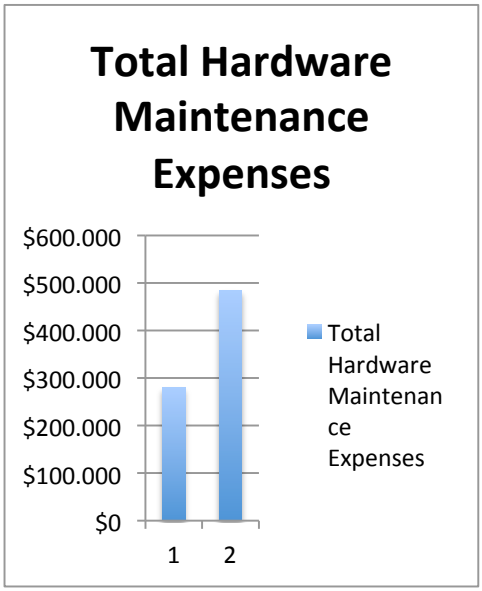
2
3
Total Software Expenses


Total Hardware Maintenance Expenses
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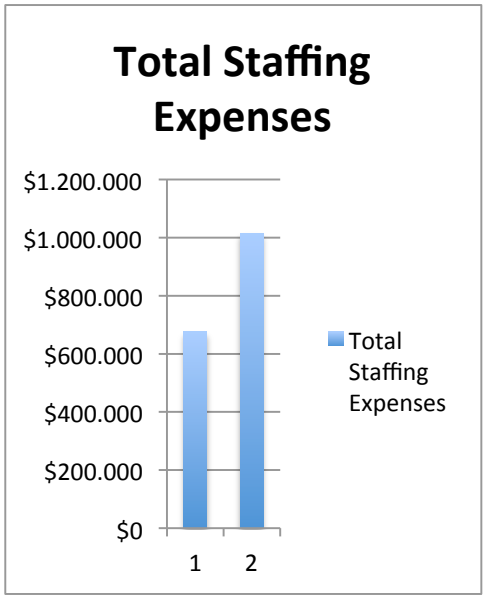
$0
1
2
Total Hardware Maintenance Expenses


Total Staffing Expenses
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$1.000.000
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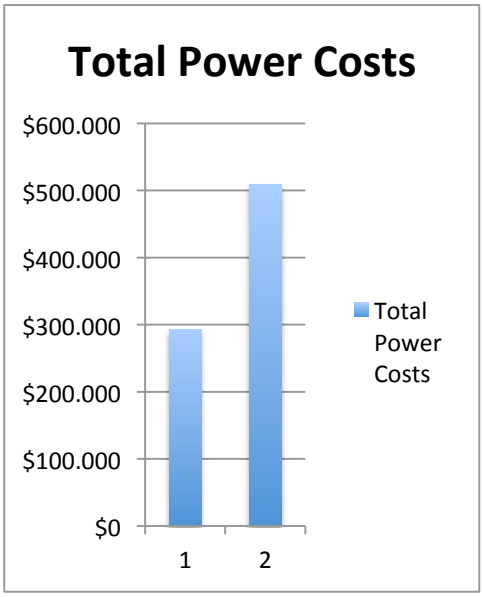
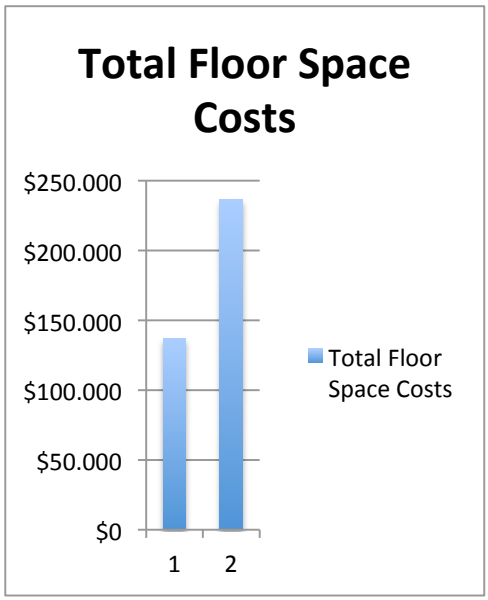
$600.000
$400.000
$200.000
$0
1
2
Total Staffing Expenses


Total Power Costs
$600.000
$500.000
$400.000
$300.000
$200.000
$100.000
$0
1
2
Total Power Costs


Total Floor Space Costs
$250.000
$200.000
$150.000
$100.000
$50.000
$0
1
2
Total Floor Space Costs

Definitions

Visualizer Inputs

Storage Assumptions

File Storage Requirements in TB, Cluster 1	Cluster storage capacity, terabytes of disk space
File Storage Requirements in TB, Cluster 2	in TB
File Storage Requirements in TB, Cluster 3	in TB
	The number of files is directly related to the number of NameNodes required in HDFS-based Hadoop deployments. Hadoop distributions which use the Hadoop distributed file system (HDFS) have a file limit of 50-100 million files before another NameNode is required because HDFS keeps file metadata in memory and does not persist to disk. When an organization has a lot of files (particularly lots of small files), they will do file management acrobatics through a LOT of extra coding to combine lots of small files and get more utilization of block size before they need to add an additional NameNode (which then of course requires implementing the journaling NameNode if you want the system to be HA). This has hard dollar costs as well as the soft costs associated with Hadoop developers writing and maintaining code and running jobs to deal with this file limitation. The MapR Distribution has a fully-distributed architecture which distributes file metadata across all data nodes and writes it to disk. This no-NameNode architecture is more reliable and scales to 1 trillion files, greatly reducing the amount of hardware required.
Storage Requirements by Number of Files, Cluster 1	
Storage Requirements by Number of Files, Cluster 2	only used in calculations for competitor
Storage Requirements by Number of Files, Cluster 3	only used in calculations for competitor

Data Growth and Compression

Compression Factor For MapR	MapR applies compression automatically to files in the cluster. Compression is 2-3x depending on file types and compression settings, which reduces storage requirements, as well as using less bandwidth on the network, resulting in improved performance. In HDFS-based distributions, compression is a manual process within the application itself and an additional administrative overhead. The moment you programmatically alter the file format, any other use of the data in that file will require knowing how to programmatically read the file.
Annual Data Growth Rate	Data growth rate is inputted at the beginning of the TCO analysis, but is adjustable here.

Node Assumptions	
Size of Drive Per Node	Disk capacity, in gigabytes. 2 TB drives is the base assumption for the node and is fairly standard today.
	The number of files is directly related to the number of NameNodes required in HDFS-based Hadoop deployments. Hadoop distributions which use the Hadoop distributed file system (HDFS) have a file limit of 50-100 million files before another NameNode is required because HDFS keeps file metadata in memory and does not persist to disk.
	When an organization has a lot of files (particularly lots of small files), they will do file management acrobatics through a LOT of extra coding to combine lots of small files and get more utilization of block size before they need to add an additional NameNode (which then of course requires implementing the journaling NameNode if you want the system to be HA). This has hard dollar costs as well as the soft costs associated with Hadoop developers writing and maintaining code and running jobs to deal with this file limitation.
	The MapR Distribution has a fully-distributed architecture which distributes file metadata across all data nodes and writes it to disk. This no-NameNode architecture is more reliable and scales to 1 trillion files, greatly reducing
Hardware Cost Per Node	the amount of hardware required.
Hardware Maintenance Cost	as percent of total node expense
Network Port Assumptions	
	10 GB ethernet is the most common in production Hadoop deployments. 1GB and 40GB (InfiniBand) are also
Type of Port	available and used depending on workload characteristics.
Software Assumptions	
	Most Hadoop vendors charge on a $/node/year subscription model, regardless of whether there is a software license or just a support & maintenance fee.
	The base assumption is $4000/node list price for the MapR Enterprise Edition (does not include MapR-DB). Assume $7k/node/year for MapR Enterprise Edition.
	When pricing Hadoop alternatives, be sure you include add-ons other vendors charge for features like backup
Per Node License + Support Fee, Per Year	and DR which are included in MapR base price.

Financial Assumptions	
Discount Rate	The cost of money over time.
Software Assumptions	
	Most Hadoop vendors charge on a $/node/year subscription model, regardless of whether there is a software license or just a support & maintenance fee.
	The base assumption is $4000/node list price for the MapR Enterprise Edition (does not include MapR-DB). Assume $7k/node/year for MapR Enterprise Edition.
Per Node License + Support Fee, Per Year (competitor)	When pricing Hadoop alternatives, be sure you include add-ons other vendors charge for features like backup and DR which are included in MapR base price.
Visualizer Outputs	
Hardware Summary	
Total Nodes, Year 1	Total number of nodes is calculated based on storage requirements and is tied to the data growth rate inputted at beginning of the TCO analysis.
Cluster 1	
NameNodes and Other Nodes Required, End of Year 1	includes name nodes, 1 administrative node, 1 high availability node, and 1 edge node
NameNodes and Other Nodes Required, End of Year 2	includes name nodes, 1 administrative node, 1 high availability node, and 1 edge node
NameNodes and Other Nodes Required, End of Year 3	includes name nodes, 1 administrative node, 1 high availability node, and 1 edge node
Cluster 2	
Main and Other Nodes Required, End of Year 1	includes name nodes, 1 administrative node, 1 high availability node, and 1 edge node
Main and Other Nodes Required, End of Year 2	includes name nodes, 1 administrative node, 1 high availability node, and 1 edge node
Main and Other Nodes Required, End of Year 3	includes name nodes, 1 administrative node, 1 high availability node, and 1 edge node
Cluster 3	

Main and Other Nodes Required, End of Year 1	includes name nodes, 1 administrative node, 1 high availability node, and 1 edge node
Main and Other Nodes Required, End of Year 2	includes name nodes, 1 administrative node, 1 high availability node, and 1 edge node
Main and Other Nodes Required, End of Year 3	includes name nodes, 1 administrative node, 1 high availability node, and 1 edge node

Scenario Inputs

Staffing Assumptions

	The number of nodes managed per full time employee (FTE) is a measure of the number of system administrator or DevOps people required to keep the system running and maintained. MapR customers state they get 25-50% better ops staff productivity using MapR than what is required with other distributions because of the better uptime, self-healing availability, the no-NameNode architecture, and higher file limit. Workers can now focus on strategic problems such as next-generation tools and technologies that are emerging rapidly in Hadoop instead of fire-fighting operations issues like name node failures and HBase region server failures. The base assumption is 2 people to manage 100 nodes for MapR and 3 people to manage 100 nodes for other distributions. Even if you assume the same ratio of FTEs:nodes between distributions, the cost of MapR is less based on the amount of hardware requred.
Nodes Managed Per FTE	There is a limit to the # of people required. Very large clusters (1000+ nodes) typically required 5-10 people.

Environmental Assumptions

Watts Per Node	These numbers assume MapR uses the Cisco C240 M3 while Cloudera uses the Dell R720

Scenario Outputs

3-Year Total Cost of Ownership (TCO)	Includes total hardware (nodes, ports) , support (hardware and software), human capital, and environmentals (power, space, and cooling)
Total Capital and Operating Cash Flows, Year 1	sum of hardware, software, maintenance, staffing, and environmental
Total Capital and Operating Cash Flows, Year 2	sum of hardware, software, maintenance, staffing, and environmental

Total Capital and Operating Cash Flows, Year 3	sum of hardware, software, maintenance, staffing, and environmental
Total Hardware Expenses	Total hardware costs over 3 years including nodes and ports, and maintenance fees.
Power Consumption, Year 1	yearly total, in kilowatts
Power Consumption, Year 2	yearly total, in kilowatts
Power Consumption, Year 3	yearly total, in kilowatts

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I hereby declare that, to the best of my knowledge and belief, this bachelor thesis titled “Evaluating Hadoop Distributions: Towards an Enterprise Guide” is my own work. I confirm that each significant contribution to, and quotation in this thesis from the work, or works of other people is indicated through the proper use of citations and references.

Münster, on the 21.03.2015

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