FLE: A Fuzzy Logic Algorithm for Classification of Emotions in Literary Corpora

Luis-Gil Moreno-Jiménez[1][a], Juan-Manuel Torres-Moreno[1,2][b], Hanifa Boucheneb[2][c] and Roseli S. Wedemann[3][d]

[1]*Laboratoire Informatique d'Avignon, Université d'Avignon, 339 Chemin des Meinajaries, 84911 Avignon, Cédex 9, France*

[2]*Département de Génie Informatique et Génie Logiciel, Polytechnique Montréal, 2500, Chemin de Polytechnique Montréal, Québec, Canada*

[3]*Universidade do Estado do Rio de Janeiro, Rua São Francisco Xavier 524, 20550-900, Rio de Janeiro, RJ, Brazil*

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Abstract: This paper presents an algorithm based on fuzzy logic, devised to identify emotions in corpora of literary texts, called Fuzzy Logic Emotions (FLE) classifier. This algorithm evaluates a sentence to define the class(es) of emotions to which it belongs. For this purpose, it considers three types of linguistic variables (verb, noun and adjective) with associated linguistic values used to qualify the emotion they express. A numerical value is computed for each of these terms within a sentence, based on its frequency and the inverse document frequency (TF-IDF). We have tested our FLE classifier with an evaluation protocol, using a literary corpus in Spanish specially structured for working with the automatic detection of emotions in text. We present encouraging performance results favoring our FLE classifier, when compared to other known algorithms established in the literature used for the detection of emotions in text.

1 INTRODUCTION

Natural Language Processing (NLP) is a very active area of interdisciplinary work, involving subjects such as computer science, statistical physics, cognitive neuroscience, linguistics and psychology (see (Clark et al., 2018; Ke and Xiaojun, 2018; Torres-Moreno, 2012; Wedemann and Plastino, 2016; Siddiqui et al., 2018) and references therein). In particular, there has been much effort in the NLP research community in recent years, to develop automatic procedures to analyse emotions or sentiment in text (Pang and Lee, 2008; Cambria, 2016; Iria et al., 2011). The task of analysing sentiment and emotions in literary texts is even more difficult, because the complexity of this genre of text presents ambiguous characteristics, which often make their understanding difficult, even for humans. We have thus concentrated our efforts on approaching this problem with fuzzy logic, as this technique tries to find good solutions for problems through the analysis of subjective information, simulating human analysis (Matiko et al., 2014).

Fuzzy logic was introduced in (Zadeh, 1965) to solve problems with imprecise information. It allows the specification and processing of imprecise information, in order to derive useful information. An example of a phrase with imprecise information is *"The temperature is high"*, as it does not provide the precise temperature value. In this example, fuzzy logic represents the imprecise information by a fuzzy set *High* and a real valued membership function μ_{High}, that associates with each numerical temperature value $t \in \Re$, a membership value $\mu_{High}(t) \in [0,1]$. The membership value $\mu_{High}(t) = 0$ means that t does not belong to the fuzzy set *High*. Conversely, membership value 1 means that t belongs to the fuzzy set *High*. A membership value between 0 and 1 means that t partially belongs to the fuzzy set *High*. In this context, the variable *temperature* is called a linguistic variable and t represents its numerical value. The fuzzy set *High* is called a linguistic value of the linguistic variable *temperature*. It represents a range with imprecise boundaries of the numerical temperature values.

[a] https://orcid.org/0000-0001-7753-7349
[b] https://orcid.org/0000-0002-4392-1825
[c] https://orcid.org/0000-0001-9158-6374
[d] https://orcid.org/0000-0001-7532-3881

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Usually, each linguistic variable can assume a linguistic value, within a collection of fuzzy sets (a set of possible linguistic values). For example, the fuzzy sets *High*, *Very_High*, *Normal*, *Low* and *Very_Low* can be used to define the linguistic values of the linguistic variable *temperature*. Each of these fuzzy sets is described by a membership function, defined over the domain of the numerical temperature t.

A fuzzy logic thus consists of a set of linguistic variables, their linguistic values (the fuzzy sets) and a set of fuzzy rules. A fuzzy set G is described by a membership function $\mu_G : x \longrightarrow [0,1]$, defined over the domain of the numerical valued variable x associated with the linguistic value G. Among the commonly used membership functions, we can cite the triangular function, the trapezoidal function, and the Gaussian function. A fuzzy rule is of the form

```
IF <condition> THEN <conclusion>,
```

where condition and conclusion are combinations of the classical logic connectors, with basic terms of the form

<linguistic variable> is G.

The condition can involve partially satisfying membership to sets for the given input data and, consequently, the conclusion may also involve partial membership. The degree of matching between the rule and the input data (its truth degree) depends on the values of the membership functions for the input data, for the fuzzy sets involved in the condition of the rule. For example,

```
IF temperature is High OR
   temperature is Very_High
THEN
   Fan_Speed is Fast
```

is a fuzzy rule. For input data $t = d$, the condition that must be evaluated regarding the value of d is $max(\mu_{High}(d), \mu_{Very\_High}(d)) > \theta$, where θ is a given threshold. When this condition is true for input d, the conclusion is `Fan_Speed is Fast`.

Fuzzy rules are thus used to infer an output based on the input data. In general, this process consists of executing the following three steps.

1. **Fuzzy Membership:** Calculate the degree of membership (the membership function) for each of the fuzzy sets.
2. **Inference:** Execute the rules in the rulebase to obtain the fuzzy conclusion.
3. **Defuzzification:** Convert the fuzzy conclusion obtained in Step 2 into a crisp one.

Fuzzy logic has been successfully used in many fields such as control systems, image processing, optimization, robotics, and natural language processing. In this work, we introduce a fuzzy logic model for detecting the emotions expressed by specialized linguistic data sets (corpora). The model has been validated on a corpus consisting of literary texts in Spanish.

In Section 2, we review some basic literature regarding algorithms developed for the classification of emotions, related to this work. We describe the corpora employed to train and test our classifier in Section 3. Section 4 describes our fuzzy logic classifier. In Section 5, we present our experimental protocol. Results and evaluations are shown in Section 6 and finally, Section 7 has our concluding remarks.

2 RELATED WORK

Fuzzy logic techniques are commonly used to analyse comments regarding products or services offered on the internet. For example in (Tashtoush and Al Aziz Orabi, 2019), a fuzzy logic model is proposed for predicting the following emotions in tweets: Joy, Sadness, Anger, Disgust, Trust, Fear, Surprise, and Anticipation, with 48.96% accuracy. In (Indhuja and Reghu, 2014), a method is proposed to classify product reviews into the categories: negative, neutral and positive. In (Dragoni et al., 2015), the authors use fuzzy logic for modeling concept polarities, and test their method by classifying product reviews in an Amazon dataset according to their polarities.

Several works approach the problem of treating emotions in cognitive agents with fuzzy logic. In (Howells and Ertugan, 2017), social media comments in tweets are treated with fuzzy logic and classified into: very negative, negative, neutral, positive and very positive, by analysing emojis, hashtags, and textual meaning. In (Arguedas et al., 2018), the authors propose a fuzzy classifier to detect the emotional states of students, by analysing their discourses in an online learning environment. In (Matiko et al., 2014), the authors present an algorithm for classifying positive and negative emotions from electroencephalograms.

Finally, (Vashishtha and Susan, 2020) propose a supervised fuzzy rule-based model to classify video reviews on social media, by analysing linguistic features and also accent and acoustic, into negative and positive categories, with 82.5% of accuracy.

3 CORPORA EMPLOYED

We have used two specially structured corpora of literary sentences in Spanish to test our model. The

CitasIn corpus was used in the learning phase and the **LiSSS** corpus for testing.

3.1 Learning Corpus

The **CitasIn**[1] corpus (Torres-Moreno and Moreno-Jiménez, 2020) composed by sentences recovered from the website https://citas.in was used in the learning phase. It consists of a large number of documents belonging to different categories (friendship, lovers, beauty, success, happiness, laughter, enmity, deception, anger, fear, etc.) These documents were manually clustered into the five following classes:

1. Anger (**A**),
2. Fear (**F**),
3. Happiness (**H**),
4. Love (**L**) and
5. Sadness or Pain (**S**).

Table 1 shows the number of sentences and words for each class, and the average value of the number of words per sentence in each class.

Table 1: **CitasIn** corpus, sentences clustered in 5 emotions.

Classes tag	# Sentences (S)	# Words (W)	# W / S
A	15 043	280 784	18.7
F	14 773	275 059	18.6
H	13 647	256 697	18.8
S	14 589	275 931	18.9
L	14 738	264 339	29.2
Total	72 790	1 352 810	18.6

3.2 Test Corpus

We employed the corpus of Emotions in Literary Sentences in Spanish (**LiSSS**)[2] (Torres-Moreno and Moreno-Jiménez, 2020) for testing the FLE classifier. The **LiSSS** corpus was especially created to test and validate algorithms for automatic emotion classification and analysis of literary texts. It consists of literary sentences and paragraphs from approximately 200 Spanish-speaking authors, and also sentences from non Spanish-speaking authors (using always official or good quality translations to Spanish)

The sentences of the **LiSSS** corpus were manually classified into the same five categories as the **CitasIn** corpus, $\{$**A, F, H, L, S**$\}$. Each sentence may be classified into more than one of the five categories. All sentences belonging to **LiSSS** were excluded from **CitasIn**, to avoid over-fitting and bias during the learning phase in our experiments. The main properties of **LiSSS** are depicted in Tables 2 and 3.

Table 2: LiSSS corpus of literary sentences.

	Sentences	Paragraphs	Words
LiSSS	500	49	9 392

Table 3 represents the distribution of sentences among the five classes of emotions, in a matrix layout, calculated by dividing the number of sentences tagged for each class by the number of annotators. For example it shows, in position [A,A] (first line, first column), that there are 74.1 sentences that have been classified exclusively in the *Anger* category. The other positions in the first row show that 12.1 sentences were tagged with **A** and **L**, 7.9 with **A** and **F**, 2.3 with **A** and **H**, and 9 with **A** and **S**. In this corpus, approximately 18% of the sentences were classified as multi-emotional sentences. For each class we obtain an overlapping degree defined in the following way. Let *mono* represent the average number of sentences classified in a unique class, and *multi* represent the average number of sentences classified in multiple classes. The proportion of sentences that were classified in a certain class and also in other classes, which we call the overlap, Ov, can be calculated as $Ov = multi/(mono + multi)$. For example, in the case of class A, we have $Ov = 31.3/(74.1 + 31.3) = 29.7\%$, so that 29.7% of the sentences that were classified in **A** were also classified in other classes. The rest of the table can be read in a similar manner. The two sets with greatest overlap are *Love* and *Sadness*/*Pain*, corresponding to the emotions that are most correlated in the sentences of **LiSSS**.

Table 3: Distribution of emotions in **LiSSS**, with correlations (Cl = classes, *Ov* = overlap).

C	**A**	**L**	**F**	**H**	**S**	***Ov*%**
A	74.1	12.1	7.9	2.3	9.0	29.7
L	12.1	89.5	5.7	10.8	19.9	35.1
F	7.9	5.7	103.2	0.6	17.2	23.3
H	2.3	10.8	0.6	92.4	18.7	26.0
S	9.0	19.9	17.2	18.7	115.3	36.0

Due to the subjective nature of the emotional perception of literary documents, the overlap of classification among different classes is comprehensible. The algorithm we propose here, based on fuzzy logic, could enable multi-classification by establishing a criterion based on a measure of *distance*, between mem-

[1] A version of *CitasIn* corpus with snippet sentences is available in website juanmanuel.torres.free.fr/corpus/lisss/CitasIn.zip. The reader should not have problem reconstituting the corpus *CitasIn* using these snippets.

[2] LiSSS V0.500 is downloadable from the website: http://juanmanuel.torres.free.fr/corpus/lisss/

bership values of a sentence and the centroid of the different classes.

4 FLE Classifier

In this section, we describe our Fuzzy Logic Emotions (FLE) classification algorithm, based on fuzzy logic. The algorithm consists of some basic procedures: determination of the linguistic variables and their values, definition of the membership function and of the fuzzy rules, and defuzzification. Figure 2 shows a graph representation of the FLE scheme.

4.1 Linguistic Variables

Our algorithm evaluates a sentence, *Sent*, to define the class(es) of emotions to which it belongs. For this purpose, we consider the set of linguistic variables to be the set consisting of action verbs, nouns and adjectives in *Sent*. We define n as the number of action verbs, adjectives and nouns in *Sent*, and thus n is the number of linguistic variables in *Sent*. We have used the *FreeLing* tool (Padró and Stanilovsky, 2012) to identify the linguistic variables in *Sent*, as *FreeLing* returns the grammatical information that characterizes a word, such as the Part of Speech (POS) label, gender and other information.

As an example, in the sentence: "*Contempt must be the most mysterious of our feelings*", there are three linguistic variables:

- contempt, a Noun,
- mysterious, an Adjective, and
- feelings, a Noun.

4.2 Linguistic Values

The next step is to associate a linguistic value (LV) to each linguistic variable of *Sent*. The LV is used to simulate the process that a human follows to classify an object according to its properties. For example, if it is required to know if a machine needs to be cooled, a human operator can consider *temperature* as a linguistic variable and the possible LVs can be those in the set {*very hot, hot, warm, cold, very cold*}. So knowing which LV applies to the observed machine, the operator may be able to take a decision. Each linguistic variable in *Sent* is associated to five LVs, corresponding to the emotions which it expresses. Each of the five LVs of a linguistic variable is related to a numerical value, equal to its term frequency - inverse document frequency (TF-IDF) (Jones, 1972). TF-IDF is a measure that indicates the importance of a term with respect to an analyzed set of documents. This well known measure is very useful and it has been used for a long time, in tasks of extraction or recovery of information (information retrieval) and text mining, among others. To calculate the TF-IDF scores, we have used the **CitasIn** corpus divided into five subcorpora, one per class, as mentioned in Section 3.1. Each document has been pre-processed with *FreeLing* to extract only the lemmas of action verbs, adjectives and nouns. We have thus generated a reduced version of **CitasIn** with 5 classes of the resulting pre-processed documents, one for each of the emotions. We then calculate the TF-IDF values for each term with respect to the documents in each class, using a tool developed in PERL 5.0. So, for example, it is expected that given the word *romance*, its TF-IDF score related to the class **Love** will be higher than with respect to the other classes. To smooth out the high increase of the TF-IDF score for a negative adverb, the TF-IDF, in these cases, is substituted by its square root.

To represent the numerical value associated to each linguistic variable in *Sent*, we associate a matrix $\boldsymbol{V}$ with *Sent*, where each element $V_{i,j}$ is the TF-IDF of the j-th linguistic variable, for the i-th class.

4.3 Membership Function

The third step consists in selecting the membership function, that will attribute a *membership value*, $MD_{i,j}$, to each $V_{i,j}$. There are various kinds of membership functions, and each of them returns a value in the interval $[0,1]$, where 1 means the word belongs to the class, and 0 means it does not. We have chosen a triangular function given by Eq. (1) (see Fig. 1). This choice has been motivated by the fact that the relevance of a word with respect to the documents in a class should increase, in proportion to its TF-IDF score, normalized in $[0,1]$. Thus, for each linguistic variable in *Sent*, and each class

$$MD_{i,j} = \mu(V_{i,j}) = \begin{cases} \frac{V_{i,j}-a_i}{b_i-a_i}, & a_i \leq V_{i,j} \leq b_i \\ 0, & \text{elsewhere}, \end{cases} \tag{1}$$

where $a_i = \min\{V_{i,k} : \forall\, k \in \text{class } i\}$ and $b_i = \max\{V_{i,k} : \forall\, k \in \text{class } i\}$. Note that to obtain a_i and b_i, one considers all the linguistic variables of **CitasIn** in class i (not only the n linguistic variables in *Sent*), this gives us a more realistic measure of the relevance of each term in a class.

4.4 Fuzzy Rule

The fuzzy rules allow the determination of the true membership value, according to a condition which

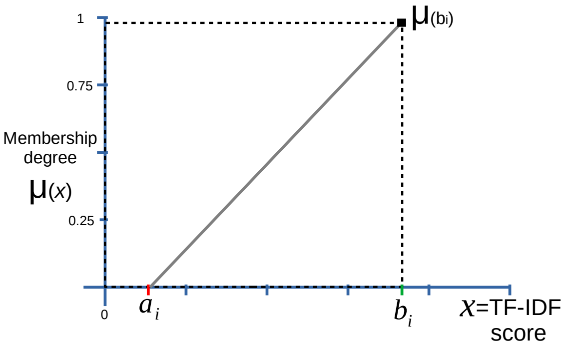

Figure 1: Triangular membership representation.

depends on the $MD_{i,j}$ previously calculated. We introduce the following variables

$$M_i = \frac{1}{n}\sum_{j=1}^{n} MD_{i,j}\,, \tag{2}$$

$$MT = \frac{1}{5}\sum_{i=1}^{5} M_i\,. \tag{3}$$

With these, we have defined one rule

$\texttt{IF}\ M_i \geq MT\ \texttt{THEN}\ M_i' = M_i$

$\texttt{ELSE}\ M_i' = 0\,.$

This rule is applied to all the classes, so that we obtain an M_i' for each class.

According to (2) and (3), M_i is the average membership value for *Sent* for each class, and MT is the average of M_i over all classes. This rule thus compares the membership of *Sent* for each class with the average for all classes, to detect and ignore scores which are very low and should not be considered.

4.5 Defuzzification

With the M_i' obtained with the fuzzy rule, we proceed to the defuzzification process by first calculating the centroid over all classes, according to

$$centroid = \frac{\sum_{i=1}^{5}(M_i' \times SumV_i)}{\sum_{i=1}^{5} M_i'}\,, \tag{4}$$

where

$$SumV_i = \frac{1}{n}\sum_{j=1}^{n} V_{i,j}\,. \tag{5}$$

We again use the triangular membership function, $\eta(x, e_i)$, with parameters $c = 0$ and $e_i = SumV_i$,

$$\eta(x, e_i) = \frac{x - c}{e_i - c}\,, \quad c \leq x \leq e_i\,, \tag{6}$$

$\eta(x, e_i) = 0$, if $x > e_i$ or $x < c$, and calculate the membership value of the centroid, $MC_i = \eta(centroid, e_i)$, with respect to to each class i. The class for which MC_i is highest corresponds to the most predominant emotion expressed by *Sent*.

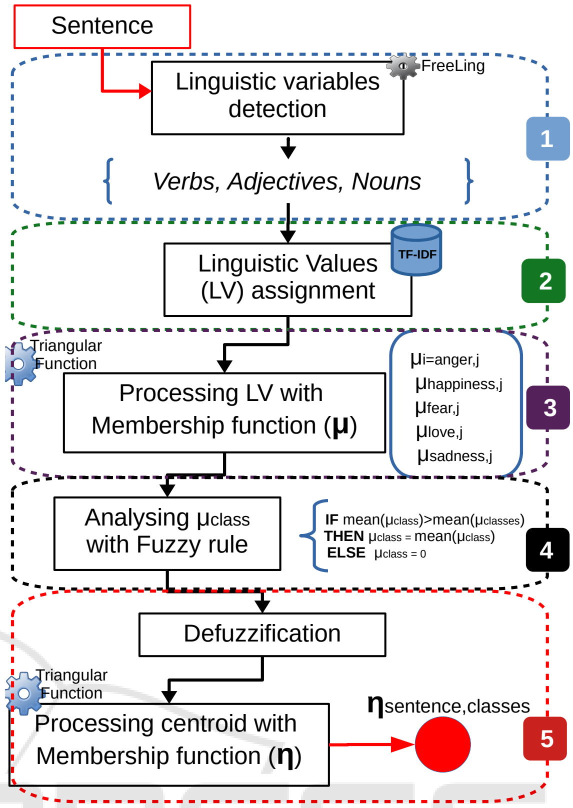

Figure 2: Overall scheme of FLE model.

Defuzzification is important because in (5), we consider only the vocabulary present in *Sent* and the centroid reveals the proximity between *Sent* and each class. This should allow us to consider the classification of *Sent* in more than one emotion with FLE, with the establishment of adequate criteria, although we have not treated this situation, in the present work.

4.6 An FLE Example

In order to illustrate how the FLE model works, we present an example of the computations, considering the sentence, *Sent*, "*Contempt is the most mysterious of our feelings.*"

Linguistic Variables. There are three linguistic variables: *contempt* = N (noun), *mysterious* = A (adjective) and *feeling*= N (noun)

Linguistic Values. Table 4 shows the $V_{i,j}$ values (TF-IDF scores), for each linguistic variable, per class. All TF-IDF scores were calculated over the **CitasIn** corpus.

Membership Function. For each score in Table 4, a

$\mu(V_{i,j})$ value is computed using the membership function, Eq. (1). For example, the variable *contempt*, with TF-IDF$= V_{4,1} = 250.02$, for class $4 \equiv$ **Love**, is processed as follows.

1. We obtain the minimum TF-IDF score considering all the text in the **Love** class in **CitasIn**, $a_4 = \min\{V_{4,k} : \forall\, k \in class\ 4\} = 0.2097$, which corresponds to a word that is not in *Sent*.
2. In the same way, $b_4 = \max\{V_{4,k} : \forall\, k \in class\ 4\} = 5798.91$, which also corresponds to a word not in *Sent*.
3. Using these two reference values, we use Eq. (1) to obtain $MD_{4,1} = \mu(V_{4,1}) = (V_{4,1} - a_4)/(b_4 - a_4) = 0.043$.

The same procedure is executed for all scores of Table 4, to obtain the $\mu(V_{i,j})$ values shown in Table 5.

Table 4: TF-IDF scores, $V_{i,j}$, for each variable and class.

var / **class**	*contempt*	*mysterious*	*feelings*
Anger A	206.28	29.48	513.31
Fear F	134.15	113.78	418.05
Happiness H	198.07	47.08	603.09
Love L	250.02	127.45	941.91
Sadness S	141.00	59.64	548.86

Table 5: Membership values, $MD_{i,j} = \mu(V_{i,j})$, for each variable and class.

var / **class**	*contempt*	*mysterious*	*feelings*
Anger A	0.060	0.008	0.149
Fear F	0.045	0.038	0.142
Happiness H	0.060	0.014	0.184
Love L	0.043	0.022	0.162
Sadness S	0.049	0.021	0.193

Fuzzy Rules. The $MD_{i,j} = \mu(V_{i,j})$ are used to calculate the M_i with Eq. (2), and MT with Eq. (3). For **Anger**, the average of the membership values, $MD_{1,j}$ in Table 5, is $M_1 = 0.072$. In the same way, one can obtain the other M_i. The value $MT = 0.079$ is the average of the M_i , *i. e.* the average of the 15 membership values in Table 5. These M_i and MT are then used to obtain the M'_i, with the fuzzy rule presented in Section 4.4, as

A: $(0.072 \geq 0.079) == False$ THEN $M'_A = 0$,
F: $(0.075 \geq 0.079) == False$ THEN $M'_F = 0$,
H: $(0.086 \geq 0.079) == True$ THEN $M'_H = 0.086$,
L: $(0.076 \geq 0.079) == False$ THEN $M'_L = 0$,
S: $(0.088 \geq 0.079) == True$ THEN $M'_S = 0.088$.

Figure 3: Position of the *centroid* and membership function η, Eq. (6), for the classes for which it is different than zero.

Defuzzification. The last procedure involves defuzzification by centroid calculation, using the new membership values M'_i obtained from the fuzzy rule step. Equations (4) and (5) are then used to obtain

$$centroid = \frac{0+0+72.94+0+65.20}{0+0+0.086+0+0.087} = 798.49\,.$$

Finally, the other membership function, $MC_i = \eta(centroid, e_i)$, Eq. (6), is used with $x_c = centroid = 798.49$, $c = 0$ and $e_i = SumV_i$ Eq. (5) to obtain:

$$\begin{aligned}
MC_{Anger} &= \eta(x_c, e_i = 749.01) = 0,\\
MC_{Fear} &= \eta(x_c, e_i = 665.99) = 0,\\
MC_{Happiness} &= \eta(x_c, e_i = 848.24) = 0.941,\\
MC_{Love} &= \eta(x_c, e_i = 1319.39) = 0.605, \text{ and}\\
MC_{Sadness} &= \eta(x_c, e_i = 749.52) = 0.
\end{aligned}$$

We observe that the centroid is closest to the **Happiness** class, as it corresponds to the highest value of η. We thus consider that *Sent* predominantly expresses this emotion. These results are illustrated in Fig. 3.

5 EXPERIMENTAL SETUP

In Section 2, we reported other fuzzy logic based approaches focused on the classification of emotions. However, most of these proposed models are for polarity detection or for classification based on the analysis of non-textual characteristics, such as the outputs of sensors or images. Our proposal is different, we deal with the classification of literary text considering psychological and emotional states. It is thus not possible to compare our model objectively with most of these works. Instead, we have compared our FLE classifier against several classical baseline methods, also tested in the evaluation proposed by the authors in (Torres-Moreno and Moreno-Jiménez, 2020). The experiments were performed using the **CitasIn** corpus for training and the **LiSSS** corpus for testing.

FLE Classifiers and Baseline Algorithms

We have conducted tests for comparison with the three following classic machine learning classifiers, used as baseline algorithms: Support Vector Machine (SVM), Naïve Bayes Multinomial Text (NBM) and Naïve Bayes (NB). We experimented with several types of pre-processed data for the FLE classifier, using: the original form of verbs, adjectives and nouns; lemmatized verbs, adjectives and nouns; ultra-stemmed[3] verbs, adjectives and nouns; original form of verbs and adjectives, and lemmatized nouns (**FLE**$_{\text{lemm}}$); and original form of verbs and adjectives, and ultra-stemmed nouns (**FLE**$_{\text{ultra}}$). We present here results of experiments using the two pre-processing methods that provided the best results, **FLE**$_{\text{ultra}}$ and **FLE**$_{\text{lemm}}$. Algorithms SVM and Naïve Bayes (multinomial and classical versions) were implemented using the Weka GUI[4] packages. Our FLE classifier was written in Python 3. The input sentences were all filtered of function words and function verbs pertaining to stop-lists, and were lemmatized or ultra-stemmed using Weka or Python libraries, respectively.

6 RESULTS

Results of experiments using the FLE method, with lemmatized and ultra-stemmed pre-processing, can be observed in Table 6. This table shows observed values of the quantities Precision, Recall and F-score [5]. The best value of each quantity is marked in bold font. It is possible to observe that, in general, **FLE**$_{\text{lemm}}$ gives better results for precision and recall (**F-score = 60.1%**) than **FLE**$_{\text{ultra}}$ (**F-score = 58.15%**), except in the case of recall for the classes *Happiness* and *Fear*.

In Table 7, we show the comparison between our FLE methods and the baseline algorithms. Average values of the F-score for each of the five classes are shown in the last column. The best performance for each class is marked in bold font.

[3]The ultra-stemming algorithm kept at most the 5 first characters of each word decreasing the execution time of the algorithm and preserving the meaning of the words (Torres-Moreno, 2012).

[4]The Weka package may be downloaded from url: https://waikato.github.io/weka-wiki/

[5]F-score is a harmonic combination of Precision (P) and Recall (R); F-score= $2 \times P \cdot R/(P+R)$.

We can see that **FLE**$_{\text{lemm}}$ obtained a better F-score in the *Angry* and *Sadness/Pain* classes, while the NBM algorithm obtained a better F-score for *Fear*, *Happiness* and *Love*. **FLE**$_{\text{lemm}}$ obtained the best average F-score value, and even in the 3 classes where it did not obtain the best score, it obtained scores that were very close to the best. Although **FLE**$_{\text{lemm}}$ outperforms **FLE**$_{\text{ultra}}$, **FLE**$_{\text{ultra}}$ has the advantage of being language independent, because it does not require a lemmatization, pre-processing procedure. As we expect that this initial proposal has perspectives of further improvements, these are relevant and encouraging results.

Table 6: Results obtained FLE$_{\text{lemm}}$ and FLE$_{\text{ultra}}$ in percentages.

	Precision		**Recall**		**F-score**	
	F_{lemm}	F_{ultra}	F_{lemm}	F_{ultra}	F_{lemm}	F_{ultra}
A	44.9	44.6	**73.5**	69.6	55.76	54.41
F	58.7	54.5	68.3	69.2	63.11	61.02
H	**81.0**	**79.0**	71.0	**72.8**	**75.70**	**75.78**
L	71.4	70.5	60.6	55.6	65.57	62.15
S	78.6	76.9	27.2	24.7	4037	37.38
$\bar{x}$	66.9	65.1	60.1	58.3	**60.1**	58.15

Table 7: F-score values in percentage obtained with various algorithms, for each class of emotion.

Model	**A**	**F**	**H**	**L**	**S**	**Mean**
SVM	55.80	54.26	59.00	50.33	55.6	44.99
NB	45.86	60.48	56.41	60.19	16.47	47.88
NBM	53.51	**64.73**	**78.73**	**66.13**	35.42	59.70
FLE$_{\text{ultra}}$	55.43	61.41	76.79	62.07	40.43	58.15
FLE$_{\text{lemm}}$	**56.73**	63.48	76.71	65.56	**43.75**	**60.10**

Comparing our results with those of some similar methods reported in Section 2, it can be noticed that in (Tashtoush and Al Aziz Orabi, 2019), where the categories are: Joy, Sadness, Anger, etc.. the authors achieved a performance of 48.96%, quite lower than the 60.1% F-score obtained by our FLE$_{lemm}$ method, indicating the difficulty involved in this kind of task. Furthermore, we have faced the challenge of dealing with literary text, which presents a more complex vocabulary than that used in tweets or product reviews. We also note that the method proposed in (Arguedas et al., 2018) achieved 82.5% accuracy, however mainly directed towards the task of polarity detection that requires a less complex analysis.

7 CONCLUSIONS

We have proposed FLE, a method for classifying literary texts according to their emotional content. The method is based on fuzzy logic and was tested and validated with literary sentences, taken from specially structured, literary corpora.

Our results show that this protocol is well suited to the task of detection and classification of emotions in literary manuscripts.

Literary works in various forms, such as paragraphs, verses, sentences, or phrases, are difficult to evaluate automatically, because they have a rich expressive diversity and present a high complexity in the employment of language. Moreover, there is the issue of multi-emotional sentences, with possible ambiguity in meaning, that adds to the complexity of the task. However, we have shown that fuzzy logic provides an interesting and efficient approach to the problem of analysing these types of corpora.

In its current version, FLE has been designed to treat only text written in Spanish. However, the protocol is modular and simple to adapt to languages other than Spanish. In particular, it should be possible to adapt our FLE implementation to other romance languages, such as French, Portuguese, Italian, Catalan, among others, with a reasonable amount of effort.

We plan to improve our model through the manipulation of the linguistic values or by combining other membership functions. We also consider the possibility of evaluating our protocol on artificial sentences, generated by Natural Language Generation (NLG) algorithms (Moreno-Jiménez et al., 2020; Ke and Xiaojun, 2018).

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