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## **Grado en Ingeniería Informática** **Informatikako Ingeniaritzako Gradua**

### **Proyecto fin de grado**

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Automatic detection of repressed anger from  
text messages

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## **Abstract**

The growth in the usage of social media, microblog and review platforms has resulted in a significant increase of the access to short text messages that reflect individual's opinion and feelings. Automatic detection of people's emotions has a wide range of applications such as producing systems that measure the satisfaction of customers and thus help companies to improve their products or services. This research project focuses on detecting anger, an emotion that is relative difficult to detect compared to other sentiments due to the usage of linguistics figurative language techniques, such as irony, that intends to communicate the opposite of what it is literally said. To this purpose, a review of the state of the art has been made and an experiment using not only traditional machine learning techniques, such as Neural Networks, K-Nearest Neighbor and Support Vector Machines, but also Deep learning algorithms has been conducted in an open social network like Twitter. The proposed methods define the repressed anger detection as a classification problem and to solve it, the task is divided into two subtasks that complement each other. The first focuses on explicit anger detection, while the second subtask's goal is to detect irony. The system make use of selected featured based on characteristics properties of English language and studies emotion and irony in psychology. The model is composed on features such as: frequency of words, style in written and spoken languages, intensity of adverbs and adjectives, structure of the document, use of emoticons, synonymy, ambiguity and the contrast of sentiment and negative situation.

## **Keywords**

Emotion Analysis, Supervised Classification, One-vs-one Classification, Convolutional Neural Networks, Repressed Anger Detection



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## 1. INTRODUCTION

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- Introduction
  - Get the important points of the state of art referring to sentiment analysis, repressed anger detection.
  - Explain the hypothesis to be worked out in the thesis.
- Planning and Methodology [OK]
  - Explain the plan. [OK]
  - Explain the methodology. [OK]
  - Show the schedule. [OK]
- State of art
  - Explain that sentiment analysis is.
  - Explain what emotion analysis is, compared to previous point.
  - Explain previous work.
    - \* Previous work in anger detection.
    - \* Previous work in irony detection.
  - Explain the that the project will focus on resolve the issue as a text classification problem.
    - \* Classification Techniques
    - \* Fundamentals of Classification
    - \* General classification problem solving
    - \* Explain the algorithms I used to make tests in WEKA.
    - \* Explain Deep Learning.
      - Explain Convolutional neural networks.
- Development
  - Early development on the exploration phase.
    - \* WEKA text classification testing.
  - Explain that on SemEval they said that the best scoring system were using DL and is becoming trending. General Problem Solving techniques (NPL) in Deep Learning perform better than those that focus on resolving in depth focusing on the topic.
    - \* Change to Deep Learning Development.
    - \* Explain the usage of architecture that Yoon Kim uses. (Previously explained in SoA)
    - \* Explain the process to detect repressed anger. (The system I made starting from dataset merging, ending with merge of 2 classification output.) Simple diagram.
      - Dataset searching and generation.
        - Developed a tweet downloader for IDs.
      - Word2vec (needed for CNN)
        - Model used for Word2vec.

## 1. INTRODUCTION

- > Spell checking
- > Slang dictionaries (difficulty on when to process the word. Detect Slang)
- > Usage of Stopwords.
- CNN classifiers
  - > hyperparams used.
- Classification output merge.
  - > Due to the labels in the dataset cannot use ensemble learning and use a 2x2 matrix to match everything.
  - > Develop a automatic Google forms and how to process them back to the original dataset.
- Research Framework
  - Searching datasets, or create one, automatically.
  - Manual labeling used to final prediction process.
- Results
  - Google Model
    - \* Explain the final result plus each classification independently.
  - Twitter Model
    - \* Explain the final result plus each classification independently.
  - Spell checking
- Conclusion and Future Work
  - Different approach now that manual label data is obtained. (Semi-supervised learning)
- Self-assessment
  - writing.

## 2. PLANNING AND METHODOLOGY

In order to accomplish the Master's thesis during the established period of eight months, the following plan will be followed:

1. **Exploratory phase:** this period of time will consist in searching and studying the literature related to the research field in order to build a solid theoretical framework on which support the rest of the investigation. Even though this process is presented as a isolated task, it is an fundamental activity that will be executed continuously throughout the whole project.
2. **First contact with the technology:** after having reviewed the first phase of the state of art and checked the advantages or limitations of each architecture, the first empirical tests will be done. These experiments will serve to for a better understanding of the literature read in the exploratory phase and to observe how they behave with the gathered sample data.
3. **Specification and design of the solution:** in this phase, based on the knowledge gathered from the empirical tests in the last point and the relevant literature that has been constantly read, the requirements of the solution that best results can achieve for this research topic will be specified.
4. **Design of the functional prototype and evaluation:** after the requirements gathering, during this task, a prototype that justify all the steps followed this far will be developed, and evaluate its performance.
5. **Thesis document writing:** Finally all the relevant knowledge that has been required to complete this research will be gathered, the procedure to develop the system will be described and the conclusion and future work on this topic will be written down altogether, resulting in this master's thesis document, that will be refined until its laster submission and defense.

Previously defined tasks will be executed according to the next schedule diagram:

Phase No.	Name	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 7	Month 8
1	Exploratory phase								
2	First contact with the technology								
3	Specification and design of the solution								
4	Design of the functional prototype and evaluation								
5	Thesis document writing								

Figure 2.1: Schedule

## 2. PLANNING AND METHODOLOGY

The figure 2.2 illustrates the methodology used during the investigation process, in which the results obtained from the prototypes might not be satisfactory or could lead to formulate new questions. To solve those doubts a redesign of the system may be needed. In addition, after reporting the results to project supervisor, new relevant information might be provided. This information has to be added to the knowledge obtained from previous state of the art review and reanalyze if the proposed solution requirements are still valid.

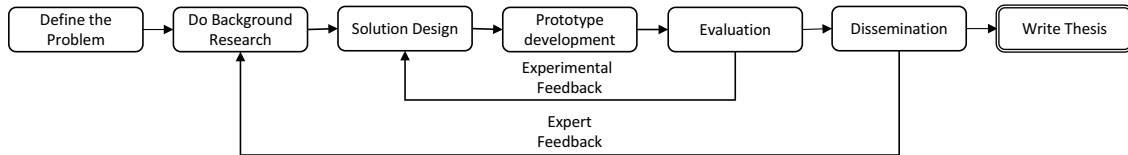


Figure 2.2: Methodology

### 3. STATE OF ART

The aim of this chapter is to conduct a study of the state of the art of automatic detection of repressed anger by first analyzing the current state of sentiment analysis and emotion detection, which are the fundamentals to detect anger and irony.

#### 3.1. SENTIMENT ANALYSIS

Sentiment Analysis (SA), sometimes referred as Opinion Mining (OM), is the field of study that aims determine the attitude of the author respect to some topic. During the last decade, due mainly to the rapid increase of the social media, the research of this area, which includes linguistics and Natural Language Processing (NLP), has gain more relevance as it has a wide range of applications that can be used commercially.

Almost the human actions are influenced by opinions. A practical example of this behavior that get repeated in daily basics occurs when before making a decision we want to know other' to contrast our thoughts. In business, when an organization requires to public or consumer opinion, it conducted different types of surveys to gather this information. However, nowadays we do not precise to ask personally to people around us to discuss about a product. Thanks to micro-blogs, Twitter and reviews in social networks, we can broaden the amount of external opinions for decision making. Due to the amusing amount of information available, sometimes we could face some challenges, such as finding reliable sources summarizing and filtering the relevant information. The same way we consume this information, companies also search for new ways to obtain and process such information efficiently without human intervention, to achieve this automated analysis is needed[48].

##### 3.1.1 Tasks

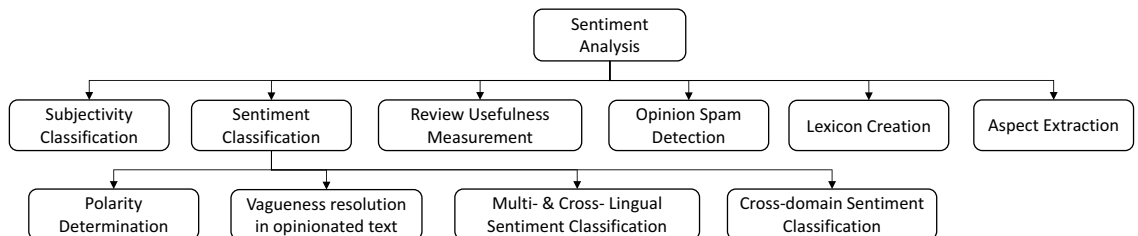


Figure 3.1: Sentiment analysis tasks.

Depending on the problem definition, different tasks have been defined related to sentiment analysis. According to [62], after the revision of more than three hundred papers related to this topic, the

### 3. STATE OF ART

survey carried out concludes that the main tasks can be categorized as (a) subjectivity classification, (b) sentiment classification, (c) review usefulness measurement, (d) opinion spam detection, (e) lexicon creation and (f) aspect extraction, as shown in the figure 3.1.

#### **Subjectivity classification**

According to [53], subjectivity classification aims to determine the "private state" of the author of a text. The Subjectivity analysis is the process of distinguish objective language from the opinion oriented. Even though there is much less literature about this field compared to other SA task, it has proven to be more difficult than determine the measuring the polarity of a document and, thus, improvements achieved in this field will positively impact on sentiment classification.

#### **Sentiment classification**

Sentiment classification consist in determine the orientation of a sentiment of a given text into two or more classes. This classification has been performed in multiple classes, such as, binary (positive or negative), ternary (positive, neutral and negative), n-ary [56], among others.

#### **Review usefulness measurement**

Review usefulness measurement tends sometimes be confused with opinion spam detection, however there are some slight differences. Of course false review are always rated as useless, as their objective is just to boast or ridicule a product. Although, there are also bad reviews that might not necessary be spam, as they reflect the honest opinion of the author. Thus, this subtask complement the opinion spam detection.

#### **Opinion spam detection**

In order to boost sales, some companies have invested on unmoral marketing techniques that consist in publishing false reviews about their own products or from the competence. In order to detect fake reviews, researches have focus their effort on (a) analyzing the content of the review, finding hidden lies by using NLP, (b) meta-data of the review, such as start rating, author information, date of writing, among many others [38], however this information sometimes is not accessible, and (c) comparison with real-life information about the product.

#### **Lexicon creation**

A lexicon is a collection of words that determines the polarity of each one of them. Lexicons are used as an approach to detect the sentiment polarity of a given document [40].

#### **Aspect extraction**

Aspect extraction is a key to detect author's opinion regarding various characteristics of a product based on the collection of opinion words and entities and identification and extraction of the aspects of those entities [54].



### 3.1.2 Techniques

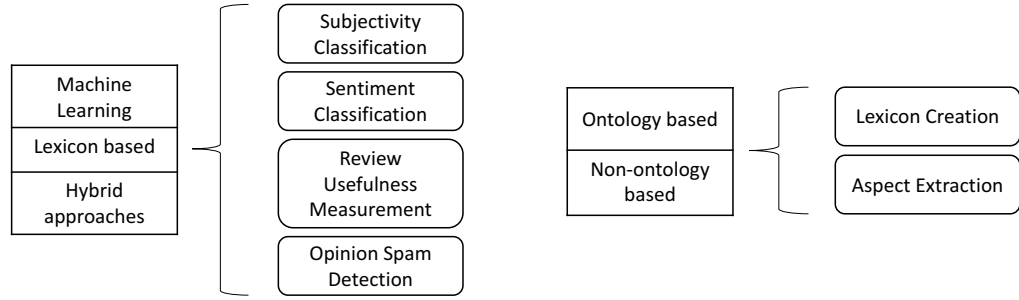


Figure 3.2: Sentiment analysis approaches for each task.

To solve all these problems in the most efficient way, multiple approaches have been conducted, such as [74]; [55] or [60]. The figure 3.2 illustrates which techniques have been used for each previously named tasks.

The figure 3.3 collects the most common techniques used for SA based the survey conducted by Walaa Medhat et al. (2014). For the purpose of this project, we will focus on making an introduction to those approaches related to sentiment classification, more precisely to Machine Learning (ML), lexicon-based and hybrid approaches.

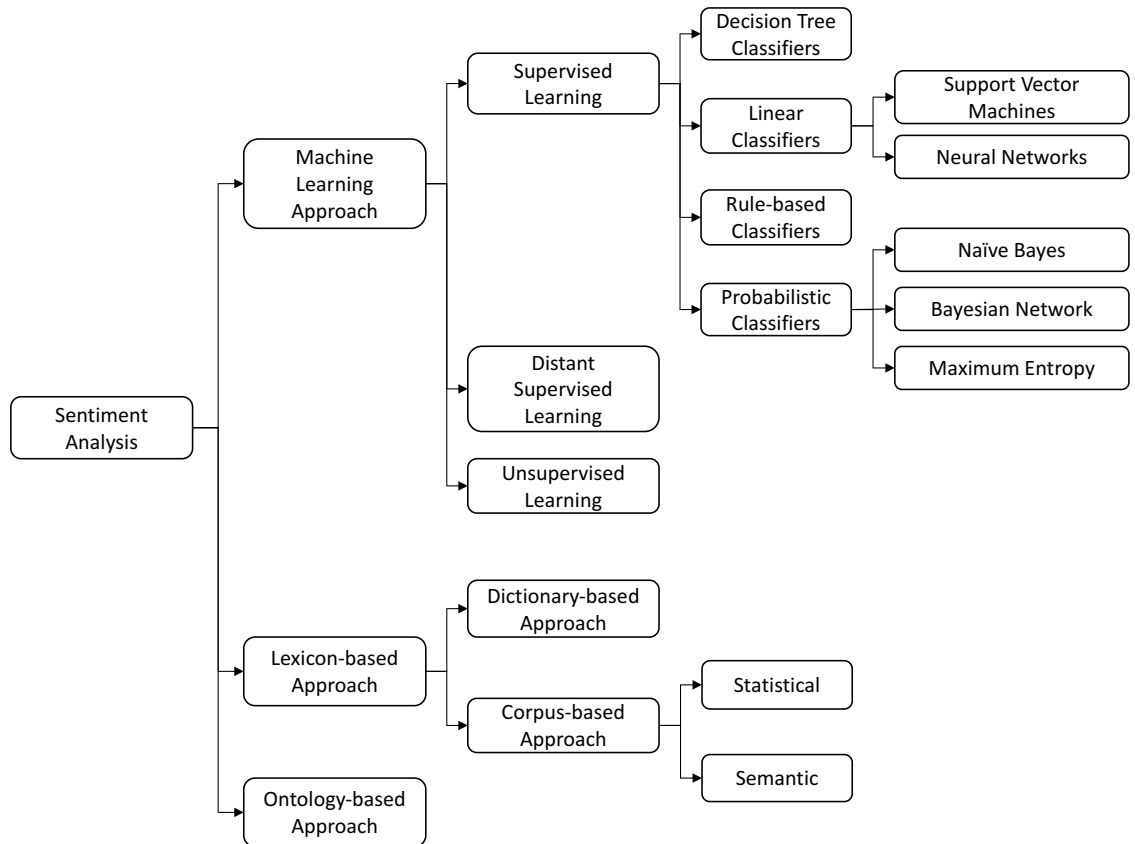


Figure 3.3: Sentiment analysis techniques[51].

#### Machine learning approach

Thanks to the good performance machine learning techniques have proved to achieve, more and more researches have gained interest on this technology. The classification process (see 3.4) used, consist on extracting a series of features vectors from the dataset and a to create a model that is able to identify different patterns among these features. The selection of relevant features is key as it directly affects the performance the model can score. Some good known features for model generation are based on n-grams, such as unigrams, bi-grams and tri-grams [22].

1. **Data gathering:** During this phase, first publicly available datasets are searched from related literature. Then if needed, to complement this data, an analysis of the social media that contains information regarding the research topic is conducted. After analyzing the sources from which data can be extracted, a crawler adapted to deal with those networks is used to collect the data. This data, usually mostly or partially, requires to be labeled with a predefined set of classes, a task generally done by crowd-sourcing.
2. **Pre-processing:** Most of the raw data obtained from social media contains information is not relevant or cannot be directly processed by the classifier. In this step, tasks like word spell checking, Uniform Resource Locator (URL) and hash-tags removal, keyword extraction, language filtering, tokenization, among many others are carried out.
3. **Classifier training:** With the dataset most commonly split into training, validation and test, the training and validation sets will be provided as an input to the classification algorithm as the learning process, which concludes with the generation of a model.
4. **Classification:** With the previously generated model on the learning process, the classifier can now be used to predict new data.
5. **Result evaluation:** To measure how accurate the learning algorithm performed, the output of the system is compared with dataset labels by means of a defined evaluation function and representation format.

#### Lexicon based approach

Sentiment analysis based on lexicon approach consist on the use of a collection of words, a dictionary, that contains a pre-tagged lexicon to classify a given text. The input document is tokenized and, thus, every token is compared with the lexicon forming the dictionary. Depending on how the lexicon is defined, the result of the comparison can be either positive or negative. If positive match is given, the total score of the text classification is increased, if negative match occurs, then the score decreases. Although this technique could be considered simplistic, some simplistic tests [36] have proven to be successful in achieving high precision.

#### Hybrid approach

As [73] suggests, both, machine learning and lexicon based approaches have their advantages and disadvantages. Thus, researchers have tried merging different methods to order to find more precise and efficient ways of classifying sentiments. The combination of techniques are varied, such as architectures that mix lexicons to automatically label data that is used as a learning input into a Naive Bayes (NB) classifier as shown in [57]; the author of [42] uses the combination of three classifiers, enhanced emoticon classifier, improved polarity classifier and a SentiWordNet

classifier to determinate the polarity of a given tweet or [61], which used multiple rule based classifiers approaches combined with SVM executed on multiple hybrid sequential executions on a semi-automatic dataset.

## 3.2. EMOTION DETECTION

Emotion detection has been always a important field of study in neuroscience and psychology. Several experiments have been conducted to recognize emotions from face expressions, voice and body gestures, such in [5]; [4] and [32]. However, these features are not always available and thus, the detection of emotion from text has gain relevance during the last decade.

Emotion detection from text documents is closely related to SA. As explained in 3.1.1, sentiment classification task consists in determine the polarity of a given text into two or more classes. Emotion detection also fits this description, since this field of study is conducted by classifying a given document into predefined emotion labels. The definition of these labels are based on previously presented emotion models, which consist on application psychological and neuroscientific theories to represent emotions. One of the first model defined was proposed by Paul Ekman, on 1972, composed by six basic emotions, *“happiness, sadness, fear, anger, surprise and disgust”*, and has been used in multiple face recognition systems and is the base emotion detection from text [34] as its definition has resulted to be the most semantically diverse [3].

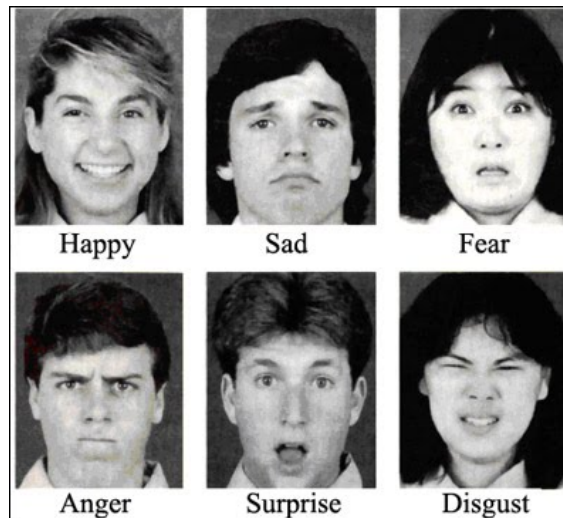


Figure 3.4: Ekamn’s basic emotions, image extracted from Expressions, Emotions and Emblems, Google Sites.

Since then, more interpretations have been made regarding the representation of the emotions as shown in [11]. Ekman himself added his list 11 new emotions stating that not all of them could be represented by facial expressions. In 1980 Robert Plutchik created another bi-dimensional model (see figure 3.5), known as wheel of emotions, that defined eight basic bipolar emotions with different levels of intensification and could be combined among them. Ortony Clore and Collins (OCC) designed in 1988 a model in which emotions were driven by an agent, based on the premise that *“emotions are not themselves linguistic things, but the most readily available non phenomenal access we have to them is through language”* [7]. The model included 22 emotion categories that

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aimed to “*model humans in general*” [7]. OCC enables the study of emotions as classes that share the same feeling, instead of specific words, proving that this “*is a theory of emotions and not a theory of the language of emotions*” [7]. For more information, authors of [6] analyze the state of art of the emotion models and the techniques used to generate them.

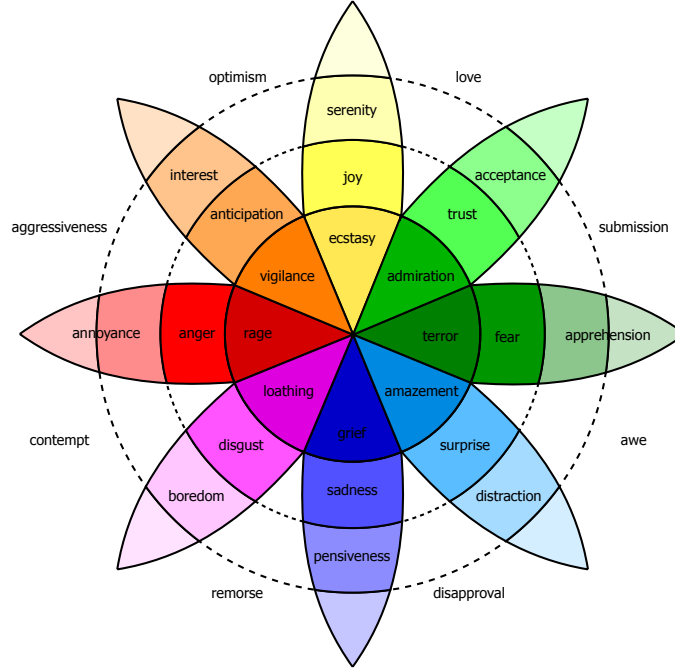


Figure 3.5: Plutchik’s emotion wheel, image extracted from Wikipedia’s public domain.

Emotion classification tasks shares the same principles as SA, and thus, the techniques used are mainly ML, lexicon-based and hybrid approaches previously explained in section 3.1.2.

## 3.3. PREVIOUS WORK

The study of anger and its management has been studied since ancient times. According to American Psychological Association (APA), anger is “*an emotion characterized by antagonism toward someone or something you feel has deliberately done you wrong*” [2]. Anger is a normal emotion all human experience. Modern psychologists have studied the health effects that may derivate from anger suppression, such as shown in [41] and [69], linking it to a more extremist and sarcastic personality. This research aims to find the answer to the question: “Can the repressed anger be detected in text?”. Based on the definition of personality of a subject that has experienced repressed anger, the problem formulation has been simplified into finding negative messages influenced by anger that covered by a layer of sarcasm. The following subsections present a brief summary of the research conducted in the detection of anger and sarcasm.

### 3.3.1 Anger

As explained in section 3.2, the increase of the usage of social media and computational viability to process all the publicly available data has enable the detection of emotions from text. However

as there is not literature that focuses on anger emotion, this section will briefly enunciate the approaches researched to classify emotions that contain anger as target label.

In 2007 during international workshop of evaluations of computational semantics analysis system, known as SemEval [67], presented an task that analyzed the affective text, in which the participants had to calculate the the valence and emotional class of news titles. Three groups participated in the emotion classification subtask: SWAT, UA and UPAR7.

The system proposed by SWAT was based on unigram trained model supervised learning. In addition to the emotion label target given this group perform a synonym expansion of these keywords by using the Roget Thesaurus. The training of the system was performed by combining the development data provided by the SemEval task organizers plus a set of 1000 headlines that was annotated from the group.

UPAR7 developed a linguistic rule-based system approach. The first step was to pre-process the data by un-capitalize the common words. Then, each word was rated separately with each emotion target label.

In order to determine the type of emotion in the headline UA group collected statistics from three web search engines to calculate the distribution of nouns, verbs, adjectives and adverbs of the headline. The emotion scores were obtained through Point-wise Mutual Information (PMI).

The F1-score obtained by SWAT, UA and UPAR7 for anger sentiment was 7.06, 16.03 and 3.02 respectively (results multiplied by 100) [71].

Authors in [70] implemented five system for emotion analysis based on a knowledge based emotion annotation and corpus based emotion annotation: WN-affect presence, LSA single word, LSA emotion synset, LSA all emotion words and NB trained on blogs. For anger annotation, the proposed system scored a F1-score of 16.77 (results multiplied by 100), outperforming the system proposed by UA in SemEval for anger annotation.

Kirk Roberts et al. developed a system composed of six SVM classifiers, one for each Ekman's sentiment basic emotion. The Features selected as input for the binary classifier where: unigrams, bigrams, trigrams, presence of interrogation or exclamation mark, Word Net synsets, WN hypernyms, Latent Dirichlet Allocation topic scores and high PMI unigrams (significant words). The anger classifier used unigrams, synsets, topis and significant words, scoring a F1-score of 0.642 [65].

Chew-Yean Yam posted at Microsoft developer Blog an example of emotion classification using Deep Learning (DL) techniques. The corpus was collected by using Amazon's Mechanical Turk to perform a Human Intelligence Task (HIT) to manually annotate the data, obtaining a total of 784,349 samples of informal short English messages classified as five classes, anger, sadness, fear, happiness and excitement. The DL architecture is described ad a Neural Network (NN) with five out nodes, three hidden layers, that contain 5, 25 and 125 nodes respectively. The loss function selected was Cross entropy with a stochastic gradient descent optimization algorithm. The learning rate was set to 0.001. The maximum training iteration was set to 100 with a greedy pre-trainer type executed though-out 25 epochs. The anger classifier in this system obtained a F1-score of 0.64958 [83].

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#### 3.3.2 Irony and Sarcasm

Sarcasm, also referred as verbal irony [28]; [27] and [26], is defined as cutting remark to express contempt or ridicule according the free dictionary [66]. Based on the literature, the boundaries of irony and sarcasm are fuzzy [9], as some authors consider irony as global term that includes sarcasm [25], [81] and [47] and others analyze the differences between both [19].

Authors in [39] conduct a survey of the approaches used to detect sarcasm. Mainly three approaches have been proposed: rule-based, statistical approaches and Deep Learning approaches.

In 2009 Paula Carvalho et al. analyzed the detection of Portuguese irony by using pattern matching rules, such as diminutive forms, interjections, verb morphology, heavy punctuation, quotation marks, laughter expressions, among others. The proposed system classified the given sentences as ironic, not ironic, undecided and ambiguous. They concluded that the best patterns for irony recognition are quote and laugh patterns, obtaining an accuracy of 68.29% and 85.40% respectively [12].

[50] developed in 2014 a rule based system to classify sentences in which the presence of sarcasm was known by analyzing hashtags in Twitter. Based on the premise that if the hashtag does not agree with the rest of the tweet the sentence is classified as sarcastic and by re-tokenizing hashtashs to split concatenated tokens, the classifier obtained a F1-score of 91.03 (result multiplied by 100).

Two important aspects must be pointed out regarding statistical approaches: the features used and the selected learning algorithms. Aditya Joshi et al.'s survey states that even though *"multiple variety of classifiers have been experimented for sarcasm detection most of the work conducted relies on SVM"* [39].

Authors in [17] proposed a system that classified Twitter and Amazon documents by employing semi-supervised techniques. The dataset was composed of 5.9 million unique tweets that contained the #sarcasm hashtag, which were pre-processed by removing any link appearance, users mentions and hashtags and replaced them by proper identification tags. The system relied on features such as High Frequency Words (HFWs), Content Words (CWs), punctuation based features to create single entry feature vectors. The classification output was defined as a number from range 1 to 5 to measure the presence of sarcasm in the given text and performed with a K-Nearest Neighbors (KNN)-like strategy [16]. To evaluate the system 5-fold cross validation was employed. The experiment that best performed used all the listed features obtained and obtained a F1-score of 0.545 on Twitter messages and 0.827 in Amazon reviews.

In 2012, Reyes et al. introduced the following features for irony detection: n-grams, Part of Speech (POS) n-grams, funny profiling, positive/negative profiling, affective profiling and pleasantness profiling. NB, SVM and Decision Tree (DT) classifiers were evaluated by comaparing positive sets against three negative subsets, begin SVM the learning algorithm that scored the highest in two out of the three subsets with a F1-score of 0.747 and 0.891 respectively.[63]. In 2013, they explored the use of skip-gram and character n-gram-based features for detecting irony representativeness and relevance with the Toyota case study. Dividing the tweets into three levels of representativeness the proposed model obtained a 0.66 F1-score on the third level [64].

Regarding DL, is a technology that is gaining popularity among researchers studying sarcasm and irony. Silvio Amir et al. in 2016 proposed a convolutional network-based system that learned content and context from user embeddings, achieving a 2% improve in absolute accuracy compared

to the Bamman and Smith's 2015 baseline system [1].

Authors in [24] proposed a system that combined Convolutional Neural Networks (CNN), Long Short Term Memory (LSTM) and Deep Neural Networks (DNN). They compare the approached system against recursive SVM and other datasets stating that their architecture obtains better F1-score than previous DL solutions, obtaining 0.901.

## 3.4. CLASSIFICATION TECHNIQUES

The aim of this section has two purposes. The first one, is to make an introduction of the basic concepts of classification, which is essential for the detection of repressed anger as the solution proposed has been defined as a classification problem. The second one, is to explain how the algorithms used in this study work.

### 3.4.1 Fundamentals of Classification

According to [77], classification can be defined as the task of predicting an outcome from a given input. This outcome is produced by the process of mapping a group of characteristics present in the input to a certain category. In other words, it consists in assigning objects (the input) to one of several predefined classes (the outcome) [58]. Examples of classification can be found in everyday life, such as e-mail spam detection, news classifiers, Optical Character Recognition (OCR), animal kingdom classification (see Figure 3.6), among many others.

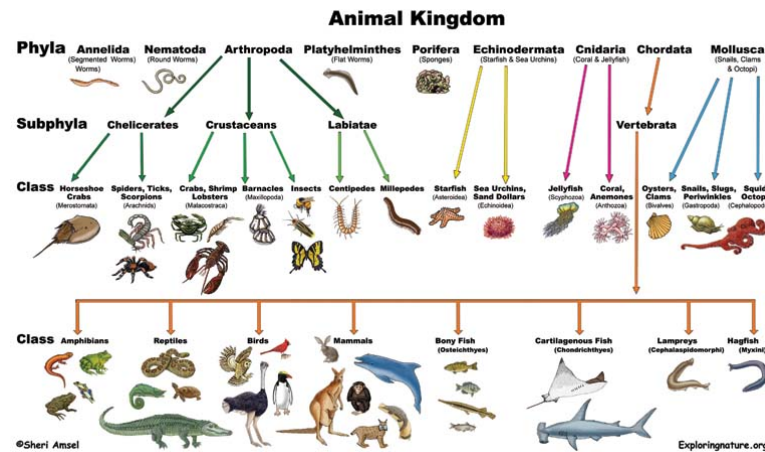


Figure 3.6: Classification of animals. The image is extracted from Exploring Nature.

The input data for a classification task is composed by a collection of records, the dataset. In the same time, each record, also known as an instance, is composed by a set attributes. From all these attributes there is one considered special, which is called the target attribute or the class label. Regular attributes can be both discrete or continuous values. For the values signed for the class label, however, they must be discrete. This characteristic is what distinguishes classification from regression. Table 3.1 shows a sample dataset for animal classification into the following categories: amphibian, bird, fish or mammal.

### 3. STATE OF ART

Common Name	Hair	Feathers	Eggs	Milk	Aquatic	Legs	Class Label
antelope	Yes	No	No	No	No	4	mammal
catfish	No	No	Yes	No	Yes	0	fish
dolphin	No	No	No	Yes	Yes	0	mammal
dove	No	Yes	Yes	No	No	2	bird
duck	No	Yes	Yes	No	Yes	2	bird
elephant	Yes	Yes	No	Yes	No	4	mammal
flamingo	Yes	Yes	Yes	No	No	2	bird
frog	No	No	Yes	No	Yes	4	amphibian
fruit bat	Yes	No	No	Yes	No	2	mammal
gull	No	Yes	Yes	No	Yes	2	bird
herring	No	No	Yes	No	Yes	0	fish
kiwi	No	No	Yes	No	No	2	bird
lark	No	Yes	Yes	No	No	2	bird
lynx	Yes	No	No	Yes	No	4	mammal
mole	Yes	No	No	Yes	No	4	mammal
mongoose	Yes	No	No	Yes	No	4	mammal
newt	No	No	Yes	No	Yes	4	amphibian

Table 3.1: Animal kingdom dataset.

Tan Pang-Ning et al. propose a more mathematical definition of classification stating that it is the process of learning a target function  $f$ , also known as classification model, that maps each attribute set  $x$  to one of the predefined class labels  $y$ .



Figure 3.7: Classification as a task of mapping a set attributes  $x$  into its fitting class label  $y$ .

A classification model is useful for the following purposes [58]:

- **Descriptive Modeling:** Since a classification model presents the main features of the data, it can serve as an explanatory tool to distinguish between instances of different categories [49].
- **Predictive Modeling:** A classification model can also be used to predict the class label of an unknown new instance. As shown in Figure 3.7, a classification model can be represented as a black box that automatically assigns a class label to an instance by providing its attribute set.

It is important to remark that classification techniques perform their best when used for predicting or describing datasets which its class label is binary or nominal, Since they no consider properties such ordinality or the implicit order among the categories, they become ineffective with ordinal class labels [20].



### 3.4.2 General classification problem solving

For general classification problems solving, popular techniques consists on a process that starts with building classification models from a sample dataset [82]. Each technique depends on a learning algorithm witch is in charge of generating the classification model. A good model should define the relationship between the input attribute set and its belonging category that suits the best. Therefore the model should be valid for both, the sample data used to generate the model and also for new unknown instances. Among popular classification techniques Support Vector Machine (SVM), Neural Networks (NNs), Naive Bayes or Decision Trees (DTs) can be found [23].

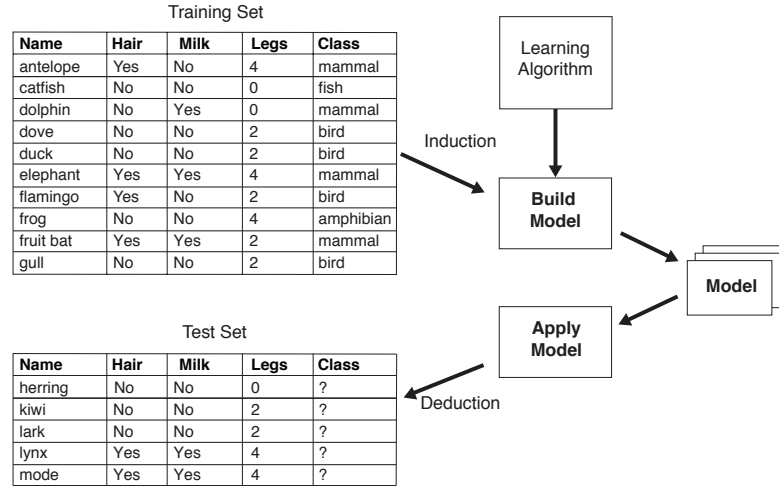


Figure 3.8: General approach for classification model building and new instance category prediction.

As shown in the Figure 3.8, to solve a classification problem a sample dataset must be provided as a training set. This sample is used to build the classification model according to the learning algorithm. After the model is built, it is applied to unlabeled dataset, also called the test set, to predict the categories of each instances of the records. To measure how good the model is, there is only need to count the number of instances have been correctly and incorrectly classified from the test set. Usually, to represent system's performance values, a confusion matrix is used [33].

		Predicted Class	
		<i>Class = Yes</i>	<i>Class = No</i>
Actual Class	<i>Class = Yes</i>	a	b
	<i>Class = No</i>	c	d

Table 3.2: Confusion matrix of a binary classification.

As a example, Table 3.2 represents the confusion matrix of a binary classification problem, in which the possible classes that can be assigned to a given instance are *Yes* or *No*. The values presented in this confusion matrix represents the counts of instances correctly and incorrectly classified as a means of model performance evaluation, being the diagonal of the table the instances classified correctly, the true positives (TP) and negatives (TN). The rest of the table corresponds to the number of instances that have been classified incorrectly, the false positives (FP) and false negatives (FN). The definition of a cell done by the value of the column and the row in which is positioned, read as the number instances of *X* classified as *Y*, where *X* and *Y* are the determined value of the

### 3. STATE OF ART

row and column respectively. For instance, the cell  $a$  is interpreted as the counts of Yes that have been classified as *Yes*, the TP.

Although the confusion matrix gives all the relevant information to determine how well the system has performed, sometimes is convenient to provide this information into a single value that summarizes the content of all the table. To do so, multiple performance metrics have been defined and one of those is the accuracy defined as:

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

Accuracy represents the percentage of correctly classified instances. However, using only accuracy may not be enough, as for example when the dataset is imbalanced or it has a majority of elements for a determined class. Of instance, on a naive classifier that always determined an instance as the element with the maximum number of appearances in the dataset, the accuracy of classifier results in a high value although, the model does not have predictive capacity. This is considered the accuracy paradox [18] and thus, to avoid the scoring a misleading measurement, it is recommendable to combine its usage with other performance metrics such as precision and recall.

Translating the precision from information retrieval context it would answer to the question *how many classified items are relevant for the current query?* and thus, the precision is defined as:

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

In the same context recall, in the other hand, answers to the question *how many relevant items are classified properly?* and such, defined as:

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

Finally, a combination of both measures, precision and recall, as a weighted average is called F-Measure or F1-Score. It allows to have a single performance metric to evaluate the classifier. Although, multiple definitions of the metric that give more relevance to the recall over the precision or vice versa exist, the general definition can be specified by the following equation:

$$F_1 = 2 \times \frac{precision \times recall}{precision + recall}$$

#### 3.4.3 Deep Learning

Introduction to Sentiment Analysis. Relevant International Workshop found: SemEval Datasets repositories: Twitter as corpus, Amazon products reviews Dataset labeling: CrowdFlower, Amazon Mechanical Turk. Word embedding: Word2vec, GloVe. Text classification features: N-grams based on Sentiment lexicon Learning Methods: Supervised, Unsupervised, Distant Deep Learning techniques: Convolutional NN, Recurrent NN, Deep Autoencoders Classifiers: Bag of Words, Naive Bayes, Logistic Regression, SVM, NN, Clustering Accuracy evaluation: Precision, Recall, F1-Score, Cross-validation Trends: Best scoring teams used Deep Learning techniques.

Next week work: Deep reading and prepare a Playground with small sample data.

Read fundamental theory about classifiers such as SVN, Bayesian, KNN, Decision Tree. Urge test what has been learned in order to set the basic knowledge. Download and test WEKAs basic functionalities for educational and research purpose. (Includes a No-Code-GUI, which makes it user friendly for initial testings) Use scikit-learn for following iterations of the classifier (More modern algorithms, better memory management, Python development environment...) Further reading about Emotion classification techniques and investigate about repressed anger in English texts. Multiclass angry classification?

Future work: Deep Learning

Depending on the generated dataset (size and labeled/unlabeled) the project could opt for a DL based classifier. Could score better results in the benchmarking. To gather large amount of data for each class is compulsory solve the overfitting problem. (Detection and prevention by using Cross-validation) If the dataset is not completely labeled weakly (distant) supervised learning could be applied. Theano and Keras have proved a DL frameworks to perform well.



## 4. PROPOSED SOLUTION

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The aim of this chapter is to explain in detail the steps followed to conduct the experiment first introduced in section ??.

As explained in section 3.3, the suppression of anger can derivate in the development on a more extremist and sarcastic personality. To recognize repressed anger from text messages, this research has based on the hypothesis that repressed anger messages contain both anger and ironic features and thus, focus on the detection of these features independently on Twitter documents.

Many research have been done to detect theses to aspects, in general, we could say that the most explored approach used for emotion classification and irony detection are based on SVM learning algorithm. However, recently introduced technology has been gaining popularity among researchers: DL. In fact, during the task four presented in the international workshop of evaluations of computational semantics, SemEval 2016, the organizers stated as follow:

*“A general trend that emerges from SemEval-2016 Task 4 is that most teams who were ranked at the top in the various subtasks used Deep Learning, including convolutional NN, recurrent NN, and (general purpose or task-specific) word embeddings. In many cases, the use of these techniques allowed the teams using them to obtain good scores even without tuning their system to the specifics of the subtask at hand [...]. Conversely, several teams that have indeed tuned their system to the specifics of the subtask at hand, but have not used Deep Learning techniques, have performed less satisfactorily. This is a further confirmation of the power of Deep Learning techniques for tweet sentiment analysis” [56].*

DL has caused a great impact on SemEval and recent researches and therefore, based on these statements the decision to implement a system that make used of this technique was made.

Since DL is a class of ML, the procedure developed in the proposed solution (see figure 4.1) follows the steps of a classical Machine Learning approach (section 3.1.2): data collection, pre-processing, learning process, prediction and evaluation. In the following sections a general perspective of the proposed solution will introduced followed up by an explanation of the four steps in detail, while evaluation results will be presented of the following chapter.

### 4.1. DATA COLLECTION

The objective of subtask is to gather already annotated tweets that contains emotions, specially anger, and irony. During this step, multiple research paper that would provide public available dataset or would provide the methodology on how to build one were analyzed, such as the explained in [35] and [72]. In the following paragraphs describe the public datasets gathered and created for this project.

#### 4. PROPOSED SOLUTION

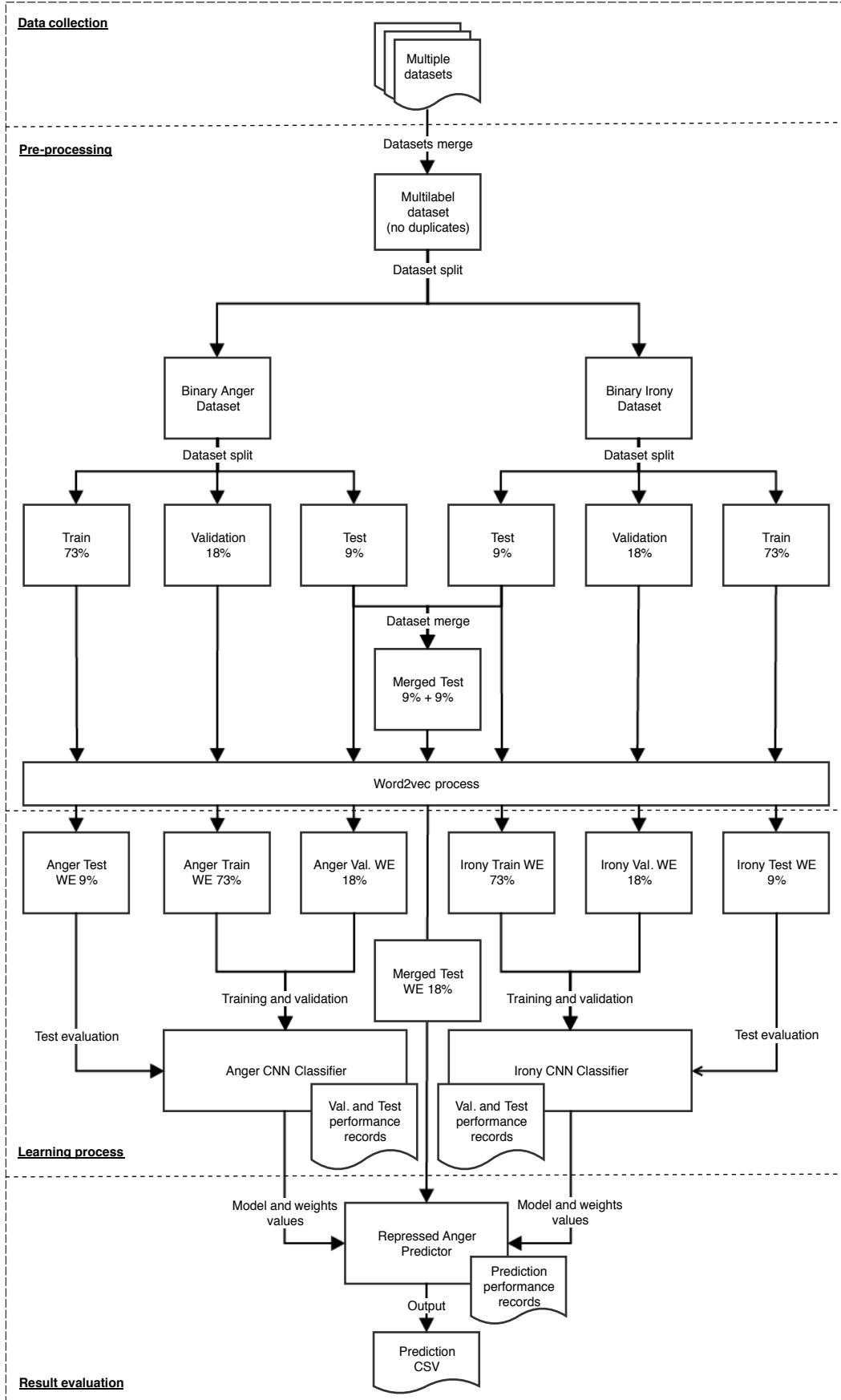


Figure 4.1: Proposed solution procedure.

#### 4.1.1 Wang's SMILE Twitter emotion dataset

At first, only Wang et al.'s SMILE Twitter emotion dataset was found, containing a total of 3,085 tweets classified as: anger, disgust, happy, no-code, not-relevant, sad and surprise [78]. By simply taking into account the number of tweets offered in this dataset as small, and probably not enough, to perform DL based classification. Figure 4.2 shows the distribution of tweets related to each annotated class. By analyzing the number of tweets related to anger the amount of tweets are reduced to 57. Moreover, the tweets labeled as not-relevant and no-code, classes that contains no value to the purpose of the research, represents around 58% of the whole dataset. However, even if not being enough, the remaining 42% would be stored to posteriorly merged to other datasets.

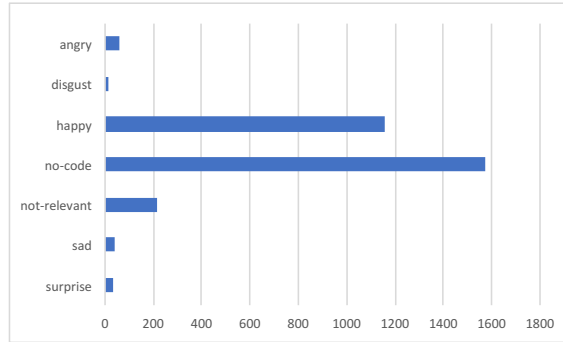


Figure 4.2: Wang's SMILE Twitter emotion dataset distribution.

#### 4.1.2 CrowdFlower's Data for Everyone, Sentiment Analysis: Emotion in Text dataset

CrowdFlower, an HIT web solution, offers publicly available datasets under its "Data for Everyone" section, where an annotated emotion dataset for sentiment analysis can be downloaded for research purposes. The dataset is composed from tweets classified as the following 13 classes: anger, boredom, empty, enthusiasm, fun, happiness, hate, love, neutral, relief, sadness, surprise and worry [14]. Figure 4.3 shows the number of tweets per annotated class, being anger and hate the most relevant for the purpose of this project representing around 3% of the dataset.

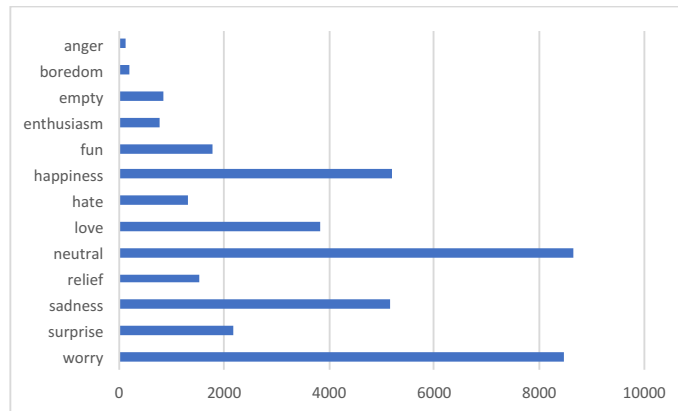


Figure 4.3: CrowdFlower's Data for Everyone, Sentiment Analysis: Emotion in Text dataset distribution.

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### 4.1.3 Wang 2012, Harnessing Twitter “big data” dataset

In 2012 Wang et al. created a publicly available dataset from Twitter messages to analyze emotions. The dataset is composed from tweets classified in 7 categories as anger, fear, joy, love, sadness, surprise and thankfulness [79]. However, due to the term of service of Twitter, *“If you provide Content to third parties, including downloadable datasets of Content or an API that returns Content, you will only distribute or allow download of Tweet IDs and/or User IDs”* [76] and thus, this dataset does not contain the proper tweet message, but a identifier number instead. To download the content of the tweet an Twitter Python API known as Tweepy [8] was used over the dataset’s “test” and “train\_2\_1” files. Although, since the originally the tweets were collected on 2011 to build the dataset, nowadays not all the tweets are available, as some users have removed their account or change their privacy settings. Figure 4.4 shows the number of tweets that were able to collect per class.

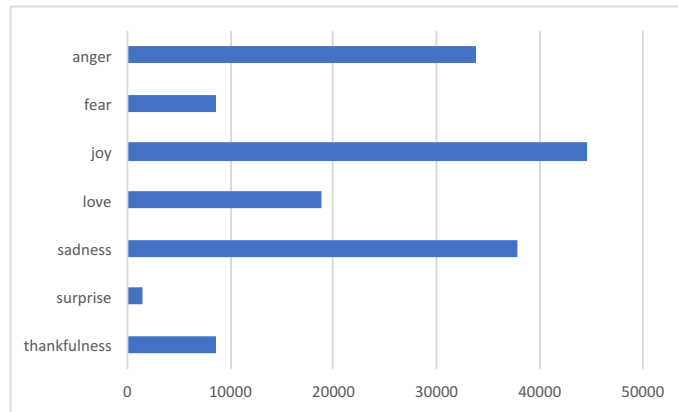


Figure 4.4: Wang 2012’s test and train\_2\_1 datasets merged distribution.

### 4.1.4 Harvesting Irony dataset

To collect tweets related to irony, as no publicly available dataset was found on a reasonable time, it was decided to harvest automatically annotated tweets directly. To do so, Twitter archiver [75], an extension of Google Sheets, was used. It enables to automatically download tweets based on features such as keywords, hashtags, language, among others. By using this tool a total of 36,274 English tweets that contained hashtags such as #irony, #ironic, #sarcasm or #sarcastic where downloaded from December 12th 2016 to January 25th 2017.

## 4.2. PRE-PROCESSING

After having collected enough data to prevent DL overfitting issue, the next step is to pre-process the datasets, to eliminate non English tweets, possible duplicates, hashtags, user references, URLs, correct spell mistakes, filter undesired classes, among others.

The first step of pre-processing was to delete all duplicates. To do so, all the data was merged into a single dataset file from which all the tweets that contain the same identification number (real duplicate instances) or tweet sharing same text message (possible re-tweets) were deleted. After



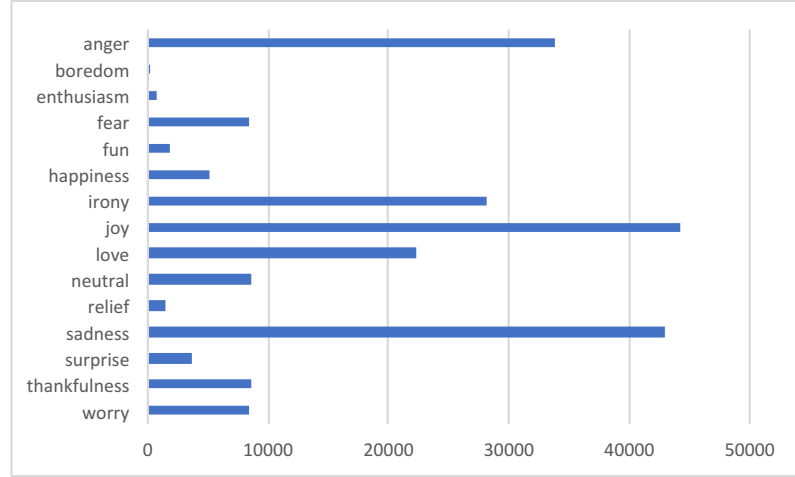
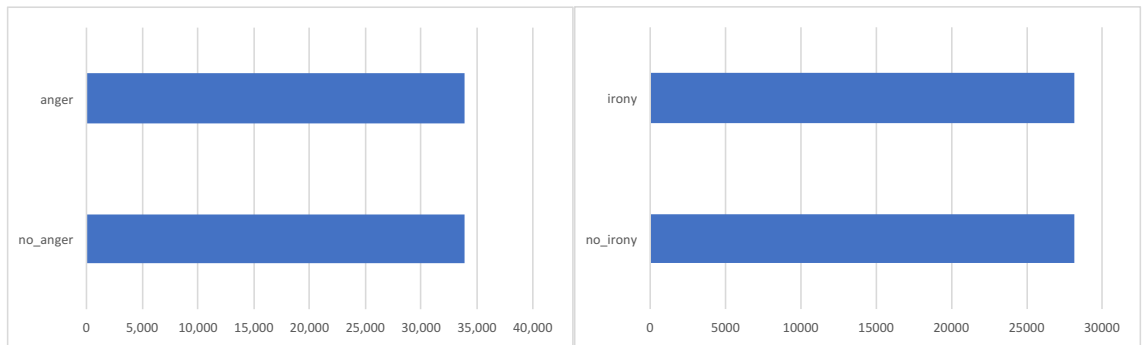


Figure 4.5: Merged multi label dataset distribution.

delete non English tweets and filter ambiguous target labels from the file, the final dataset was composed by a total of 218,619 tweets grouped into 15 categories classified as: anger, boredom, fear, fun, happiness, irony, joy, love, neutral, relief, sadness, surprise, thankfulness and worry. Figure 4.5 shows the distribution of each label target.

Because anger and irony are analyzed independently in this project, to isolate each classifier two datasets were built: binary anger dataset and binary irony dataset. As their name suggest, each dataset is composed by tweets grouped into two classes, the pairs “anger”, “no\_anger” and “irony”, “no\_irony” label targets. To prevent the learning process to be biased into one class or the other, the data was under-sampled to match the number of instances appearances of the anger and irony tweets in the previously merged multi-label dataset to created balanced datasets. Thus, binary anger dataset is composed by a total of 67,748 tweets, 33,874 for “anger” annotated tweets and the same amount for “no\_anger” related tweets (see Figure 4.6a). Regarding to binary irony dataset, it is formed by 28,132 tweets for irony and the same amount for “no\_irony”, making a total 56,264 tweets (see Figure 4.6b).



(a) Balanced binary anger dataset

(b) Balanced binary irony dataset

Figure 4.6: Dataset under-sampling

To prepare the datasets for the posterior learning process, each dataset is divided into train, validation and test subsamples. Normally the division would be split into 70% training, 15% validation and 15% test, however, as in the last prediction phase the test sample is produced by

#### 4. PROPOSED SOLUTION

merging both anger and irony test files, these percentages were changed to 73%, 18% and 9% respectively, to make the merged test file size have nearly the same size as each dataset validation files. Once both dataset have been split and the final prediction file generated by merging both datasets' test files, all the resulting files enter the word2vec process to generate the word embeddings files that will later on serve as input for the CNN learning process.

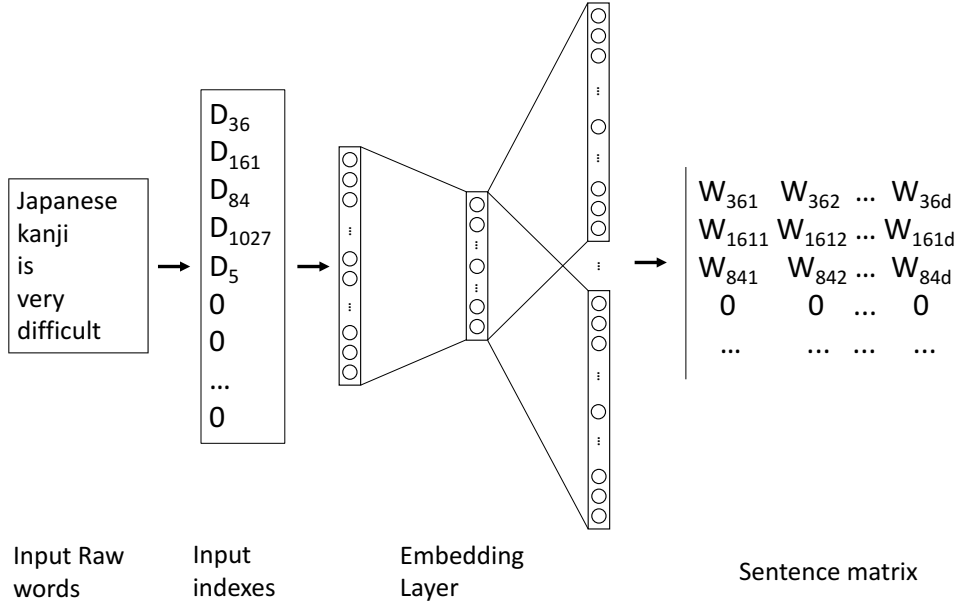


Figure 4.7: Raw word sentence to word vector matrix transformation.

During this process the pre-processing of the tweets that compose the corpus occurs and all the hashtags, user references, URLs are replaced by identification tags such as TAG, MENTION and URL, stopwords are removed from the sentences and optionally all the remaining words are checked and replaced by using Peter Norvig's spell checker [37] with an own made language model generated from calculating the word appearance of 36,173 free English HTML eBooks extracted by Kiwix harvester (2014) [46] Project Gutenberg [21], most used frequency words list obtained from TV programs and contemporary fiction books from Wiktionary [80], film series from Opensubtitles extracted by Hermit Dave [15] and British National Corpus (BNC) [43]. Since the learning process requires to introduce a sequence of words of a fixed length, we decided the value based on the length of the phrase length of our corpus, and thus, calculated the maximum sentence length of both anger (29) and irony (28) datasets and select the maximum value (29) as the fixed sequence length for the model generation. All tweets sentences composing the corpus are transformed sequences of 29 indexes by using a dictionary  $D$  that contains the mapping to indexes of millions of words. Then, by playing a embedding layer, each of those indexes are converted into space vectors, which are initialized by using the Word2Vec algorithm [52]. The combination all the space vectors that compose the original tweet sentence creates an output matrix  $M \in \mathbb{R}^{29 \times d}$ , where  $d$  represents the length of the word embeddings (see figure 4.7). As not all the input sentences contain 29 words, each matrix is padded with 0s until reaching the fixed sentence length. Finally, the list of generated matrices are stored for their later use on the learning and prediction processes.

### 4.3. LEARNING PROCESS

The learning solution proposed consist on a hybrid approach that combines the prediction output of two deep neural network classifiers. To design the architecture of each classifier, we followed the work of Kim [44], which uses CNN for sentence classification. The input of this architecture is an sequence of words, more precisely, the list of word embedding matrices generated on the previous word2vec process. Our model is fed with each matrix and performs convolution operations with multiple filters to learn from multiple features as stated in [84]. We have experimented using 200 filters of 3 sizes (3, 4 and 5) with a ReLU activation function. The functionality of these filters can be compared with how n-grams based classification work [13]. Our model relies on what on n-grams would be considered as 3-grams, 4-grams and 5-grams. The n-grams are extracted from input matrix, in which each row represents a word from the tweet. Each filter combines a groups of 3, 4 or 5 rows obtaining all the possible n-grams from the sentence, generating as a result, a feature map. This map serve as the input of the next max-pooling layer. Its objective is to reduce the profile and bandwidth of the input matrix for computational purposes. Although multiple pooling strategies exist [10], the experiments performed in [84] shows that max-pooling strategy outperforms the rest and thus, selected this strategy to develop our model. It extracts only the feature with the highest value from the initial feature map. When all the features maps from each filter have been processed, the extracted features are then concatenated into a single feature vector to which a dropout layer of rate 0.5 is applied as a measure to prevent the model from over-fitting [68]. The model ends with a final softmax layer that calculates the probability distribution over the output vector, representing the classification into the target labels. For training purpose, a categorical cross-entropy loss function has been used with Adam optimizer [45]. The figure 4.8 illustrates designed architecture using 2 filters instead of 200 for explanatory purposes.

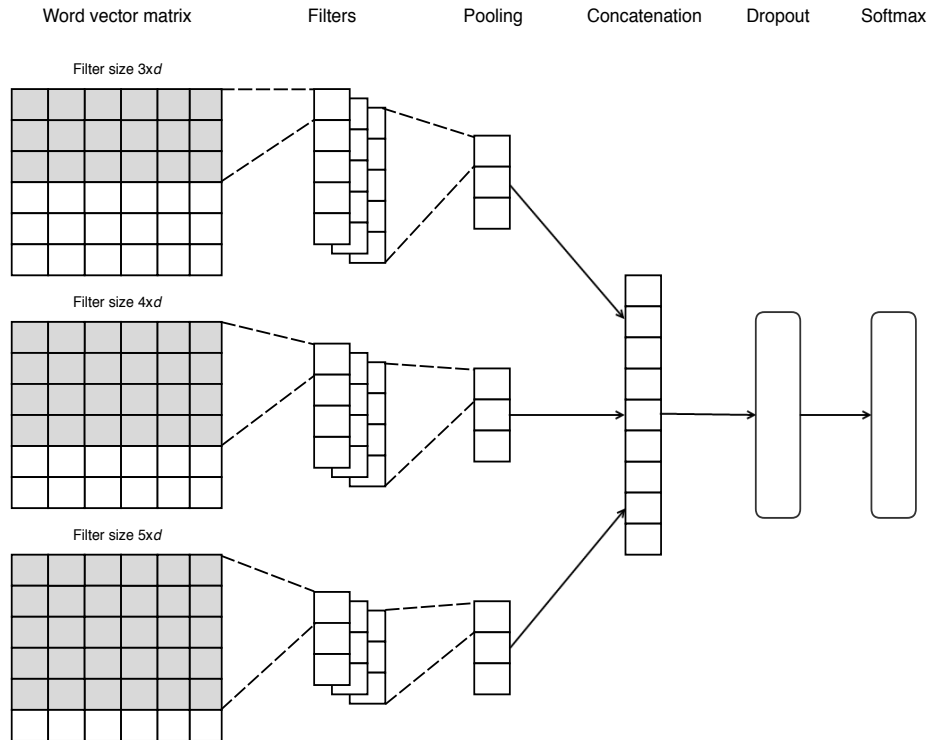


Figure 4.8: Designed architecture.

#### 4.4. PREDICTION

Once both classifiers have been trained and validated with the corresponding word embeddings matrices files two files are generated per classifier: the model, which saves the architecture of the classifier, and the weights in which the classifier has obtained best result during the learning process. Having as a input file the combination of each classifier test sample, theses four files are used to load the anger and irony classifiers' parameters to perform the prediction of new data. Each classifier generates a binary class output prediction of a given tweet that need to be combined. Although the usage Ensemble Learning based on divide and conquer [59] approach was studied to merge classifiers, as each classifier works with its own set target labels independently this idea was discarded. Thus, the solution proposed, following the definition of repressed anger personality first presented in section 3.3, consists on merging the output of the classifiers generating four target labels according to the matrix presented in figure 4.9.

	Anger	No Anger
No Irony	Explicit Anger	Normal
Irony	Repressed Anger	Irony (Check output)

Figure 4.9: Classification prediction output's merge matrix.

## 5. RESULTS

The aim of this chapter is to explain the procedure followed to evaluate the system throughout the different experiments conducted, concluding with the presentation of the results of each test.

### 5.1. MANUAL ANNOTATION

Since the target labels that repressed anger predictor outputs does not match with the classes of either anger and irony binary datasets, a manual annotation of the merged test data must be conducted in order to be able to evaluate the performance of the proposed model. From the 11,074 tweets dedicated for the prediction phase, 1,000 were selected randomly to be part of the manual annotation phase. As the reliability of a single human classification is proven to be low [30] a HIT was conducted to prevent the annotation to be biased.

The HIT was conducted by means of online surveys that were automatically generated as forms by using Google Apps Script. To get a better sense of how difficult the task of repressed anger identification is, the contents of the tweets were presented without anger and irony related hashtags. A total of five non English native collaborators performed the annotation task. The comments received by judges reflect the uncertainty to determine which category a tweet belonged to, as sometimes either context of the tweet was missing or the topic was unknown. We considered valid all the classification which, at least, more that half of the judged agreed. From the 1,000 annotated tweets 824 fulfilled this condition as the remaining 176 was considered ambiguous and thus, discarded from the dataset. The figure 5.1 illustrates the distribution of the manually classified dataset that was used to evaluated the performance of the system.

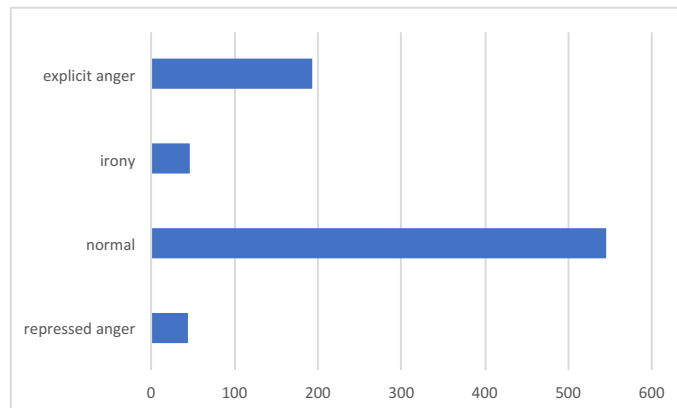


Figure 5.1: Manual annotated dataset distribution.

## 5.2. EXPERIMENTS

The project baseline parts from a naive classifier that determines every given instance as the the element with the maximum number of appearances in the dataset, in this case, the *normal* label. From this solution, the designed model is implemented and compared with the baseline to measure how better the proposed solution is. Finally, variations in the proposed procedure are made to try to improve the results.

Because the model designed depends on the word sequence matrices to generate the features maps, from which the model learns, and motivated by the fact that the written style contains features used on oral speech, usually containing spelling mistakes that affect on how the word sequence matrices are generated, the purpose of the modifications done in the procedure aim to improve the data pre-processing and thus, indirectly improve the performance of the model. The experiments conducted in this experiments are the following:

### 5.2.1 Naive classifier

As explained before, this is the baseline the project bases on to compare the improvement achieved against the proposed solution. It consist of a dummy classifier that assign to each given tweet the *normal* target label.

The results provided make used of the confusion matrix and performance metrics first introduce in the section 3.4.2.

	irony	normal	repressed anger	explicit anger
irony	0.0	1.0	0.0	0.0
normal	0.0	1.0	0.0	0.0
repressed anger	0.0	1.0	0.0	0.0
explicit anger	0.0	1.0	0.0	0.0

Table 5.1: Naive classifier: normalized confusion matrix

### 5.2.2 Google News word2vec pre-trained model

This is original proposed solution, first introduced in chapter 4. It uses the publicly available Google News pre-trained model [31] to generate the word sequence matrices in the pre-processing phase.

	anger	no_anger
anger	0.77	0.23
no_anger	0.2	0.8

Table 5.2: Binary anger classifier (Google News): normalized confusion matrix

	irony	no_irony
irony	0.83	0.17
no_irony	0.14	0.86

Table 5.3: Binary irony classifier (Google News): normalized confusion matrix

	irony	normal	repressed anger	explicit anger
irony	0.47	0.3	0.13	0.11
normal	0.14	0.56	0.1	0.2
repressed anger	0.23	0.2	0.43	0.14
explicit anger	0.09	0.24	0.25	0.42

Table 5.4: Google News: normalized confusion matrix

### 5.2.3 Frédéric Goding word2vec pre-trained model

This experiments consist on the same idea as original solution. However, to generate the word sequence matrices, instead of using the Google-News-Vector(300) pre-trained model, which has been created by using the words from the Google News articles, the Frédéric Goding 400 feature pre-trained model [29] that was generated directly from tweets was used. As tweets are composed by words and a written style that differs from news, using a pre-trained model developed from the content generated from Twitter users could increase the chances of tweet's word appearance in the pre-trained model dictionary and thus be able to convert the word into a vector space instead of initialize the unknown words with Zero padding vectors.

	anger	no_anger
anger	0.83	0.17
no_anger	0.24	0.76

Table 5.5: Binary anger classifier (Frédéric Goding): normalized confusion matrix

	irony	no_irony
irony	0.86	0.14
no_irony	0.14	0.86

Table 5.6: Binary irony classifier (Frédéric Goding): normalized confusion matrix

### 5.2.4 Google News word2vec pre-trained model plus spell checker

This variation consist on adding a spell checker to those words that the Google-New-Vector(300) does not know. The usage of a spell checker would increase the chances of recognizing more words in the pre-trained model's dictionary and thus, initialize its space vector with Word2vec algorithm.

## 5. RESULTS

	irony	normal	repressed anger	explicit anger
irony	0.45	0.3	0.21	0.04
normal	0.13	0.65	0.07	0.14
repressed anger	0.34	0.23	0.25	0.18
explicit anger	0.1	0.28	0.2	0.41

Table 5.7: Frédéric Goding: normalized confusion matrix

	anger	no_anger
anger	0.76	0.24
no_anger	0.19	0.81

Table 5.8: Binary anger classifier (Google News + spell checker): normalized confusion matrix

	irony	no_irony
irony	0.83	0.17
no_irony	0.12	0.88

Table 5.9: Binary irony classifier (Google News + spell checker): normalized confusion matrix

	irony	normal	repressed anger	explicit anger
irony	0.47	0.3	0.13	0.11
normal	0.16	0.59	0.08	0.17
repressed anger	0.3	0.18	0.43	0.09
explicit anger	0.08	0.25	0.27	0.4

Table 5.10: Google News + spell checker: normalized confusion matrix



## **6. CONCLUSION AND FUTURE WORK**

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## **7. SELF-ASSESSMENT**

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## Acronyms

<b>APA</b>	American Psychological Association.	10
<b>API</b>	Application Program Interface.	22
<b>BNC</b>	British National Corpus.	24
<b>CNN</b>	Convolutional Neural Networks.	13, 24, 25
<b>CW</b>	Content Word.	12
<b>DL</b>	Deep Learning.	11–13, 19, 21, 22
<b>DNN</b>	Deep Neural Networks.	13
<b>DT</b>	Decision Tree.	12, 15
<b>FN</b>	Flase Positive.	15
<b>FP</b>	False Positive.	15
<b>HFW</b>	High Frequency Word.	12
<b>HIT</b>	Human Intelligence Task.	11, 21, 27
<b>HTML</b>	Hypertext Markup Language.	24
<b>KNN</b>	K-Nearest Neighbors.	12
<b>LDA</b>	Latent Dirichlet Allocation.	11
<b>LSA</b>	Latent Semantic Analysis.	11
<b>LSTM</b>	Long Short Term Memory.	13
<b>ML</b>	Machine Learning.	7, 10, 19
<b>NB</b>	Naive Bayes.	8, 11, 12
<b>NLP</b>	Natural Language Processing.	5, 6
<b>NN</b>	Neural Network.	11, 15, 19
<b>OCC</b>	Ortony Clore and Collins.	9, 10

. *Acronyms*

**OCR** Optical Character Recognition. 13

**OM** Opinion Mining. 5

**PMI** Point-wise Mutual Information. 11

**POS** Part of Speech. 12

**SA** Sentiment Analysis. 5–7, 9, 10

**SVM** Support Vector Machine. 9, 11–13, 15, 19

**TN** True Negative. 15

**TP** True Positive. 15

**URL** Uniform Resource Locator. 8, 22, 24

**WN** Word Net. 11