# RESEARCH ARTICLE

## AFFECTIVE COMPUTING FOR SMART OPERATIONS: A SURVEY AND COMPARATIVE ANALYSIS OF THE AVAILABLE TOOLS, LIBRARIES AND WEB SERVICES.

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*Abstract:*

    In this paper, we make a deep search of the available tools in the market, at the current state of the art of Sentiment Analysis. Our aim is to optimize the human response in Datacenter Operations, using a combination of research tools, that allow us to decrease human error in general operations, managing Complex Infrastructures. The use of Sentiment Analysis tools is the first step for extending our capabilities for optimizing the human interface. Using different data collections from a variety of data sources, our research provides a very interesting outcome. In our final testing, we have found that the three main commercial platforms (IBM Watson, Google Cloud and Microsoft Azure) get the same accuracy (89-90%). for the different datasets tested, based on Artificial Neural Network and Deep Learning techniques. The other stand-alone Applications or APIs, like Vader or MeaninCloud, get a similar accuracy level in some of the datasets, using a different approach, semantic Networks, such as Concepnet[1], but the model can easily be optimized above 90% of accuracy, just adjusting some parameter of the semantic model. This paper points to future directions for optimizing DataCenter Operations Management and decreasing human error in complex environments.

*Key Words:-* Affective computing, Sentiment Analysis, Computation models of emotion, Text sentiment analysis, Ready-to-use and modelling tools for, sentiment analysis, Contextual polarity of information.

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# Introduction: -

    Sentiment Analysis, also called Opinion Mining, is currently becoming one of the most studied research fields. It is used to analyze emotions, opinions or sentiments, normally related to a specific application, topic or service. We may use some procedures and tools from previous research and developments. Some of them are becoming big platforms proceeding from big vendors from the market. This market is spinning around Artificial Intelligence nowadays, and the use of unassisted learning systems in different tasks, involving both machines and humans, is transforming the way of doing or delivering business between big and small players. Small companies with these abilities, will be able to have room for growing and improvement, living together with the big fishes of the Tech market. This would become a disruptive advantage to compete and to cooperate.

    In this work, we tackle the "traditional" use of the available tools in the market at the current state of the art. Our aim is to optimize the human response in Datacenter Operations using a combination of research tools that will give us the ability to decrease the human error in the operations management in Complex Infrastructures. The use of Sentiment Analysis tools is the first step for extending our capabilities for optimizing the human interface.

    The problem addressed by our research line is the optimal management of complex infrastructures, focusing on the use case of large data centers.

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[1] Concepnet. Originated from the crowdsourcing project Open Mind Common Sense, which was launched in 1999 at the MIT Media Lab. http://conceptnet.io/

Having said that, we find today that a global level, the average cost of a datacenter outage is increasing from $ 0.5M in 2010 to $ 0.75M in 2016. In addition, the duration this unplanned outages on most of data processing based business (Industry 4.0) is rising, above the average for other businesses.

This is an urgent matter, since 50% of data centers are not prepared for current high-density computers (Gartner), and cyberattacks are increasing dramatically (being the cause of 0.2% of DataCenter outages in 2010 to 22% in 2016). Already today, on average, each data center has annual losses of more than 2M $ for total or partial outages.

The current management systems are clearly inefficient. According to a Ponemon Institute study[2], more than half of data center crashes could have been avoided, and 22% were due to operation human errors.

Apparently, the problem is growing with the emerging of new technologies such as Big Data, Internet of things or Smart Cities, which make the needs to grow exponentially because of the huge data processing needs.

The main root causes of the datacenter outages are:
- Power systems failure (25%);
- Cyberattacks (22%); and
- Human errors (22%).
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Both cyberattacks and human errors involve people, decision makers, in a highly complex environment with a high degree of uncertainty.

However, the current solutions are focused on recording information and the availability of tools for analyzing such information. Information is available, but decisions are left to the operations staff. And often these decisions are complex and the information available is too broad and not very specific.

Some notable examples are the decisions to:
- Optimize the energy consumption of the data center.
- Minimize the risks of attacks.
- Optimize preventive maintenance.
- Maximize profit considering business drivers.
- Maximize the capacity of renewable energy generation.
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The efficiency and effectiveness of today's data centers management requires more powerful tools, aware that there are people making decisions, capable to perform the automated analysis, able to offer to the operations personnel all the relevant information, at the appropriate level at the right time.

Therefore, a holistic approach to optimize resource management is essential.

The use of Affective Computing applied to solve these problems will affect positively in the success of the decision-making optimization.

**Affective Computing Research Matrix:-**
As affective computing is becoming a broadly studied matter that enables Complex Infrastructures to interpret human emotions[3], applied to text, the opinion mining tries to discover the human emotions extracted from one or more sentences. This is not an easy task, especially if you want to be able to difference between human expressions and colloquial language.

In this context, text sentiment analysis and emotion recognition play a significant role. Sentiment analysis (also known as opinion mining) could be defined as a type of data mining that measures the inclination of people's opinions through natural language processing (NLP), computational linguistics and text analysis. Tools that are used to extract and analyze subjective information from a specific topic.

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[2] Ponemon Institute. 2016 Study on Data Center Outages.
[3] A review of affective computing: From unimodal analysis to multimodal fusion. Elsevier, 2017. Authors: Soujanya Poriaa, Erik Cambria, Rajiv Bajpai, Amir Hussain.

Sentiment analysis give us the information not only of the sentiments or reactions of a person toward certain products, but also people or ideas, revealing the contextual polarity of the information. This polarity can be positive, negative or neutral, depending on the main sentiment which is present in the text.

As it was rightly said in the introduction, the main idea of this article is to avoid (or reduce) human errors inside a Data Center. This requires knowledge of the emotional state of both machines (expressed by their logs) and staff, in such a way as, in addition to understand the state of the last one and influence their concentration, stress or tiredness, we can know, besides, in real time, machines status, being able to predict a failure before it occurs.

To do this, the fundamental step consists in having a tool so reliable as to be able to detect, through a text, how the system is, that is, which is the state of the machine and the person responsible of its supervision.

There are many products that allow us to analyze the sentiment or the emotions of a text. In this review, we will focus on all those ones that are able to find the polarity of the writing and have a free use, even if it is for a brief time.

They are represented in the Table 1, in which will be made a categorization of several available products based on different aspects or characteristics, which are described below. Each one will correspond to a column of the Table.

**Application/Usability:-**

The first classification that is made is about the application or usability of the product, this is, the main purpose of the product. They have been distinguished two different applications: Polarity Detection (Sentiment Analysis) and Emotion Recognition.

- PD: Polarity Detection. As it has been already said, the goal of sentiment analysis is discovering the polarity of the text. All the products described in Table 1 have the ability of predicting the sentiment (or polarity) of a writing.
- ER: Emotion Recognition. In this case, it has been indicated if the product, besides being useful for sentiment analysis, can be used for identifying a set of emotion levels, such us angry, happiness, disappointment or joy.

**Type of Products/Services: -**

In this column, it will be indicated the typology of products. We have distinguished between APIs, web services, software libraries or packages, software programs and distributions. Below, it is defined every type of product.

- API. In computer programming, an Application Programming Interface (API) is a set of subroutine definitions, protocols, and tools for building application software. In general terms, it is a set of clearly defined methods of communication between various software components. The separation of the API from its implementation can allow programs written in one language to use a library written in another.
- Web Service. A web service is a service offered by an electronic device to another electronic device, communicating with each other via the World Wide Web. In a Web service, Web technology such as HTTP, originally designed for human-to-machine communication, is utilized for machine-to-machine communication, more specifically for transferring machine readable file formats such as XML and JSON. So, a web service can be described as a technology that uses a set of protocols and standards that serve to exchange data between applications.
  The terms "module", "package" and "library" are defined differently by diverse programming languages. As we are mainly going to use Python modules, packages and libraries, these three terms are described in context of Python.
- Module. Simply put, a module is a .py file that defines one or more function/classes which are intended to be reused in different codes of your program.
- Library. When used in Python, a library is used loosely to describe a collection of the core modules. The term "standard library" in Python language refers to the collection of exact syntax, token and semantics of the Python language which comes bundled with the core Python distribution. "Additional libraries" refer to those optional components that are commonly included in Python distributions.
- Package. A Python package refers to a directory of Python module(s). This feature comes in handy for organizing modules of one type at one place.
- Software Distribution. A distribution, or distro, is a collection of software components built, assembled and configured so that it can be used essentially "as is" for its intended purpose.

- Software. A software or computing program is a collection of instructions that performs a specific task when executed by a computer. This is, a set of instructions, modules or procedures, that allow for a certain type of computer operation.
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**Languages:-**

The fifth column of Table 1 expresses the languages supported for the products in polarity detection. If they have also the option of recognize emotions and the languages supported for this last one, are different, they are specified in the own column of Emotion Recognition.

**Functionality:-**

In this section, corresponding to the sixth column of the Table 1, is described for what these products can be used for. We have distinguished two different cases: ready-to-use products and modelling tools. The difference between them is explained below.

- Ready-to-use products. These products are defined as those ones which are already made. Their models have been trained and are ready to be used.
- Modelling tools. They are products that need to be trained. It is necessary build their own models and train it with a huge amount of data before can be used.
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**Free Services and Availability: -**

Table 1 has been thought as a complete review of products for sentiment analysis with good accessibility. This is, products that can be used with a free plan and have an easy usage.

For this reason, the penultimate and last column of Table 1 include the available free use for each product and the links where it is possible to access or get them.

Below, it is presented Table 1.

| Name | Polarity Detection | Emotion Recognition | Type of Product | Languages | Functionality | Free Services | Availability |
|---|---|---|---|---|---|---|---|
| Watson Natural Language Understanding | X | X (only in English) | API | Arabic, English, French, German, Italian, Portuguese, Russian, Spanish | Ready-to-use/ Modelling Tool (with Watson Knowledge Studio) | 1,000 requests/ day | https://www.ibm.com/watson/developercloud/natural-language-understanding.html#pricing-block |
| **Name** | **Polarity Detection** | **Emotion Recognition** | **Type of Product** | **Languages** | **Functionality** | **Free Services** | **Availability** |
| Lymbix | X | X | API | English | Ready-to-use | 3,000 requests | http://www.lymbix.com/ |
| Opendover | X | | API | English | Ready-to-use | 1 month | http://opendover.nl/ |
| Repustate | X | | API | Arabic, Chinese, Dutch, French, German, Hebrew, Italian, Polish, Portugu | Ready-to-use | Free Trial | https://www.repustate.com/ |

| Name | Polarity Detection | Emotion Recognition | Type of Product | Languages | Functionality | Free Services | Availability |
|---|---|---|---|---|---|---|---|
| | | | | ese, Russian, Spanish, Turkish, Thai, Vietnamese, English | | | |
| Sentiment Analyzer | X | | Web Service | English, German, French | Ready-to-use | Unlimited | http://sentimentanalyzer.appspot.com/ |
| Google Cloud Natural Language | X | | API | English, Spanish, Japanese | Ready-to-use | 5,000 requests/ month | https://cloud.google.com/natural-language/?utm_source=google&utm_medium=cpc&utm_campaign=2017-q1-cloud-emea-gcp-skws-freetrial&gclid=CLnE9PmAxNICFcLGGwod60gCUQ |
| Uclassifier | X | | API | English, French, Spanish, Swedish | Ready-to-use | 500 requests/ day | https://uclassify.com/ |
| Stride | X | | API | English, German, French | Ready-to-use | Free Trial | http://texsie.stride.ai/ |
| Microsoft Azure | X | | API | English, Spanish, French, Portuguese | Ready-to-use | 5,000 requests/ month | https://azure.microsoft.com/en-us/services/cognitive-services/text-analytics/ |
| Monkey Learn | X | | API | English, Spanish, Portuguese, French, Italian, German, Dutch, Russian | Ready-to-use/ Modelling Tool (for text classifiers) | 50,000 requests/ month | http://monkeylearn.com/ |
| **Name** | **Polarity Detection** | **Emotion Recognition** | **Type of Product** | **Languages** | **Functionality** | **Free Services** | **Availability** |
| Receptivity LIWC | X | X | API | English | Ready-to-use | Free trial for 1 month | https://liwc.wpengine.com/ |
| Datumbox | X | | API | English | Ready-to-use | 1,000 requests/ day | http://www.datumbox.com/ |
| Twin Word | X | | API | English | Ready-to-use | 500 requests/ month | https://www.twinword.com/api/ |
| Meaning Cloud | X | | API | English, Spanish | Ready-to-use/ | 40,000 request | https://www.meaningcloud.com/ |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | | | , French, Italian, Portuguese, Catalan | Modelling Tool (with polarity of entries and multiwords) | s/ month | |
| Sentiment140 | X | | API | English, Spanish | Ready-to-use | Free non-commercial use (limited to 1 qps) | http://help.sentiment140.com/api |
| Rosette | X | | API | English, Spanish, Japanese | Ready-to-use | 10,000 requests/ month (up to 1,000 per day) | https://www.rosette.com/function/sentiment-analysis/ |
| Intellexer | X | | API | English | Ready-to-use | Free Trial for personal use with 5,000 requests | http://www.intellexer.com/ |
| Semantria | X | | API | Arabic, Chinese, Danish, Dutch, English, French, German, Hebrew, Italian, Japanese, Korean, Malay, Norwegian, Polish, Portuguese, Russian, Spanish, Swedish, Turkish | Ready-to-use | Free Trial | https://www.lexalytics.com/semantria |
| Skyttle | X | | API | English, French, | Ready-to-use | 500 request | http://www.skyttle.com/ |

| Name | Polarity Detection | Emotion Recognition | Type of Product | Languages | Functionality | Free Services | Availability |
|---|---|---|---|---|---|---|---|
| | | | | German, Russian | | s/ day | |
| Data Science Toolkit | X | | API | English | Ready-to-use | Unlimited | http://www.datasciencetoolkit.org/ |
| Sentiment. vivekn | X | | API | English | Ready-to-use | Unlimited | http://sentiment.vivekn.com/ |
| **Name** | **Polarity Detection** | **Emotion Recognition** | **Type of Product** | **Languages** | **Functionality** | **Free Services** | **Availability** |
| Pattern.en | X | | Package (Python) | English | Ready-to-use / Modelling Tool | Unlimited | https://pypi.python.org/pypi/Pattern or  http://www.clips.ua.ac.be/pattern |
| SenticNet | X | | Web Service | English | Ready-to-use | Free demo | http://sentic.net/ |
| Vader [1] | X | | Module (Python) | English | Ready-to-use | Unlimited | https://github.com/cjhutto/vaderSentiment |
| TextBlob | X | | Library (Python) | English | Ready-to-use / Modelling Tool | Unlimited | http://textblob.readthedocs.io/en/dev/index.html |
| NLTK | X | | Package (Python) | Danish, Dutch, English, Finnish, French, German, Hungarian, Italian, Norwegian, Portuguese, Russian, Spanish, Swedish, Turkish, etc. | Modelling Tool | Unlimited | http://www.nltk.org/ |
| GraphLab SFrame | X | | Package (Python) | English | Ready-to-use / Modelling Tool | Unlimited for 1 year (with academic licence) | https://turi.com/ |
| LibShort Text | X | | Package (Python) | English | Modelling Tool | Unlimited | https://www.csie.ntu.edu.tw/~cjlin/libshorttext/ |
| RText Tools (R) | X | | Package (R) | English | Modelling Tool | Unlimited | http://www.rtexttools.com/ or https://cran.r- |

| Name | Polarity Detection | Emotion Recognition | Type of Product | Languages | Functionality | Free Services | Availability |
|---|---|---|---|---|---|---|---|
| | | | | | | | project.org/web/packages/RTextTools/index.html |
| Sentiment (R) | X | X | Package (R) | English | Ready-to-use | Unlimited | https://github.com/timjurka/sentiment |
| Stanford Core NLP | X | | Software Distribution (Java, Python, R, etc.) | Arabic, Chinese, English, English (KBP), French, German, Spanish | Ready-to-use (only in English)/ Modelling Tool | Unlimited | https://stanfordnlp.github.io/CoreNLP/index.html |
| Apache Open NLP | X | | Library (Java) | English | Modelling Tool | Unlimited | https://opennlp.apache.org/index.html |
| Apache Mahout | X | | Software Distribution | English | Modelling Tool | Unlimited | https://mahout.apache.org/ |
| Apache UIMA | X | | Software Distribution | English | Modelling Tool | Unlimited | http://uima.apache.org/ |
| LingPipe | X | | Package (Java) | English | Ready-to-use/ Modelling Tool | Unlimited | http://alias-i.com/lingpipe/index.html |
| Gate | X | | Software | English | Modelling Tool | Unlimited | https://gate.ac.uk/sentiment/ |
| RapidMiner | X | | Software | English | Ready-to-use (with AYLIEN)/ Modelling Tool | Unlimited (with academic licence) | https://rapidminer.com/solutions/text-mining/ |
| Weka | X | | Software | English | Modelling Tool | Unlimited | http://www.cs.waikato.ac.nz/ml/weka/ |

**Table 1:-** Review of products for sentiment analysis

### Analysis of Products: -
This section summarizes the main features of the products with Sentiment Analysis functionalities presented in Table 1.

We are going to introduce them one by one.

### Watson Natural Language Understanding: -
Natural Language Understanding[4] is an API of the Watson platform of IBM. They define it as natural language processing for advanced text analysis, capable to analyze text to extract meta-data from content (such as concepts, entities, keywords, categories, sentiments, emotions, relations, semantic roles, using natural language understanding) using Recurrent Neural Networks. [2]

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[4] https://www.ibm.com/watson/developercloud/natural-language-understanding.html#pricing-block

It measures the polarity in two levels: positive or negative, and five categories of emotions: joy, anger, disgust, sadness and fear.

Bluemix is IBM's cloud platform where the Watson services can be accessed, including Natural Language Understanding and, even if the free plan of this API includes the analysis up to 1,000 items per day.

**Lymbix: -**

The Lymbix Sentiment API[5] is the core of Lymbix sentiment technology that is exposed for developers to determine the variations of emotions that are present in any piece of text. This company is focused on the analysis of social media through Natural Language Processing and adaptive learning. [3].

It classifies the sentiment into three categories: positive, negative and neutral, and group the content into various categories of emotions:
- On the one hand, positive emotions:
  - affection/friendship
  - enjoyment/joy
  - fun/excitement
  - gratitude
- On the other hand, negative emotions:
  - sadness/pain
  - fear/restlessness
  - humiliation/shame
  - anger/aversion.

Both concepts, sentiments and emotions, are not only classified but also measured in the range [-10, 10].

**Opendover: -**

OpenDover[6] is a webservice that allows you to extract the next generation semantic features within blogs, content management systems, websites or other applications. It uses semantic technologies for sentiment tagging texts that you send to the service. Sentiment/emotion tags are returned to users for implementing in web applications, searches, blogs and so on.

It is necessary to create the API key to connect to OpenDover. The content is sent through a webservice to the OpenDover servers, that will analyze and process the content using their semantic technologies. The content is sent back with sentiment tags and negative/positive appraisal of the whole document. [4]

**Repustate: -**

Repustate[7] is a multilingual sentiments engine, which allows the treatment of text in several languages like English, French, German, Spanish or Arabic. It allows you to process texts from many sources, such as Facebook pages, Twitter or just text fragments.

Repustate's API can be integrated into any workflow seamlessly and quickly, and it also provides client libraries in C#, Java, PHP, Ruby and Python to help you get started. [5]

All sentiments are scored in the range [-1, 1] and it uses entity extraction (based on semantic analysis) and topic level sentiment for more accurate results.

**Google Cloud Natural Language: -**

Google Cloud Natural Language API[8] reveals the structure and meaning of text by offering powerful machine learning models (based on Deep Learning) in an easy to use REST API.

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[5] http://www.lymbix.com/

[6] http://opendover.nl/

[7] www.repustate.com

[8] https://cloud.google.com/natural-language/?utm_source=google&utm_medium=cpc&utm_campaign=2017-q1-cloud-emea-gcp-skws-freetrial&gclid=CLnE9PmAxNICFcLGGwod60gCUQ

You can use it to extract information about people, places, events and much more, or simply understand sentiments.

The features of the API include:

▪ Syntax Analysis: Extract tokens and sentences, identify parts of speech (PoS) and create dependency parse trees for each sentence.
▪ Entity Analysis: Identify entities and label by types such as person, organization, location, events, products and media.
▪ Sentiment Analysis: Understand the overall sentiment expressed in a block of text.
▪ Entity Sentiment Analysis: Understand the sentiment for each mention of an entity within a block of text.
▪ Multi-Language: Enables you to easily analyze text in multiple languages including English, Spanish, Japanese, Chinese (Simplified and Traditional), French, German, Italian, Korean and Portuguese.
▪ Integrated REST API: Access via REST API. Text can be uploaded in the request or integrated with Google Cloud Storage. [6].
▪

Sentiment Analysis module classifies the sentiment into three different categories: negative (with a punctuation between -1 and -0,25), neutral (with a punctuation between -0,25 and 0,25) and positive (with a punctuation between 0,25 and 1), expressing not only the global sentiment of the text but also the sentiment of each sentence.

**Uclassifier:-**
UClassify[9] is a free machine learning web service where you can create and use text classifiers.
Sentiment classifier determines if a text is positive or negative. It is well suited for both short and long texts (tweets, Facebook statuses, blog posts, product reviews, etc.), and it has been trained on 2.8 million documents with data from Twitter, Amazon product reviews and movie reviews. [7].

It has a free plan with 500 calls per day, performing many functionalities such as language detection, text genre and age recognition, spam filtering, feelings analysis, document labeling, detection of emotions, among others.

**Stride:-**
Stride's[10] AI's platform TEXSIE comprises of host of proprietary algorithms, for carrying out nuanced text analysis. These algorithms are available as developer APIs. [8].

Sentiment Analysis provides sentiments scored in the range [-10, 10], differentiating five classes: very negative, negative, neutral, positive and very positive.

**Microsoft Azure:-**
Microsoft Azure[11] is a growing collection of integrated cloud services that developers and IT professionals use to build, deploy, and manage applications through Microsoft global network of datacenters.

Within its cognitive services, it highlights the Text Analytics API which is able to detect sentiments, key phrases, topics, and language from the text through Neural Networks. In the case of sentiments, the API returns a numeric score between 0 and 1. Scores close to 1 indicate positive sentiment and scores close to 0 indicate negative sentiment. Sentiment score is generated using classification techniques. The input features of the classifier include n-grams, features generated from part-of-speech tags, and word embeddings. [9].

**Monkey Learn: -**
Monkey Learn[12] produces text Analysis with Machine Learning. It turns tweets, emails, documents, webpages and more into actionable data. [10].

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[9] https://uclassify.com/
[10] http://texsie.stride.ai/
[11] https://azure.microsoft.com/en-us/?v=17.14
[12] https://monkeylearn.com/

Regarding Sentiment Analysis, it is possible to choose the API which fits best with your text, that means, if we want to analyze products reviews we can choose the API of Product Reviews Sentiment Analysis or if we want to know the polarity of a tweet, we can analyze the data with Tweets Sentiment Analysis.
The platform in which is all integrated allows you to classify the text, a file or call directly to the API.

**Receptivity LIWC: -**

The LIWC[13] API is available exclusively from Receptiviti. It provides developers and data scientists with an easy-to use API that delivers deep insights into people's psychology states by analyzing natural language and text. [11]

It allows analyzing the sentiments of a text (giving the score of the polarity in the range [0,100] and the rating (negative or positive)), recognizing the percentage of some emotions in the text (sadness, fear, anger), gender detection, age and practically all the issues related with the analysis of people. You can upload csv files, or directly text from Twitter, Facebook or Email.

**Datumbox: -**

The Datumbox[14] API offers a large number of off-the-shelf Classifiers and Natural Language Processing services which can be used in a broad spectrum of applications including: Sentiment Analysis, Topic Classification, Language Detection, Subjectivity Analysis, Spam Detection, Reading Assessment, Keyword and Text Extraction and more. All services are accessible via the REST API which allows you to develop your own smart Applications in no time.

The Sentiment Analysis is used to evaluate the opinions of the users and classify them as positive, negative or neutral. In addition, it can be used to detect whether the posts are objective or subjective, what is the natural language of the posts and whether the posts were written by a man or woman. [12]

**Twin Word: -**

Twin Word's Sentiment Analysis API[15] is a good place to find out the tone of a sentence or paragraph. This API can be useful if you have a large amount of user responses or reviews and you want to quickly find the negative comments to see what your customers don't like and vice versa.

However, the API gives you more power than that. Besides just reading the type response (negative, neutral, or positive), you can determine for yourself what you consider positive or negative and not only gives you the global punctuation of the text but also of each key word inside this one. [13]

**Meaning Cloud: -**

Sentiment Analysis is a MeaningCloud[16] solution for performing a detailed multilingual sentiment analysis of texts from different sources.

The text provided is analyzed to determine if it expresses a positive/negative/neutral sentiment; to do this, the local polarity of the different sentences in the text is identified and the relationship between them evaluated, resulting in a global polarity value for the whole text.

Besides polarity at sentence and global level, Sentiment Analysis uses advanced natural language processing techniques to also detect the polarity associated to both entities and concepts in the text. It provides a reference in the relevant sentence and a list of elements detected with the aggregated polarity derived from all their appearances, also considering the grammatical structures in which they are contained.

Sentiment Analysis also gives the user the possibility of detecting the polarity of user-defined entities and concepts, making the service a flexible tool applicable to any kind of scenario.

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[13] http://www.receptiviti.ai/liwc-api-get-started/ or https://liwc.wpengine.com/
[14] http://www.datumbox.com/
[15] https://www.twinword.com/api/
[16] https://www.meaningcloud.com/developer/sentiment-analysis/doc/2.1/what-is-sentiment-analysis

Additionally, Sentiment Analysis detects if the text processed is subjective or objective and if it contains irony marks at a global level, giving the user additional information about the reliability of the polarity obtained from the sentiment analysis. [14]

**Sentiment140: -**

Sentiment140[17] was created by Alec Go, Richa Bhayani, and Lei Huang, Computer Science graduate students at Stanford University. [15]

It allows you to discover the sentiment of a brand, product, or topic on Twitter. It uses classifiers built from machine learning algorithms, like Maximun Entropy classifier, and gives you the polarity of the text by three numbers: 0 (negative), 2 (neutral) and 4 (positive).

**Rosette: -**

Rosette[18] text analytics API analyzes the sentiment of your text and entities as either positive, neutral or negative. It has a free plan with 10,000 calls per month and distinguishes between three types of languages: English, Spanish and Japanese.

**Intellexer: -**

Intellexer[19] API is a cloud service that enables developers to embed natural language processing and text analysis tools in consumer and enterprise applications, or web-services using JSON or XML. It includes natural language processing solutions for sentiment analysis, entity recognition, summarization, document comparison, natural language interface for search engines, language detection, spell-checking, etc.

Intellexer Sentiment Analyzer is a powerful and efficient solution that automatically extracts sentiments (positivity/negativity), opinion objects and emotions (liking, anger, disgust, etc.) from unstructured text information. Besides, Intellexer Sentiment Analyzer can be successfully used for document sentiment classification and review rating prediction tasks. [16]

**Semantria: -**

Semantria[20] API is a tool in the cloud for Text and Sentiment Analysis. It belongs to Lexalytics, and its operation consists of three steps:
- Firstly, evaluate semantics, syntax, and context using state of the art unsupervised machine-learning techniques and expert-tuned text analytics industry rules
- Then, they combine machine-learning, natural language processing, and dictionaries to extract features like entities, themes, categories, summaries, intentions, and sentiments.
- Finally, highly accurate algorithms associate features with each other; surfacing relationships in the text, like themes and sentiment of individual entities, or the sentiment of categories, and even relationships between entities. [17]

**Skyttle: -**

Skyttle API[21] is a software as a service (SaaS) system that provides text analytics services to extract interesting patterns from text and store them in a structured format for in-depth data analysis. It is easily scalable and customizable to specific applications. [18]

Among its features highlights the terminology/keyword/concept extraction, named entity recognition and Sentiment Analysis, giving the global sentiment scores of the document (divided into the three categories: positive, negative and neutral), the most prevalent and a phrase-level sentiment analysis.

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[17] http://help.sentiment140.com/home

[18] https://www.rosette.com/

[19] http://esapi.intellexer.com/

[20] https://www.lexalytics.com/

[21] http://www.skyttle.com/

**Data Science Toolkit: -**

Within Data Science Toolkit[22] (DSTK) API, Text to Sentiment attempts to predict whether the text represents a positive or negative comment, returning a score between -5 (negative) and 5 (positive). A score of 0 means that no words were loaded, or that the positive and negative words were balanced.

It uses a very simple algorithm, based on Finn Årup's annotated list of words originally designed to analyze the feeling of Twitter messages. [19]

Query the API with a GET call (usual limit of 8,000 characters) or POST (for larger texts).
"http://www.datasciencetoolkit.org/text2sentiment"
DSTK has been receiving a lot of traffic lately, exceeding the limits of the servers, so they advise to host a server of its own so that it is not affected by interruptions.

**Sentiment.vivekn: -**

Sentiment.vivekn[23] is an API created by Vivek Narayanan for Sentiment Analysis, who proposed a fast and accurate sentiment classification using an enhanced Naive Bayes model along with authors Ishan Arora and Arjun Bhatia.

This tool works by examining individual words and short word sequences (n-grams), comparing them with a Bayesian probability model. The probability model is based on a set of pre-tagged reviews of IMDb movie reviews.

Developed by Cornell University (Ithaca, NY) (last reviewed 09/16/13), it offers a free web service and API that returns you a JSON file with text polarity (positive, negative, neutral) and level trust. [20]

**Pattern.en: -**

Pattern[24] is a web mining module for the Python programming language. It has tools for data mining (Google, Twitter and Wikipedia API, a web crawler, a HTML DOM parser), natural language processing (part-of-speech taggers, n-gram search, sentiment analysis, WordNet), machine learning (vector space model, clustering, SVM), network analysis and canvas visualization.

The pattern.en[25] module, part of Pattern, contains a fast part-of-speech tagger for English (identifies nouns, adjectives, verbs, etc. in a sentence), sentiment analysis, tools for English verb conjugation and noun singularization and pluralization, and a WordNet interface.

Regarding Sentiment Analysis, written text can be broadly categorized into two types: facts and opinions. Opinions carry people's sentiments, appraisals and feelings toward the world. The pattern.en module bundles a lexicon of adjectives (e.g., good, bad, amazing, irritating, ...) that occur frequently in product reviews, annotated with scores for sentiment polarity (positive ↔ negative) and subjectivity (objective ↔ subjective). The system is based on a knowledge database with adjectives/adverbs with different ratings, after the total word sum, Pattern.en gives you the final polarity of the text.

The sentiment() function returns a (polarity, subjectivity)-tuple for the given sentence, based on the adjectives it contains, where polarity is a value between -1.0 and +1.0 and subjectivity between 0.0 and 1.0. The sentence can be a string, Text, Sentence, Chunk, Word or a Synset.

The positive() function returns True if the given sentence's polarity is above the threshold. The threshold can be lowered or raised, but overall +0.1 gives the best results for product reviews. [21]

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[22] http://www.datasciencetoolkit.org/

[23] http://sentiment.vivekn.com/

[24] http://www.clips.ua.ac.be/pages/pattern

[25] http://www.clips.ua.ac.be/pages/pattern-en

**Sentic Net: -**

SenticNet[26] is an initiative conceived at the MIT Media Laboratory in 2009 within an industrial Cooperative Awards in Science and Engineering (CASE) research project born from the collaboration between the Media Lab, the University of Stirling, and Sitekit Solutions Ltd.

Since then, SenticNet has been further developed and applied for the design of emotion-aware intelligent applications in fields spanning from data mining to human-computer interaction.

The main aim of SenticNet is to make the conceptual and affective information conveyed by natural language (meant for human consumption) more easily-accessible to machines.

This is done by using the bag-of-concepts model, instead of simply counting word co-occurrence frequencies as in latent semantic indexing, and by leveraging on linguistic patterns, to allow sentiments to flow from concept to concept based on the dependency relation between clauses.

Currently, both the SenticNet knowledge base and the SenticNet framework are being maintained and further developed by the Sentic Team, a multidisciplinary research group based at the School of Computer Science and Engineering of Nanyang Technological University in Singapore, but also by many other sentic enthusiasts around the world. [22]

It is possible to access to Senticnet API using Python installing the package senticnet 1.0.1[27].

**Vader: -**

Vader[28] (Valence Aware Dictionary and sEntiment Reasoner) is a lexicon and rule-based sentiment analysis tool that is specifically attuned to sentiments expressed in social media. It is fully open-sourced under the MIT License and is made as a module for Python. [23]

It recognizes emoticons and it is possible to analyze sentiments in other languages with internet access.

Among its modules, we can find polarity analysis (positive or negative text), lexicons and examples dataset.

Regarding the punctuation of polarity analysis module, Vader gives two different measures: a compound one, which is calculated by summing the valence scores of each word in the lexicon, adjusted according to the rules, and then normalized to be between (-1, +1), and the positive, negative and neutral scores, which measure the text proportions that fall into each category (the sum of the three punctuation is equal to 1).

**TextBlob: -**

TextBlob[29] is a Python (2 and 3) library for processing textual data. It provides a consistent API for diving into common natural language processing (NLP) tasks such as part-of-speech tagging, noun phrase extraction, sentiment analysis, and more.

The textblob.sentiments module contains two sentiment analysis implementations, PatternAnalyzer (based on the pattern library) and NaiveBayesAnalyzer (an NLTK classifier trained on a movie reviews corpus).

The default implementation is PatternAnalyzer, but you can override the analyzer by passing another implementation into a TextBlob's constructor.

For instance, the NaiveBayesAnalyzer returns its result as a named tuple of the form: Sentiment (classification, p_pos, p_neg). [24]
TextBlob also allows us to create our own Sentiment Analysis model, based on Machine Learning Algorithms.

**NLTK: -**

Natural Language Toolkit (NLTK)[30] is a leading platform for building Python programs to work with human language data. It provides easy-to-use interfaces to over 50 corpora and lexical resources such as WordNet, along with a suite of text processing libraries for classification, tokenization, stemming, tagging, parsing, and semantic reasoning, wrappers for industrial-strength NLP libraries, and an active discussion forum.

Thanks to a hands-on guide introducing programming fundamentals alongside topics in computational linguistics, plus comprehensive API documentation, NLTK is suitable for linguists, engineers, students, educators, researchers, and industry users alike. NLTK is available for Windows, Mac OS X, and Linux. Best of all, NLTK is a free, open source, community-driven project. [25]

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[26] http://sentic.net/

[27] https://pypi.python.org/pypi/senticnet

[28] https://github.com/cjhutto/vaderSentiment

[29] http://textblob.readthedocs.io/en/dev/index.html

[30] http://www.nltk.org/

We can generate models of text polarity classification based on Machine Learning Algorithms.

**GraphLab SFrame: -**

GraphLab Create[31] is a machine learning modeling tool for developers and data scientists. It includes a module called SFrame, which allows you to take text and predict whether it contains positive or negative sentiment. For instance, the model will predict "positive sentiment" for a snippet of text - whether it is a movie review or a tweet - when it contains words like "awesome" and "fantastic". Likewise, having many words with a negative connotation will yield a prediction of "negative sentiment".

When a target column name is not provided, a pre-trained model can be used. Predicted scores from the current model are between 0 and 1, where higher scores indicate more positive predicted sentiment. The model is a graphlab.logistic_classifier.LogisticClassifier model that can be obtained via m['classifier']. This model is currently tuned to focus on English-only text corpuses, and works best when each piece of text has similar length.

However, you can also train your own model. This can be useful when you want to tune the model to your data set to take advantage of vocabulary that is particular to your application, or you are attempting to predict something such as "utility" by training on whether users thought a review was useful. [26]

**LibShortText: -**

LibShortText[32] is an open source tool for short-text classification and analysis. It can handle the classification of, for example, titles, questions, sentences, and short messages. Main features of LibShortText include:

▪ It is more efficient than general text-mining packages. On a typical computer, processing and training 10 million short texts takes only around half an hour.
▪ The fast training and testing is built upon the linear classifier LIBLINEAR
▪ Default options often work well without tedious tuning.
▪ An interactive tool for error analysis is included. Based on the property that each short text contains few words, LibShortText provides details in predicting each text.

The current release (Version 1.1, August 2013) of LibShortText can be obtained by downloading the zip file or tar.gz file from its official page. The package includes the source code in Python and C/C++. [27]

**RText Tools: -**

RTextTools[33] is a free, open source machine learning package in R for automatic text classification that makes it simple for both novice and advanced users to get started with supervised learning. The package includes nine algorithms for ensemble classification (svm, slda, boosting, bagging, random forests, glmnet, decision trees, neural networks, maximum entropy), comprehensive analytics, and thorough documentation, so it is simple to create your own model for Sentiment Analysis. [28]

**Sentiment (R): -**

Sentiment[34] is an R package, developed by Timothy P. Jurka. with tools for sentiment analysis including bayesian classifiers for positivity/negativity and emotion classification. The model has been already trained so it is ready to use and discover the sentiment of your text. [29]

**Stanford Core NLP: -**

Stanford CoreNLP[35] provides a set of natural language analysis tools. It can give the base forms of words, their parts of speech, whether they are names of companies, people, etc., normalize dates, times, and numeric quantities, mark up the structure of sentences in terms of phrases and word dependencies, indicate which noun phrases refer to the same entities, indicate sentiment, extract particular or open-class relations between entity mentions, get quotes people said, etc.

CoreNLP is designed to be highly flexible and extensible. With a single option, you can change which tools should be enabled and which should be disabled. Stanford CoreNLP integrates many of Stanford's NLP tools, including the part-of-speech (POS) tagger, the named entity recognizer (NER), the parser, the coreference resolution system, sentiment analysis, bootstrapped pattern learning, and the open information extraction tools. Moreover, an

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[31] https://turi.com/

[32] https://www.csie.ntu.edu.tw/~cjlin/libshorttext/

[33] http://www.rtexttools.com/about-the-project.html

[34] https://cran.r-project.org/web/packages/RSentiment/index.html

[35] https://stanfordnlp.github.io/CoreNLP/

annotator pipeline can include additional custom or third-party annotators. CoreNLP's analyses provide the foundational building blocks for higher-level and domain-specific text understanding applications.
The basic distribution provides model files for the analysis of well-edited English, but the engine is compatible with models for other languages.

Stanford CoreNLP is written in Java; current releases require Java 1.8+. But, you can use Stanford CoreNLP from the command-line, via its Java programmatic API, via third party APIs for most major modern programming languages, or via a service. It works on Linux, macOS, and Windows. [30]

**Apache Open NLP: -**

The Apache Open NLP[36] library is a machine learning based toolkit for the processing of natural language text. It supports the most common NLP tasks, such as tokenization, sentence segmentation, part-of-speech tagging, named entity extraction, chunking, parsing, and coreference resolution. These tasks are usually required to build more advanced text processing services. OpenNLP also included maximum entropy and perceptron based machine learning. [31].

As happened with Standford Core NLP, Apache OpenNLP is also written in Java.
It is possible to build a model for classifying the text into different categories, so we can have our own model for Sentiment Analysis.

**Apache Mahout: -**

The Apache Mahout[37] project's goal is to build an environment for quickly creating scalable performant machine learning applications.

Apache Mahout software provides three major features:
- A simple and extensible programming environment and framework for building scalable algorithms.
- A wide variety of premade algorithms for Scala + Apache Spark, H2O, Apache Flink.
- Samsara, a vector math experimentation environment with R-like syntax which works at scale. [32]
  It is possible to create a model for Sentiment Analysis using algorithms of Machine Learning.

**Apache UIMA: -**

Apache UIMA is an Unstructured Information Management applications are software systems that analyze large volumes of unstructured information in order to discover knowledge that is relevant to an end user.

UIMA enables applications to be decomposed into components, for example "language identification" => "language specific segmentation" => "sentence boundary detection" => "entity detection (person/place names etc.)". Each component implements interfaces defined by the framework and provides self-describing metadata via XML descriptor files. The framework manages these components and the data flow between them. Components are written in Java or C++; the data that flows between components is designed for efficient mapping between these languages.

UIMA additionally provides capabilities to wrap components as network services, and can scale to very large volumes by replicating processing pipelines over a cluster of networked nodes.
We can find in Apache UIMA:
- Frameworks
- Components, and
- Infrastructure

All of them licensed under the Apache license. The dashed-line boxes above are placeholders for possible future additions.
The Frameworks run the components, and are available for both Java and C++. The Java Framework supports running both Java and non-Java components (using the C++ framework). The C++ framework, besides supporting annotators written in C/C++, also supports Perl, Python, and TCL annotators. [33]
Applicating Apache UIMA to the problem of Sentiment Analysis, we can use the algorithms of Machine Learning for building a text classification model capable to predict the polarity of a text.

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[36] https://opennlp.apache.org/
[37] http://mahout.apache.org/

**LingPipe: -**

LingPipe[38] is tool kit for processing text using computational linguistics written in Java. LingPipe is used to do tasks like:

- Find the names of people, organizations or locations in news
- Automatically classify Twitter search results into categories
- Suggest correct spellings of queries
  LingPipe's architecture is designed to be efficient, scalable, reusable, and robust. Highlights include:
- Java API with source code and unit tests;
- multi-lingual, multi-domain, multi-genre models;
- training with new data for new tasks;
- n-best output with statistical confidence estimates;
- online training (learn-a-little, tag-a-little);
- thread-safe models and decoders for concurrent-read exclusive-write (CREW) synchronization; and
- character encoding-sensitive I/O. [34]

It is possible to build or implement an already made model for Sentiment Analysis and classify the text or the document into the established categories.

**Gate: -**

Gate[39] is an open source software capable of solving almost any text processing problem, with a mature and extensive community of developers, users and scientists, capable of creating robust and maintainable text processing workflows.

It is in active use for all sorts of language processing tasks and applications, including: voice of the customer; cancer research; drug research; decision support; recruitment; web mining; information extraction or semantic annotation. [35].

**RapidMiner: -**

RapidMiner[40] is a software program for data science, fast and simple, whose platform unifies data prep, machine learning, and model deployment.

We can develop our own model for Sentiment Analysis, using Machine Learning Algorithms, or use a module called AYLIEN, which allow us to know the polarity (positive or negative) of our data without training any kind of model and it is available in the marketplace of RapidMiner. [36]

**Weka: -**

Weka[41] is a software program with a collection of machine learning algorithms for data mining tasks. The algorithms can either be applied directly to a dataset or called from your own Java code. Weka contains tools for data pre-processing, classification, regression, clustering, association rules, and visualization. It is also well-suited for developing new machine learning schemes. [37]

## Comparative Analysis: -

In this chapter, there will be used several of the products described in Table 1. The goal of this section is to compare the results of polarity detection in different datasets (which will contain different kinds of products, such as tweets, movies or books reviews), so that we can measure the effectiveness of the used tools.

**Datasets: -**

For the achievement of this goal, benchmark datasets are being used. Many of them have been used in numerous scientist papers, and others come from important web platforms as Twitter or Amazon, which have a huge weight in the current social frame.

A review and study about the present textual datasets available in Internet for our convenient use of polarity detection is presented at Table 2.

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[38] http://alias-i.com/lingpipe/index.html

[39] https://gate.ac.uk/

[40] https://rapidminer.com/

[41] http://www.cs.waikato.ac.nz/ml/weka/

This Table is compound of eight columns, which are being explained below.
- Name. It is expressed the name under which is known the dataset.
- Data Size. It corresponds with the text size of the dataset, this is, number of reviews, tweets or sentences.
- Labels. In this column, it is expressed the labels of the dataset used for polarity detection.
- Languages. Language in which is written the text of the dataset.
- Content. Dataset information.
- Data Source. Data generating platforms, from which it has been extracted the dataset.
- Reference. Author/s of the dataset.
- Data Link. Web link in which is possible access and download the dataset.

| Name | Data Size | Labels | Languages | Content | Data Source | Reference | Data Link |
|---|---|---|---|---|---|---|---|
| MCE Corpus | 3,875 reviews | 1-5, where 1 is very negative and 5 very positive | English Spanish | Spanish Movies Reivews | MuchoCine | [38] | http://timm.ujaen.es/recursos/mce-corpus/ |
| Large Movie Review Dataset (Stanford) | 50,000 labeled reviews (25,000 Train and 25,000 Test) 50,000 unlabeled | Positive-Negative | English | Movies Reviews | IMDb | [39] | http://ai.stanford.edu/~amaas/data/sentiment/ |
| Twitter Dataset | 1.6M (Train) 497 (Test) | 0 - Negative 2- Neutral 4 - Positive | English | Tweets | Twitter | Sentiment140 | http://help.sentiment140.com/for-students |
| Sarcasm Corpus | Ironic (437 reviews) Regular (817 reviews) | Ratings from 1 to 5 | English | Products reviews | Amazon | [40] | http://storm.cis.fordham.edu/~filatova/SarcasmCorpus.html |
| Movie Review Data | 2,000 reviews | Positive-Negative | English | Movies Reviews | IMDb | [41] | http://www.cs.cornell.edu/people/pabo/movie-review-data/ |
| Amazon Product Data | 142.8 million reviews and small subsets for experimentation (from 8,9 million to 10,000 reviews) | Ratings from 1 to 5 | English | Products reviews | Amazon | [42] [43] | http://jmcauley.ucsd.edu/data/amazon/ |
| Twitter Sentiment Corpus | 5,513 hand-classified tweets | Positive, Neutral, Negative, Irrelevant | English | Tweets | Twitter | Sanders Analytics | http://www.sananalytics.com/lab/twitter-sentiment/ |
| Kaggle Competition (UMICH SI650 - Sentiment Classification) | 7,086 labeled sentences (Train) 33,052 unlabeled sentences (Test) | Positive (1) Negative (0) | English | Sentences from social media | Social data collected from opinmind.com | Kaggle | https://inclass.kaggle.com/c/si650winter11 |
| Feature | Dataset 1: | Positive- | English | Products | KDD 2004 | [44] | http://people.mp |

| Specific Dataset (CICLING 2012) | 1,257 reviews Dataset 2: 3,834 reviews Dataset 3: 425 reviews | Negative | | reviews | and SDM 2011 | | i-inf.mpg.de/~smukherjee/data/ |
|---|---|---|---|---|---|---|---|
| Twitter Data (Annotated) for Spam and Sentiment Analysis | Manually-Annotated-Tweets: 8,510 tweets Auto-Annotated Tweets: 15,219 tweets | Positive, negative, objective-not-spam and objective-spam. | English | Tweets | Twitter | [45] [46] | http://people.mpi-inf.mpg.de/~smukherjee/data/ |
| Twitter Sentiment Analysis Dataset | 1.58 million tweets | Positive (1) Negative (0) | English | Tweets | Twitter | Sentiment140 | http://thinknook.com/twitter-sentiment-analysis-training-corpus-dataset-2012-09-22/ |
| Sentiment Labelled Sentences Data Set | 3,000 reviews | Positive (1) Negative (0) | English | Movies reviews. Products reviews. Restaurants, shopping… reviews | IMDb Amazon Yelp | [47] | http://archive.ics.uci.edu/ml/datasets/Sentiment+Labelled+Sentences |

**Table 2:-** Datasets review

For the comparative study, we have selected four datasets (belonging to Table 2):
▪ Twitter Dataset.
▪ A subset of the source Amazon Product Data with books reviews.
▪ Kaggle Competition (UMICH SI650 - Sentiment Classification).
▪ Sentiment Labelled Sentences Data Set.

Selecting these four files we seek for heterogeneity and a wide variety of data uses. With Twitter, Amazon, IMDb and Yelp, all the principal current platforms of social media are covered and we can obtain a good approach of the quality and accuracy of the products from a global point of view.

Ready-to-use products have been already trained, so, they have been trained with a complete corpus and lexicon or some of them are only useful for predicting the sentiment of texts in a specific context. For that reason, we will select the best suitable products for our final aim: detecting the emotional state and make decisions, if needed.

**Product Utilization/Implementation: -**

All the products should be tested against a single test dataset, which is a proportion of the whole data. Obviously, using ready-to-use products shouldn't be a complicated task.

We have selected ten different ready-to-use products from the whole list and fixed a test of 3,000 reviews for each selected dataset. Neutral reviews have been removed, because not all the products have the ability to predict neutral sentiments nor the whole datasets have this type of polarity. In the case of Amazon dataset, as it has reviews with a rating between 1 and 5 stars, positive reviews have been considered the ones with 5 stars and negatives those with 1 star.

We consider that positive and negative reviews have the same distribution in all datasets, this is split into 50%-50%, that is 1,500 positive reviews and 1,500 negative reviews.
The products and the datasets chosen for the analysis are expressed in Table 3.

| PRODUCTS | DATASETS | | | |
|---|---|---|---|---|
| | Twitter Dataset | Amazon (Books | Kaggle Competition | Sentiment Labelled |

| | | | Reviews) | | Sentences Data Set |
|---|---|---|---|---|---|
| Watson Natural Language Understanding | 3,000 reviews | 3,000 reviews | 3,000 reviews | 3,000 reviews |
| Google Natural Language | 3,000 reviews | 3,000 reviews | 3,000 reviews | 3,000 reviews |
| Micrososft Azure | 3,000 reviews | 3,000 reviews | 3,000 reviews | 3,000 reviews |
| Sentiment140 | 3,000 reviews | 3,000 reviews | 3,000 reviews | 3,000 reviews |
| Pattern | 3,000 reviews | 3,000 reviews | 3,000 reviews | 3,000 reviews |
| Textblob | 3,000 reviews | 3,000 reviews | 3,000 reviews | 3,000 reviews |
| Vader | 3,000 reviews | 3,000 reviews | 3,000 reviews | 3,000 reviews |
| RapidMiner | 3,000 reviews | 3,000 reviews | 3,000 reviews | 3,000 reviews |
| MonkeyLearn | 3,000 reviews | 3,000 reviews | 3,000 reviews | 3,000 reviews |
| MeaningCloud | 3,000 reviews | 3,000 reviews | 3,000 reviews | 3,000 reviews |

**Table 3:-** Datasets and Products for Analysis

## Product Performances Evaluation: -

We compare the categorized products listed in Table 3. We can calculate the performance of each product based on commonly used metrics. These ones are the following:

- Accuracy: is a measure of the instances that have been correctly classified by the model among the entire data instances.
  The formula is the following one:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

  Where TP is True Positive instances, TN True Negative instances, FP False Positive instances and FN False Negative instances.

- Precision (also called Positive Predictive Value): is the fraction of true positive instances among the positives instances detected by the model.
  The formula is the following:

$$Precision = \frac{TP}{TP + FP}$$

- Recall (also called sensitivity): is the true positive rate, that is, the fraction of true positive instances detected by the model among the real true positive instances of the data.
  The formula is the following:

$$Recall = \frac{TP}{TP + FN}$$

- F1: is a measure that combines precision and recall is the harmonic mean of precision and recall.
  The standard formula is the following:

$$F1 = (1 + \beta^2)\frac{(Precision * Recall)}{\beta^2 Precision + Recall}$$

  It is possible to interpret precision and recall not as ratios but as probabilities:

- Precision is the probability, that, once positive instances have been detected, they are really positive ones.
- Recall is the capacity, or probability of the model, to predict positives instances.
  Final results are presented in
  Table *4*.1 and Table 4.2.

| READY-TO-USE PRODUCTS | DATASETS | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Twitter Dataset | | | | Amazon (Books reviews) | | | |
| | Accuracy | Precision | Recall | F1 | Accuracy | Precision | Recall | F1 |
| IBM Watson | 69.44% | 84.88% | 58.86% | 69.52% | 86.23% | 87.20% | 86.27% | 86.73% |
| Google Natural Language | 68.29% | 63.09% | 87.61% | 73.36% | 90.57% | 87.40% | 94.80% | 90.95% |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Micrososft Azure | 73.92% | 70.76% | 81.45% | 75.73% | 73.20% | 69.69% | 85.07% | 76.61% |
| Sentiment140 | 50.77% | 90.09% | 50.90% | 65.05% | 60.30% | 76.82% | 61.87% | 68.54% |
| Pattern | 62.70% | 58.25% | 89.87% | 70.68% | 65.43% | 59.48% | 96.87% | 73.70% |
| Textblob | 62.53% | 58.13% | 89.81% | 70.58% | 65.53% | 59.55% | 96.87% | 73.76% |
| Vader | 68.70% | 63.25% | 89.34% | 74.07% | 70.40% | 63.58% | 95.53% | 76.35% |
| RapidMiner | 57.07% | 76.89% | 50.88% | 61.24% | 60.03% | 72.37% | 56.93% | 63.73% |
| Monkey Learn | 55.67% | 72.09% | 56.63% | 63.43% | 79.93% | 74.56% | 90.87% | 81.91% |
| Meaning Cloud | 50.93% | 73.24% | 53.96% | 62.14% | 63.50% | 73.86% | 88.53% | 80.53% |

**Table 4.1: -** Evaluation of selected products (I)

| READY-TO-USE PRODUCTS | DATASETS | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Kaggle Competition | | | | Sentiment Labelled Sentences Data Set | | | |
| | Accuracy | Precision | Recall | F1 | Accuracy | Precision | Recall | F1 |
| IBM Watson | 81.33% | 96.28% | 69.95% | 81.03% | 79.39% | 93.24% | 78.25% | 85.09% |
| Google Natural Language | 87.00% | 88.66% | 84.47% | 86.51% | 89.57% | 84.97% | 96.13% | 90.21% |
| Micrososft Azure | 83.53% | 88.58% | 76.50% | 82.10% | 75.16% | 69.72% | 89.26% | 78.29% |
| Sentiment140 | 54.77% | 98.20% | 58.95% | 73.67% | 25.53% | 93.65% | 18.67% | 31.13% |
| Pattern | 82.33% | 78.09% | 89.26% | 83.30% | 70.80% | 64.09% | 94.60% | 76.41% |
| Textblob | 82.50% | 78.32% | 89.26% | 83.43% | 70.83% | 64.16% | 94.40% | 76.40% |
| Vader | 86.67% | 80.76% | 95.81% | 87.65% | 74.77% | 67.52% | 95.47% | 79.09% |
| RapidMiner | 75.90% | 83.90% | 77.79% | 80.73% | 72.40% | 78.41% | 77.47% | 77.93% |
| Monkey Learn | 55.67% | 72.09% | 56.63% | 63.43% | 85.87% | 84.62% | 87.67% | 86.12% |
| Meaning Cloud | 86.30% | 92.50% | 89.06% | 90.75% | 69.60% | 83.94% | 81.20% | 82.55% |

**Table 4.2: -** Evaluation of selected products (II).

## Conclusions: -

Looking the results of

Table *4*.1 and Table 4.2, APIs like IBM Watson, Google Natural Language and Microsoft Azure seem to be more precise. Independently of the dataset, their accuracy is always between 70-90%, achieving the higher punctuation in all of them. However, the access to their platforms is restricted to a limited number of instances, apart from that, you can always buy an enterprise license of use, and the unrestricted use will be granted.

On the other hand, we have APIs like MonkeyLearn and MeaningCloud, which allow us a higher free use (50,000 and 40,000 calls per month, respectively) whose accuracy is between 50-86%, and, in some datasets, not far from the best score.

Packages do not obtain bad results either, the accuracy is always between 60-85% and, in this case, we have unlimited use of the package. Another positive point is that these packages allow us to create our own model, that's very convenient for us, if we want to apply opinion mining not only to people but also to machines, so we can combine out-of-the-box models with new customized ones.

At this point we can conclude that the average punctuation of analyzed products is good enough for sentiment analysis, but the use of a combination of them depends on the nature of the data and the use case, basing our opinion not only in best punctuation but also in our business needs.

## Future lines: -

Once we have tested the most important products, the next step is to create our own models for Sentiment Analysis using the modelling tools exposed in Table 1. In that way, we would be able to compare the results

between the two kinds of products and determine if creating a model is worthy or if it's better to use the out-of-the-box tools.

Modelling tools are based on Machine Learning Algorithms for text classification. So, if we have a group of instances with their polarity, it is possible to train and create models for classifying new instances according to this polarity. The problem of these products is that they need a huge amount of data for training and, also, a bag of words, with expressions and concepts to correct and interpret what is really said.

The most common algorithms for classification are SVM (Support Vector Machines), Naive Bayes, Decision Trees, Maximum Entropy, Random Forests, Logistic Regression and Neural Networks (see Table 5 for more details about the modelling tools and their classification algorithms).

Other future line will be the use of new techniques based on unsupervised systems, for instance, using Neural Networks and their unknown behavior for Sentiment Analysis. The best recorded score we get is dated in April 2017. A group of scientists [48] discovered a sentiment neuron while they were trying to develop a system capable to predict the next character in a chunk of text. After training the multiplicative LSTM with 4,096 units on a corpus of 82 million Amazon reviews, they turned the model into a sentiment classifier by taking a linear combination of these units, learning the weights of the combination via the available supervised data. While training the linear model with L1 regularization, they noticed it used surprisingly few of the learned units. Digging in, they realized that actually appeared a single "sentiment neuron" that was highly predictive of the sentiment value. Without knowing it, they have developed an unsupervised system which learns an excellent representation of sentiment, despite being trained only to predict the next character in the text of Amazon reviews, getting 91.8% accuracy versus the previous best of 90.2% on a small but extensively-studied dataset, the Stanford Sentiment Treebank.

| Modelling Tools | Classification Algorithms | Algorithms Link |
| --- | --- | --- |
| Pattern.en | Naïve Bayes, SVM, Single Layer Perceptron | http://www.clips.ua.ac.be/pages/pattern-vector#classification |
| TextBlob | Base, Decision Tree, Maximum Entropy, Naive Bayes | http://textblob.readthedocs.io/en/dev/api_reference.html#module-textblob.classifiers |
| NLTK | Naive Bayes, Maximum Entropy, Decision Tree, Logistic Regression | http://www.nltk.org/api/nltk.classify.html |
| LibShortText | SVM | http://www.csie.ntu.edu.tw/~cjlin/libshorttext/doc/classifier.html |
| RTextTool | SVM, Maximum Entropy, Decision Tree, Neural Networks | https://journal.r-project.org/archive/2013/RJ-2013-001/RJ-2013-001.pdf |
| Apache Mahout | Logistic Regression, Naive Bayes, Hidden Markov Models | https://mahout.apache.org/users/basics/algorithms.html |
| Weka | SMO, Naive Bayes, Filtered Classifier | http://weka.sourceforge.net/doc.dev/weka/classifiers/Classifier.html#buildClassifier-weka.core.Instances- |

**Table 5:-** Some of the modelling tools and their most important classification algorithms

## References: -

[1] C. Hutto and E. Gilbert, "VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text.," Eighth International Conference on Weblogs and Social Media (ICWSM-14). Ann Arbor, MI, June 2014., 2014.

[2] W. D. Cloud, "Natural Language Understanding," [Online]. Available: https://www.ibm.com/watson/developercloud/natural-language-understanding.html. [Accessed 06 06 2017].

[3] Lymbix, "Lymbix: Clear Sentiment. Real Tone. Super Simple.," [Online]. Available: http://lymbix.com/. [Accessed 06 06 2017].

[4] OpenDover, "What's going on in Dover?," [Online]. Available: http://www.opendover.nl/whats-going-dover. [Accessed 06 06 2017].

[5] Repustate, "Text Analytics API," [Online]. Available: https://www.repustate.com/text-analytics-api/. [Accessed 06 06 2017].

[6]   Google Cloud, "Natural Language," [Online]. Available: https://cloud.google.com/natural-language/?hl=es. [Accessed 06 06 2017].

[7]   UClassify, "Sentiment Classifier," [Online]. Available: https://uclassify.com/browse/uclassify/sentiment. [Accessed 06 06 2017].

[8]   Stride, "Stride Technology," [Online]. Available: http://stride.ai/. [Accessed 06 06 2017].

[9]   Microsoft Azure, "Sentiment Analysis," [Online]. Available: https://azure.microsoft.com/en-us/services/cognitive-services/text-analytics/. [Accessed 06 06 2017].

[10]  MonkeyLearn, "Text Analysis with Machine Learning," [Online]. Available: https://monkeylearn.com/#analyze-text-data. [Accessed 06 06 2017].

[11]  Receptivity LIWC, "LIWC API: Get Started," [Online]. Available: http://www.receptiviti.ai/liwc-api-get-started/. [Accessed 06 06 2017].

[12]  Datumbox, "Machine Learning API," [Online]. Available: http://www.datumbox.com/machine-learning-api/. [Accessed 06 06 2017].

[13]  Twin Word, "Sentiment Analysis," [Online]. Available: https://www.twinword.com/api/sentiment-analysis.php. [Accessed 06 06 2017].

[14]  Meaning Cloud, "What is Sentiment Analysis?," [Online]. Available: https://www.meaningcloud.com/developer/sentiment-analysis/doc/2.1/what-is-sentiment-analysis. [Accessed 06 06 2017].

[15]  Sentiment140, "Sentiment140 API," [Online]. Available: http://help.sentiment140.com/api. [Accessed 06 06 2017].

[16]  Intellexer, "Intellexer Sentiment Analyzer," [Online]. Available: https://www.intellexer.com/sentiment_analyzer.html. [Accessed 06 06 2017].

[17]  Lexalytics, "Text Analytics Software with Sentiment Analysis, Categorization & Named Entity Extraction," [Online]. Available: https://www.lexalytics.com/. [Accessed 06 06 2017].

[18]  Skyttle, "Skyttle API," [Online]. Available: http://www.skyttle.com/. [Accessed 06 06 2017].

[19]  Data Science Toolkit, "Text to Sentiment," [Online]. Available: http://www.datasciencetoolkit.org/developerdocs#text2sentiment. [Accessed 06 06 2017].

[20]  V. Narayanan, "About Sentiment.vivekn," [Online]. Available: http://sentiment.vivekn.com/about/. [Accessed 06 06 2017].

[21]  CLIPS: Computational Linguistics & Psycholinguistics Research Center , "Pattern.en," [Online]. Available: http://www.clips.ua.ac.be/pages/pattern-en#sentiment. [Accessed 06 06 2017].

[22]  SenticNet, "SenticNet. Helping machines to learn, leverage, love.," [Online]. Available: http://sentic.net/. [Accessed 06 06 2017].

[23]  C. Hutto, "vaderSentiment," [Online]. Available: https://github.com/cjhutto/vaderSentiment. [Accessed 06 06 2017].

[24]  TextBlob, "TextBlob: Simplified Text Processing," [Online]. Available: http://textblob.readthedocs.io/en/dev/index.html. [Accessed 06 06 2017].

[25]  NLTK, "NLTK 3.2.4 documentation," [Online]. Available: http://www.nltk.org/. [Accessed 06 06 2017].

[26]  Turi, "Turi Machine Learning Platform User Guide. Sentiment Analysis," [Online]. Available: https://turi.com/learn/userguide/sentiment_analysis/sentiment-analysis.html. [Accessed 06 06 2017].

[27]  C.-H. H. a. Y.-C. J. (. Hsiang-Fu Yu, "LibShortText: A Library for Short-text Classification and Analysis," [Online]. Available: https://www.csie.ntu.edu.tw/~cjlin/libshorttext/. [Accessed 06 06 2017].

[28]  RTextTools, "RTextTools: a machine learning library for text classification," 02 11 2011. [Online]. Available: http://www.rtexttools.com/. [Accessed 06 06 2017].

[29]  A. d. Vries, "Sentiment: [R] package to perform sentiment analysis," [Online]. Available: https://github.com/andrie/sentiment. [Accessed 06 06 2017].

[30]  Stanford CoreNLP, "Stanford CoreNLP – Core natural language software," [Online]. Available: https://stanfordnlp.github.io/CoreNLP/. [Accessed 06 06 2017].

[31]  Apache OpenNLP, "Welcome to Apache OpenNLP," [Online]. Available: https://opennlp.apache.org/.

[Accessed 06 06 2017].

[32] Apache Mahout, "What is Apache Mahout?," [Online]. Available: http://mahout.apache.org/. [Accessed 06 06 2017].

[33] Apache UIMA, "What is UIMA?," [Online]. Available: https://uima.apache.org/. [Accessed 06 06 2017].

[34] LingPipe, "What is LingPipe?," [Online]. Available: http://alias-i.com/lingpipe/index.html. [Accessed 06 06 2017].

[35] Gate, "Gate: General Architecture for Text Engineering," [Online]. Available: https://gate.ac.uk/. [Accessed 06 06 2017].

[36] RapidMiner, "About us," [Online]. Available: https://rapidminer.com/us/. [Accessed 06 06 2017].

[37] Weka, "Weka 3: Data Mining Software in Java," [Online]. Available: http://www.cs.waikato.ac.nz/ml/weka/. [Accessed 06 06 2017].

[38] M. T. Martín-Valdivia, E. Martínez-Cámara, J. M. Perea-Ortega and L. Alfonso Ureña-López, "Sentiment polarity detection in Spanish reviews combining supervised and unsupervised approaches. Expert Systems with Applications.," 2012.

[39] A. L. Maas, R. E. Daly, P. T. Pham, D. Huang, A. Y. Ng and C. Potts., "Learning Word Vectors for Sentiment Analysis.," The 49th Annual Meeting of the Association for Computational Linguistics (ACL 2011), 2011.

[40] E. Filatova, " Irony and Sarcasm: Corpus Generation and Analysis Using Crowdsourcing," Proceedings of LREC 2012, 2012.

[41] B. Pang and L. Lee, "A Sentimental Education: Sentiment Analysis Using Subjectivity Summarization Based on Minimum Cuts," Proceedings of the ACL, 2004.

[42] J. McAuley, C. Targett, J. Shi and A. v. d. Hengel, "Image-based recommendations on styles and substitutes," SIGIR, 2015.

[43] J. McAuley, R. Pandey and J. Leskovec, "Inferring networks of substitutable and complementary products," Knowledge Discovery and Data Mining, 2015.

[44] S. Mukherjee and P. Bhattacharyya, "Feature Specific Sentiment Analysis for Product Reviews," Lecture Notes in Computer Science, vol. 7181, no. 978-3-642-28603-2, pp. 475-487, 2012.

[45] S. Mukherjee and P. Bhattacharyya, "Sentiment Analysis in Twitter with Lightweight Discourse Analysis," COLING, pp. 1847-1864, 2012.

[46] S. Mukherjee, A. Malu, B. A.R. and P. Bhattacharyya, "TwiSent: A Multistage System for Analyzing Sentiment in Twitter," Proceedings of the 21st ACM International Conference on Information and Knowledge Management, pp. 2531--2534, 2012.

[47] Kotzias et. al, "From Group to Individual Labels using Deep Features," KDD 2015, 2015.

[48] A. RADFORD, I. SUTSKEVER, R. JOZEFOWICZ, J. CLARK and G. BROCKMAN., "Unsupervised Sentiment Neuron," Open AI, APRIL 6, 2017.

[49] S. Poriaa, E. Cambria, R. Bajpai and A. Hussaina, "A review of affective computing: From unimodal analysis to multimodal fusion," ELSEVIER, 2017.