BigTexts
A Framework for the Analysis of Electronic Health Record Narrative Texts based on Big Data Technologies

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Abstract: In the healthcare domain the analysis of Electronic Medical Records (EMR) may be classified as a Big Data problem since it has the three fundamental characteristics: Volume, Variety and Speed. A major drawback is that most of the information contained in medical records is narrative text, where natural language processing and text mining are key technologies to enhance the utility of medical records for research, analysis and decision support. Among the tasks performed for natural language processing, the most critical, in terms of time consumption, are the pre-processing tasks that give some structure to the original non-structured text. Studying existing research on the use of Big Data techniques in the healthcare domain reveals few practical contributions, especially for EMR analysis. To fill this gap, this paper presents BigTexts, a framework that provides pre-built functionalities for the execution of pre-processing tasks over narrative texts contained in EMR using Big Data techniques. BigTexts enables faster results on EMR narrative text analysis improving decision making in healthcare.

1 INTRODUCTION

Nowadays, the amount of information stored in the world is estimated at around of 1,200 exabytes (10^{18} bytes), which come from multiple sources; for example, Google processes over 24 petabytes (10^{15} bytes) of data per-day and Facebook gets more than 10 million photos every hour (Mayer-Schonberger and Cukier, 2013). Given these large amounts of data that are currently being generated, the paradigm of Big Data has been proposed to describe the phenomenon and suggest the need for organizations to adopt innovative tools that can help to accurately determine opportunities for improvement and creating value (Moore et al., 2013). A Big Data problem is one that complies with the three Vs: Volume (scale of data), Variety (different forms of data) and Velocity (on data flow analysis) (McAfee and Brynjolfsson, 2012). As in other domains, the healthcare domain is generating increasingly large amounts of data, significantly within Electronic Medical Records (EMR). Such data becomes an invaluable source for analysis and research to address public health issues, improve service quality and increase the coverage and efficiency of health services (Sengupta, 2013).

Considering the large volume of data contained in EMR, the variety going from structured to unstructured data, and the speed which certain studies require, the analysis of EMR using computational techniques may be classified as a Big Data problem (Moore et al., 2013). In particular, the existence of narrative text in fields such as nursing notes, treatment plans, and lab tests, among others, generates a major challenge that needs to be addressed natural language processing technologies, text mining and Big Data.

To face this requirement from the healthcare domain, the aim of this paper is to present Big Texts, a Big Data *framework* for the pre-processing of narrative texts contained in EMRs. Big Texts provides pre-built functions for the execution of pre-processing tasks required to apply text mining techniques like tokenization and Part-of-Speech recognition over the text. In order to improve the performance of pre-processing tasks, Big Texts uses big data technologies like Map Reduce, Yarn and HDFS, and can be used by running a standalone application or using its Java Application Programming Interface (API).

In order to present Big Texts, this paper is organized as follows: Section 2 presents an overview

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of Big Data technologies and some related previous work. Section 3 specifies the characteristics and architecture of Big Texts. Then Section 4 describes the evaluation of the *framework* and its use for the analysis of patient with a chronic disease. Finally, Section 5 presents conclusions and future work.

2 RELATED WORKS

Big data techniques have already been used by different projects. This section describes the most relevant techniques related to Big Data; then, it presents a set of related proposals for using them to improve the analysis of data in the healthcare domain as well as those created to enhance the execution of preprocessing tasks and text mining techniques in any context.

2.1 Big Data Technologies

Big Data is not a technology by itself, it is rather a paradigm that has promoted the creation of several products and frameworks; Table 1 presents a subset of them including their classification according to the V property they are intended for.

Table 1: Big Data Technologies Classification.

Technology	Sub-technology	Velocity	Variety	Volume
NoSQL			X	X
Analytics	Exploratory Data Analysis (EDA)		X	X
	Confirmatory Data Analysis (CDA)		X	X
	Qualitative Data Analysis (QDA)	X	X	X
MapReduce		X		X
Apache Hive		X		X
Apache Pig		X		X

MapReduce: is a computing style that can be used to manage large-scale calculations in a way that is hardware fault tolerant (Rajaraman and Ullman, 2012).

NoSQL: or Not Only SQL, is a data management approach and database design that is useful for very large datasets that are distributed (Sadalage and Fowler, 2012).

Analytics: is the science of examining raw data with the purpose of obtaining conclusions and convert them to information (Maheshwari, 2015).

Hadoop: is a framework that allows distributed processing of large sets of data across computer clusters using simple programming models (White, 2012).

Apache Hive: provides a SQL-based dialect called Hive Query Language (HiveQL) to query data stored in a Hadoop cluster (Capriolo et al., 2012).

Apache Pig: provides an engine for a parallel data flow execution in Hadoop and a language called Pig Latin for the expression of such data flows (Gates, 2011).

2.2 Big Data Applied to the Health Care Domain

Table 2 summarizes relevant projects related to the application of Big Data technologies in the healthcare domain. One of the main conclusion of this analysis is that they are mostly theoretical proposals of desirable uses of Big Data technologies in that domain. Similarly, there are few tangible practices and approaches of using this paradigm in products or prototypes that make the expected benefits a reality. Also it was evident that one of the recurring factors in papers is the high amount of data required to analyze by medical professionals and administrative personal to make better decisions. Having in mind that one of the major sources of information is the narrative text in the EMRs, it is worth reviewing previous work that use the Big Data paradigm to enhance the management of textual data (Section 2.3).

2.3 Big Data Solutions to Improve Text Analysis

The literature review of solutions that provide natural language processing and/or text mining techniques indicates that there is an important platform called GATECloud.net that provides several strategies to improve response time in natural language processing, among which has two options: the use of MapReduce and the Cloud Computing technologies management. From these two options the authors of these products recommend the second one, under a model PaaS, since it is not necessary to rewrite the processing algorithms to be executed. GATECloud.net is a Web platform where scientists can conduct experiments on text mining, and whose services are collected through payment for use. It is important to note that this product does not provide libraries (APIs) that can be used from other systems (Tablan et al., 2012).

In addition to this proposal, there are other projects that create customized solutions that use Big Data technologies to analyze a specific set of narrative texts. It is the case of the project presented in (Das and Mohan Kumar, 2013) that proposes the use of Big Data technologies and text mining techniques to analyze public tweets. It uses technologies such as HBase, Java, REST and Hadoop to enhance the performance of the analysis. Even though these kind of projects are important to mature the conjunction of Big Data and Text Mining, they do not provide open products or frameworks that can be used by

Table 2: Comparison of Big Data Projects in the HealthCare Domain.

Project	Technology	Problem Solved	Type	Content
Use of Big Data and Cloud Computing for operational Health BI (Purkayastha and Braa, 2013)	Cloud Computing	Bridging the digital divide for Medical Information Systems in developing countries	Practical	Text
Big Data in personalized health care (Chawla and Davis, 2013)	Data mining	Risk Profile Custom diseases	Theoretical - Practical	Text
Big Data in Functional Echocardiography (Sengupta, 2013)	Cloud computing, Robots, Artificial Intelligence	To have more variables in the functional echocardiography	Theoretical	Images
Acquisition, compression, encryption and storage of Big Data in Health (Brinkmann et al., 2009)	File processing	Compressing data from electrophysiological recordings	Practical	Images
Big Data in medical devices (Meeker and Hong, 2014)	Sensors	Reliability and availability of medical devices	Theoretical	Text
Development of an ecosystem of healthcare using IPHIs (Liyanage et al., 2012)	Ontologies	Ecosystem health interoperability for heterogeneous systems	Theoretical	Text
Big Data to assess the impact of medical programs (Fox, 2011)	Analytics	Allocate and keep real patients	Theoretical	Text

other projects, which is our need to analyze medical records.

As is evident, although there are approaches that try to unify the paradigm of Big Data to text processing, they are not still mature enough or do not provide APIs through which existing systems can run tasks (such as pre-processing) in large amounts of text, providing a great opportunity to attacked by BigTexts (Section 3), the proposal of this paper.

3 BIGTEXTS

BigTexts is a framework that allows the execution of pre-processing tasks over narrative texts required to apply text mining techniques. It was developed using Big Data technologies, which allows it to improve the performance when it is necessary to analyze large volumes of medical records and texts contained in them. BigTexts allows the pre-processing of hundreds, thousands or millions of narrative texts when a research required the analysis at institutional, regional or national level. BigTexts provides pre-built functionalities that can be used as an independent application (with a graphical user interface - GUI) or as a library (API) from an existing application.

Figure 1 shows highlighted the BigData technologies used in BigTexts. BigTexts uses Apache Pig at the data access level, MapReduce for distributed processing, YARN as a resource manager, HDFS for distributed storage and Linux Ubuntu as the operating system. BigTexts, takes the EMR texts and partition them in the Hadoop cluster using HDFS. Using MapReduce to execute the pre-processing tasks in parallel, in order to finally obtain the set of pre-processed documents.

As it is shown in Figure 2, typically the analysis of EMRs are executed sequentially (As-Is). This way of running generates a bottle neck when the number of EMR is large. With BigTexts the execution is parallelized across the set of machines available in the

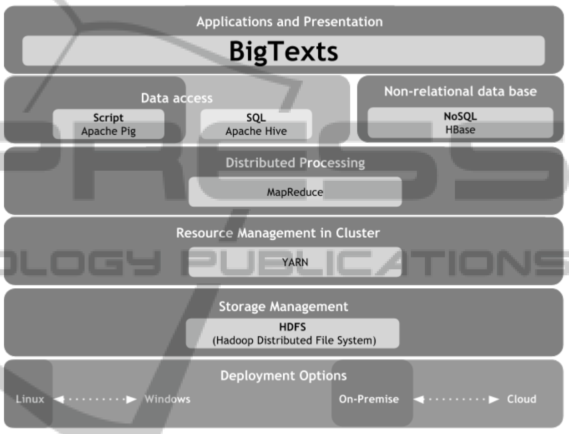


Figure 1: BigTexts in the Reference Architecture.

cluster where BigTexts is running. BigTexts takes the EMR texts and partitions them in the Hadoop cluster using HDFS. Using MapReduce it executes the pre-processing tasks in parallel. Finally, it obtains the set of pre-processed texts.

The following sections explain the functionalities provided by BigTexts and its architecture.

3.1 BigTexts Tasks

As it was mentioned, BigTexts provides pre-processing tasks required to give some structure to the originally unstructured texts. These tasks allow for example the division of the text in tokens, to identify sentences, to recognize the role of each word in a sentence, to recognize patterns in the text, etc. The following list explains the current tasks provided by BigTexts, which are based on the Stanford CoreNLP library (The Stanford NLP Group, 2014b) and the Weka library (The University of Waikato, 2014). It is important to notice that these tasks can be extended according to the requirements of the analysis.

- Identification of co-reference: It identifies when two or more expressions in a text refer to the

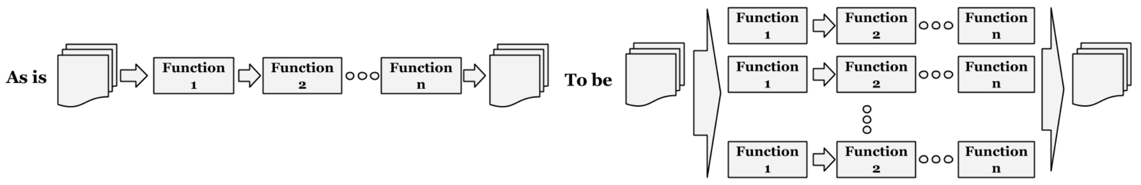


Figure 2: Current Situation vs. BigTexts Situation.

same person or thing (The Stanford NLP Group, 2014a).

- Lemmatisation Lovins: It reduces a word to its lemma, root or canonical form using the Lovins Stemmer algorithm (Lancaster University, 2014).
- Named Entity Recognition: It locates and gives a label to some elements in text taking into account pre-defined categories such as the names of persons, organizations, locations, dates, monetary values, etc (The Stanford NLP Group, 2014d).
- Part of Speech: It recognizes and gives a label indicating the grammar role a word plays in a sentence (The Stanford NLP Group, 2014c).
- Named Entity Recognition based on regular expressions (NE Transducer): It locates and gives a label to some elements in text taking into account rules described using regular expressions.
- Lemmatisation Snowball: It reduces a word to its lemma, root or canonical form using the snowball stemmer algorithm.
- Partition text by phrases: It splits a text into its sentences using a set of configurable terminators like ., ?.
- Tokenization: It breaks down a text into tokens using a set of configurable separators like space, punctuation tokens, among others.
- Switch a text to upper case.

The implementation of the pre-processing tasks was made using Apache Pig, particularly the option for creating User Defined Functions (UDFs). Each pre processing tasks is represented by a Java class that inherits from *org.apache.pig.EvalFunc* and packaged using Apache Maven. After that the resulting jar is added to the Pig pipeline and the UDF is called inside of Pig instructions. As mentioned before, the pre-processing tasks use two NLP libraries, Stanford CoreNLP and Weka.

The addition of a new pre-processing task is designed to be a simple and flexible process. To do this, a new class is created in which the functionality is implemented and added to the preprocessing tasks catalog[1].

[1] An XML file with all the pre-processing tasks and their parameters.

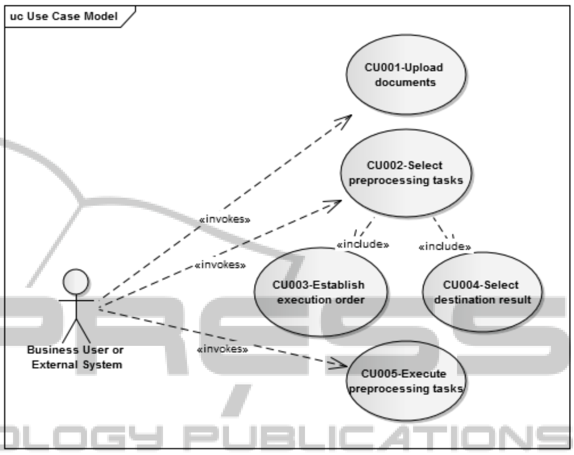

uc Use Case Model
CU001-Upload documents
CU002-Select preprocessing tasks
CU003-Establish execution order
CU004-Select destination result
CU005-Execute preprocessing tasks
«invokes»
«invokes»
«invokes»
«include»
«include»
Business User or External System

Figure 3: BigTexts Use Cases.

Each one of the previous tasks can be executed using an API provided by BigTexts or directly using its graphical user interface. Figure 3 describe the use cases of BigTexts:

1. CU001-Upload documents: The actor can load a set of documents for further processing.
2. CU002-Select preprocessing tasks: The actor can select the pre-processing tasks he/she wants to execute in BigTexts.
3. CU003-Establish execution order: The actor can give the order in which the selected tasks must be executed and configured on the CU002.
4. CU004-Select destination result: The actor chooses the way the results are going to be delivered, with two options: FTP or HDFS directory.
5. CU005-Execute preprocessing tasks: The actor can launch the execution of the pre-processing task list over the uploaded documents.

3.2 BigText Process and Architecture

Figure 4 shows an overview of how BigTexts interacts with the BigData technology. As it can be seen it is composed by a Client component (BigTexts Client) and a Server component(BigTexts).

The Client offers a graphical user interface through which the user can select the files to be processed, the pre-processing tasks to run (and their settings) and the delivery method. This client application can also be used by an external application as a library. Once a user sends the files to the server using FTP and indicates the tasks he/she wanted to execute, the client component sends an XML format message to the server queue.

The BigTexts server component connects to the server queue (ActiveMQ) and gets the queued message, transforming it from XML (using the library JAXB[2]) to objects. Subsequently, the converted message to object is executed in the Hadoop cluster by an Apache Pig script that uses UDFs (User Defined Functions) with the pre-processing tasks. The Hadoop cluster is composed of a main machine (the master), which manages both storage and parallel processing, and a number of secondary machines (slaves) that stores data blocks and process them in parallel. Finally, a set of pre-processed documents are delivered in the HDFS or in the FTP directory, according to what the user has selected.

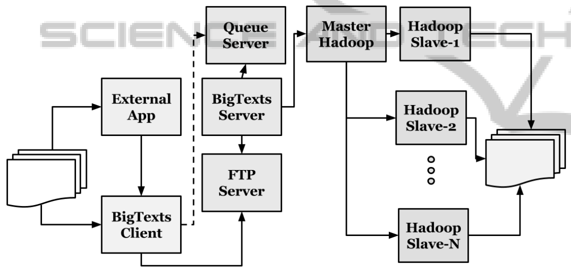


Figure 4: BigTexts.

The internal architecture of BigTexts Server[3] is presented in Figure 5.

1. pig-client-0.13.0.jar: It is the library that allows the connection with the installation of Pig.
2. bigtexts-util-1.0.jar: BigTexts utility classes.
3. log4j-1.2.17.jar: The application log manager.
4. hadoop-client-2.5.0.jar: Library that allows interaction with HDFS and Hadoop.
5. bigtexts-dto-1.0-jar: Package with the classes that allow the communication between the BigTexts client and server.
6. automaton-1.11-8.jar: Finite state automata library, used by the Pig client.
7. eclipselink-2.3.2.jar: Java Persistence API implementation created by The Eclipse Foundation

[2]Java Architecture for XML Binding

[3]bigtexts-1.0.jar: Server application, is responsible for executing the pre-processing tasks into the BigData infrastructure.

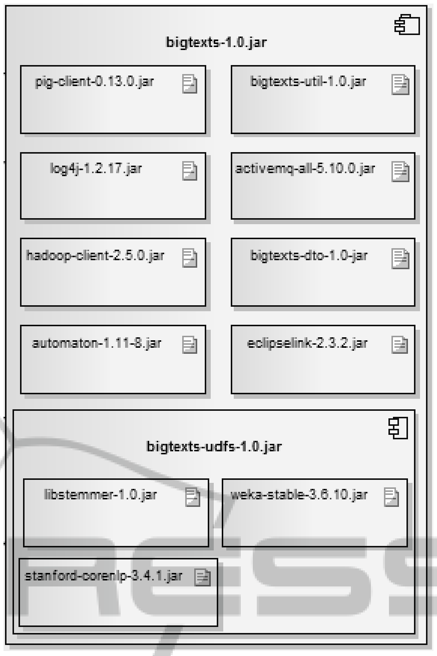


Figure 5: BigTexts Physical View.

8. bigtexts-udfs-1.0.jar: Component with the implementations of the pre-processing tasks.
   (a) libstemmer-1.0.jar: Library with the Snowball Stemmer implementation.
   (b) stanford-corenlp-3.4.1.jar: Natural Language Processing library.
   (c) weka-stable-3.6.10.jar: Library for the implementation of Lovins Stemmer.

4 CASE STUDY AND VALIDATION

In order to validate the functionality and the performance of BigTexts, the framework was used for the analysis of EMRs contained in a Hospital EMR System. The goal of the analysis was to identify a set of patients with specific characteristics required by medical researchers for a retrospective cohort study. This section presents first the scenario in which the validation of the system was performed (Section 4.1) and then its results (Section 4.2).

4.1 Validation Scenario

The validation scenario requires searching, from a set of EMRs, those records that match different characteristics required to include them in a study on Heart Failure. The input for the analysis of each record includes terms related to the diagnosis, personal and family antecedents, lab exams, medications, symptoms, treatment plans complications and outcomes. The intention of the case study was to find the set of EMRs that include most of the characteristics defined by the group of researchers to include them in a retrospective cohort study around this chronic disease. BigTexts was used for this purpose. It was configured for the pre-processing of 10.000 narrative texts provided by the hospital. In order to assure the confidentiality of the patients the records were previously anonymized and provided in 4 files. In addition, the *Named Entity Recognition* task of BigTexts was configured for the identification of terms related to the searched diagnosis like Cardiac Failure, Cardiopathy, chronic heart failure, CHF, among others;related to lab exams like bnp, echocardiogram; related to symptoms like Paroxysmal Nocturnal Dyspnea, and related to complications as death.

From the technical point of view, the machines used for the configuration of the Hadoop cluster (Table 3) were not high specification computers (server type), but rather common computers in order to simulate real hospital environments, where was not possible to have dedicated servers. A main machine (master) was used and a set of secondary machines (slaves). The client application was installed on the master machine as well as the BigTexts server. All computers were installed with the Ubuntu operating system 14.0.LTS. The machines were connected in a local area network (LAN) establishing static IP addresses. All machines had Intel processors.

The size of the files provided was the following: 1.945.886 bytes (1.945 Mb), 1.423.803 bytes (1.423 Mb), 437.643 bytes (437.643 Kb) and 761 bytes. The validation consisted of the execution of five iterations per file in each of the following pre-processing tasks:

- RegexNamedRecognition: Given the list of terms related to the diagnosis and the lab exams with a label for each of them, the system identified using regular expressions if a word was in the token list and set the corresponding label.

- Tokenizer: Partition files into tokens.

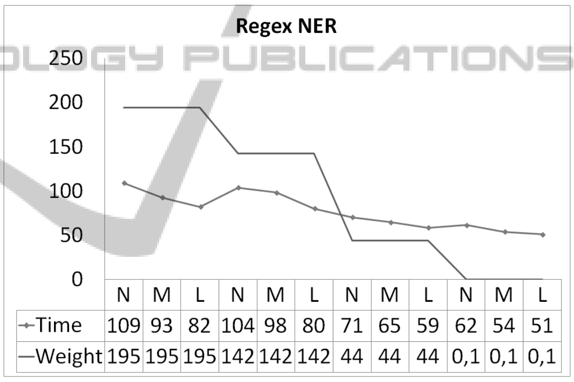
- Tokenizer + POS-Tagger: Two preprocessing tasks were performed. The first one broke up the file into tokens and then applied Part of Speech task identifying whether each word was a verb, an adjective, an adverb, etc.

- Tokenizer + SnowballStemmer: It breaks up the file into tokens and then identified the root of each one of them.

4.2 Perfomance Results

The analysis of the data, using figures of lines to identify trends is shown below. For a clear display on the graph the file size was divided for 10.000, having all of them in the same scale. There was used a combination of *N*, *M* and *L* machines, where $N < M < L$.

Finding that the Regex Entity Recognition task (Figure 6) execution with the 1,945,886 bytes file and *N* machines obtained an average time of 109.13 seconds, for *M* machines of 92.78 seconds and for *L* machines of 82.25 seconds. For the 1.423.803 bytes file, the times were 104.07, 98.33 and 80.45 seconds. Likewise, the file of 437,643 bytes had times of 70.54,65.13 and 58.71 and the file of 761 bytes had times of 61.57, 54 and 51 seconds for *N*, *M* and *L* active machines in the cluster. As it can be seen, there is a downward trend on time when the number of machines is increased.



	N	M	L	N	M	L	N	M	L	N	M	L
Time	109	93	82	104	98	80	71	65	59	62	54	51
Weight	195	195	195	142	142	142	44	44	44	0,1	0,1	0,1

Figure 6: Validation - RegexNER.

For the tokenization task (Figure 7) for the file of 1.945.886 bytes, times obtained were 50.22, 46.63 and 36 seconds. For the file of 1.423.803, time average was 56.25, 41.33 and 33.6 seconds. Similarly, for the 437.643 files and 761 bytes, execution times improved when the number of machines in the cluster was increased.

Regarding the tokenization task added to the Part of Speech (Figure 8) task, for the 1.945.886 bytes files, times were 181, 113.75 and 85.67 seconds; for the 1.423.803 bytes the times were 118.33, 96.67 and 76.33 seconds; and for the 761 bytes the times were 69.67 , 65 and 52.5 seconds. These results show an improvement when the number of available machines in the cluster were increased. However, in the case of the 437.643 bytes file there was a not an improvement in time when the number of machines was increased slightly, but a substantial improvement was presented when the number of machines was changed radically.

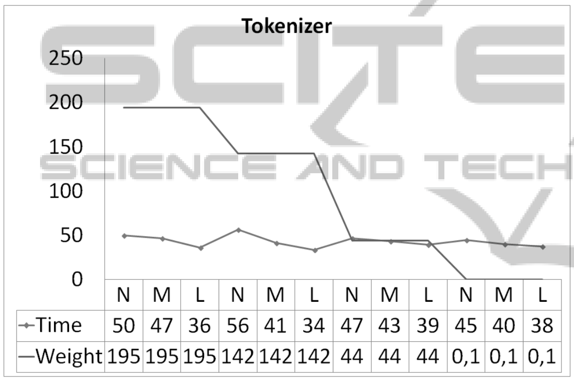
For the tokenization task added to Stemming using

Table 3: Cluster Machines.

Name	Hostname	IP Interna	Brand	Memory	Hard drive	Processor
bigtexts-1	master	192.168.0.101	HP	3,8 GiB	155,3 GB	Intel Core 2 Duo CPU E7200 2.53GHz x 2
bigtexts-2	slave-2	192.168.0.102	HP	1.9 GiB	155.3 GB	Intel Core 2 Duo CPU E7200 2.53GHz x 2
bigtexts-3	slave-3	192.168.0.103	Lenovo	1.9 GiB	76.5 GB	Intel Core 2 CPU 4400 2.00GHz x 2
bigtexts-4	slave-4	192.168.0.104	HP	1.9 GiB	155.3 GB	Intel Core 2 Duo CPU E4600 2.40GHz x 2
bigtexts-5	slave-5	192.168.0.105	HP	1.9 GiB	155.3 GB	Intel Core 2 Duo CPU E7200 2.53GHz x 2

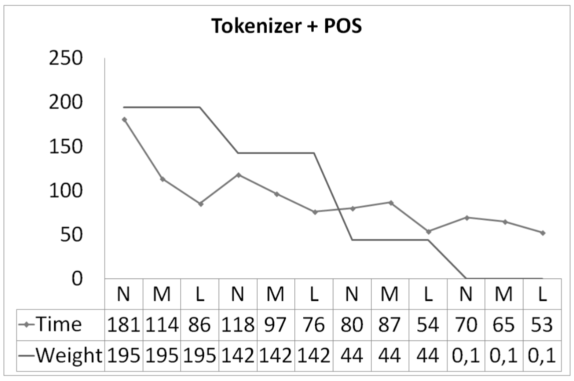
Snowball algorithm (Figure 10) the following times for *N*, *M* and *L* machines were obtained, respectively:

- 1.945.886 bytes: 69.15, 53.86 and 49 seconds
- 1.423.803 bytes: 47.05, 45.4 and 43.71 seconds
- 437.643 bytes: 46.46, 43.6 and 40.67 seconds
- 761 bytes: 50.21, 47.42 and 42.25 seconds



	N	M	L	N	M	L	N	M	L	N	M	L
Time	50	47	36	56	41	34	47	43	39	45	40	38
Weight	195	195	195	142	142	142	44	44	44	0,1	0,1	0,1

Figure 7: Validation - Tokenizer.

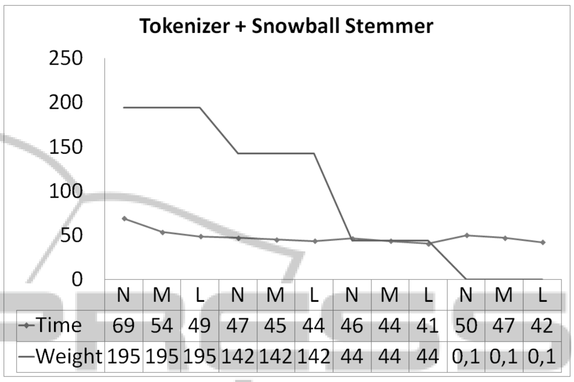


	N	M	L	N	M	L	N	M	L	N	M	L
Time	181	114	86	118	97	76	80	87	54	70	65	53
Weight	195	195	195	142	142	142	44	44	44	0,1	0,1	0,1

Figure 8: Validation - Tokenizer + POS.

Allowing identifying a downward trend as they were adding available machines to the cluster as a possible option.

As it can be seen the execution time for the same file in a same task, differs depending on the number of available slaves. It improves as new slaves were added to the cluster. Besides, it can be seen that the improvement is much more noticeable when complex tasks need to be executed like RegexNER and Part Of



	N	M	L	N	M	L	N	M	L	N	M	L
Time	69	54	49	47	45	44	46	44	41	50	47	42
Weight	195	195	195	142	142	142	44	44	44	0,1	0,1	0,1

Figure 9: Validation - Tokenizer + Snowball.

Speech. Additionally, the larger is the file, the greater the processing speed, for example, for the 761 bytes file the times for different scenarios (*N*, *M* and *L* machines) are very similar.

From the point of view of the requirements of the medical researchers BigTexts allowed the identification of the set of EMRs that include all or part of the terms required for the analysis. The result allowed reducing the time previously required to select records and analyze which of them actually met the characteristics desired for the study.

5 CONCLUSIONS AND FUTURE WORK

Shortening large EMR data analysis helps clinical and administrative data management in the health domain with both decision making and quality improvement as benefits.

BigTexts demonstrated its utility to improve efficiency in narrative text analysis of electronic medical records, this will not only allow performing more analysis projects in the health sector but also allow generating new products that can be constructed based on BigTexts.

Additionally, BigTexts showed that the addition of an abstraction layer to the entire ecosystem of technology of Big Data and text mining avoids installation, configuration and integration efforts of the Big Data components that, although powerful, are limited in terms of accurate and reliable documentation.

The validation results let us to conclude that it is worth to use the entire infrastructure of Big Data when the analysis include large files or complex tasks, because it was found that only in those situations the addition of nodes into the cluster markedly improves performance.

As future work it is proposed to use cloud computing to address the problems encountered in the present project, to evaluate the changes in development effort, and to promote scalability of BigTexts. Additionally, another field of work is the development of more UDFs to increase the catalogue of BigTexts preprocessing tasks.

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