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Automatic Classification of Literature Pieces by Emotion Detection

A Study on Quevedo's Poetry

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***Abstract*— In this work, we describe an experiment on the categorization of poems based on their emotional content, which is automatically measured. For that purpose, we center on the poetry of Francisco de Quevedo and a well-known sentiment categorization of it. Thereby, we explore how emotions can help in the classification process. The goal was to verify whether the information about emotional content can be used to build classifiers reproducing that categorization.**

Keywords—emotion detection; emotion classification; automation literature classification

I. INTRODUCTION

Besides communicating, language also conveys emotions; we all know how the different literary genres and specially poetry aim at evoking emotional states in the readers. However, not always texts convey the emotions we would expect or even recognize at a first glance. There are many examples in the literature where different authors, writing on the same topic or literary genre can produce texts transmitting very different emotions.

Obviously, the subtle task of literature classification lies with the Philologists, both on topic and emotion classification, but trying to approximate to that research field from a computational point of view is quite challenging, especially when centered on emotion classification.

With that goal, in this work we explore the possibilities of automatically classifying poems according to their emotion content, automatically detected too. For that purpose, we center on the poetry of the Spanish Francisco de Quevedo and a well-known sentiment categorization of it. In that context, we decided to explore along two different paths: on the one hand, we wanted to check if the original categories of the classification could be distinguished in terms of the sentiment reflected by the corresponding poems; on the other hand, we explored different automatic learning techniques looking for the algorithm able to produce better results with our dataset.

The rest of this work is as follows. Firstly, Section II provides an overview emotions and classification of texts. Section III presents the methodology followed in this research study, including a description of the poetry and the emotion classification of Francisco de Quevedo that we have used as reference for the rest of this work. Next, Section IV and V present the results obtained in different scenarios and with different datasets, as well as discussion on them, respectively. Finally, some conclusions are presented in Section VI.

II. EMOTIONS AND CLASSIFICATION OF TEXTS

Numerous techniques and tools have been developed and combined in order to measure, evaluate or identify emotions [26] [1] [13].

Within the text based emotion recognition context, different systems have been developed during the last decades, dealing with human emotions from different points of view. Some of the developed works, center on analyzing the emotional meaning of a text divided into paragraphs and sentences [23]; others, like [25], extract emotions from online news headlines. Also, at present another well-known approach is the web-scale text sentimental analysis. That large corpus-based analysis has been used over the evaluation of blogs [11] [22], songs and president's speeches [11] and commercial web pages as Epinions, which collects users' opinions about different categories of brands or places [28].

Regarding conversation analysis we can find the Chat-See tool, used to evaluate the emotional behavior of a group of students in a task oriented chat [5] or [20] which shapes the gross national happiness of United States by evaluating Facebook profiles updates over a year. Within the social networks, Twitter has been used to measure happiness from different points of view, like in [10], which created a hedonometer that evaluated the happiness during the day over three years. Following the former research study, the hedonometer developed in [10] was used later to measure and study the topics that people use to talk about and which ones make them happier [3], positivity and negativity are usually associated to happiness and unhappiness, respectively, and are directly related to the valence dimension in studies such as the developed in [4]. All the aforementioned works present quite interesting results, mostly based on a positive-negative classification of the emotions gathered in the analyzed texts.

Concerning the classification of literary texts, quite different from headlines or tweets, an interesting research area

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centers on the authorship attribution, like [16], which presents a comparative study of machine learning methods for that purpose, or [21], which uses content analysis for the same purpose. Closer to relating emotions and classification of literary texts, [31] tackles the computational emotion classification of two literary text classification problems: the eroticism classification in Dickinson's poems and the sentimentalism classification in early American novels. For its purpose, [31] compared the performance of two popular algorithms: naïve Bayes and support vector machines (SVMs).

III. Methodology

In this section the methodology for the analysis carried out is presented. Firstly, we describe the four emotions used in this work. Secondly, the method for emotional labeling is explained. Thirdly, we introduce the classification of Quevedo's works used as reference. Finally, we explain the setup for automatically building classifiers aimed to replicate the previous classification.

A. Emotions Gathered

The universal emotional expressions identified in several works (see [12] f.i.) are: happiness, sadness, anger, fear, disgust and surprise. As observed, and in spite of the fact that there is not a commonly agreed classification regarding basic emotions, the one proposed in [12], or a subset of it, is widely used. In that sense, one of the results of [2] is that maybe that the disgust and surprise emotions belong to a different category, being somehow associated to anger and fear, respectively. Then, the remaining four ones could be identified like the basic ones.

That idea is also supported in [32], where four basic emotions are identified: joy, anger, fear and sadness. Authors state that those four basic emotions are directly related to the so named "fundamental challenges" such as danger (leading to fear), separation from positive conditions, including inadequate self-efficiency (leading to sadness), frustration of expectancies and registration of inhibitions (leading to anger) or self-efficiency and social acceptance (producing joy).

Though the possible different emotions to detect is an open issue, in this research study we have centered on identifying joy, anger, fear and sadness, as the poems' emotion footprints; which have been used afterwards for the automatic emotion classification.

B. Procedure for Emotion Identification

The procedure followed in order to identify the former emotions in the texts is based on associating a set of emotion evocative words to each of the four emotions we center on, instead of tagging words (somehow) emotionally.

The approach we have followed is based on cross-linguistic information retrieval: our starting point are the names and adjectives associated to the four basic emotions. Concretely, we started with the following English words:

- "Joy" and "Joyful"
- "Sadness" and "Sad"
- "Anger" and "Angry"
- "Fear" and "Afraid"

Next, we looked up their synonyms in English[1]. The possible translations of the former English words into Spanish were looked up afterwards. As a result, a list of emotion evocative words in Spanish was obtained (one list for each emotion to be gathered).

For the translation process, we looked up all the English emotion words in the bab.la[2] English-Spanish dictionary, checking dozens of suggested translations per word. In this process, we retrieved not only nouns and adjectives, but also some verbs that were used in the translated sentences. Finally, the words obtained were processed in order to *computationally* use them, taking gender and number of variations into account, as well as other Spanish grammatical characteristics.

Once we had the Spanish emotion evocative words, we searched for their occurrences in the Quevedo's poems. Then, for each poem, we obtained an array of four numbers, which correspond to the number of emotion evocative words detected per emotion. Certainly, the significance of the number of retrieved words is associated to the length of the poem: for the same number, the shortest the most significant. For that reason, we have worked with relative values that were obtained by dividing the number of emotion words by the total length of each poem. For visualization purposes, the final numbers obtained were calculated times 100, making use of only one decimal expansion.

It is also worth mention that in this research study, we were only interested in detecting the emotion evocative words "as is", and not in their shifting meaning depending on the context where they are used (f.i. negative adverbs affecting [6]).

C. Francisco de Quevedo and a Classification of his Poetry

Francisco de Quevedo (1580-1645) was one of the greatest writers of the seventeenth century, the Spanish Golden Age of the literature. He wrote both novels and poetry, and his poetic production comes close to around 900 poems. Throughout his life, Quevedo's poems were not officially published, but informally distributed. Later on, in the same seventeenth century, some of his poems were edited in different volumes by J. González de Salas (in 1648) and P. Villegas Aldrete (in 1670).

Since then, and for centuries, Philologists have paid a lot of research efforts to the study of Quevedo's poetry from different points of view. One of those research lines is related to the compilation and edition of Quevedo's poems that, in many cases, are been classified from an emotion perspective. That is the case, for example of the J. M. Blecua's edition of Quevedo's "Selected Poems" [8] (in Spanish) or the C. Johnson's edition of "Selected Poetry of Francisco de Quevedo: A Bilingual Edition" (also translated by the editor) [9].

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[1] Retrieved January 2012, http://bab.la, Synonyms provided by © Princeton University

[2] Retrieved January 2012, http://bab.la

As expected, the number of poems included in each collection, as well as emotion classification of the poems, differs between editors. Then, Johnson's book includes 46 poems under 8 poem categories, namely: Metaphysical, from *Christian Heraclitus*, Moral, Lyric Poems on Different Subjects, Elegies and Epitaphs, Love, Songs to Lisi and Satiric and Burlesque poems [9]. In the case of Blecua's book, the number of poems collected is 185, organized under 4 different poem categories: Love, Songs to Lisi, Satiric and, Philosophical, Moral and Religious poems. In spite of the total number of poems collected, it is clear that some mapping exists between both classifications. Concretely, three categories coincide: love, Songs to Lisi and Satiric poems. The five remaining categories that are found in [8] are, somehow, included in a single one in [8]: Philosophical, Moral and Religious poems.

So, being both classifications quite similar, we decided to analyze the poems collected in Blecua's edition, mainly because of the bigger number of classified poems that we had available (185 vs 46). We also used the four classed proposed there. A priori, the emotion differences between the four poem categories seems to be clear, with the exception the "Songs to Lisi" category, which could be considered as a special one and calls for a special comment. That category includes a set of poems to a fictitious woman named "Lisi", which represents a real or an ideal woman or, might be, a combination of both. Anyway, Philologists have not given a definitive answer to that question. Apart from the real existence of Lisi, the emotional classification of those poems as different of the Love ones seems also to be a subjective matter. For instance, [30] states that the poems addressed to Lisi differ little, if at all, from the rest of Quevedo's love poetry and, consequently, does not make any distinction between both categories.

Once we had decided on the poems and the reference classification, next step consisted in obtaining the four emotion values detected in every one of the 185 poems that constituted our initial dataset. As mentioned, our goal was to test whether it was possible to build an automatic classifier able to mimic a reference poem classification. In addition, we were particularly interesting in observing whether the poems to Lisi were classified as being close to the Love ones (or the other way around).

D. Building classifiers

We were interested in exploring if data mining techniques could be used to build classifiers that, given the emotional values related with a particular Quevedo's poem, would classify that poem accordingly to Blecua's categorization. In other words, we wanted to check whether the information about the emotions reflected by a given poem reduce the uncertainty about its classification accordingly to Blecua's categorization.

In this context, we decided to explore along two different paths: on the one hand, we wanted to check if the original categories of Blecua's classification could be distinguished in terms of the sentiment reflected by the corresponding poems; on the other hand, we explored different automatic learning techniques looking for the algorithm able to produce better results with our dataset.

Regarding the first research path, the question was whether Blecua's classification could be explained in terms of common patterns of sentiments, or if, in turn, some combination of the original categories would be better supported by the sentiment analysis. For example, would the sentiments detected in the corresponding pieces of text explain the different between Love Poems and the Songs to Lisi? Would a better classifier been obtained by removing one of the four categories?

In order to avoid differences produced by the learning algorithms, in this first stage only Decision Trees [24] were used. That technique is simple enough to enable an efficient testing of different configurations, while still generating an explicit readable classifier that can be analyzed looking for the reasons behind a given classification. Particularly, the J48 implementation of Decision Trees provided by the Weka [29] toolset was used.

The following subsections describe the variations of the dataset tested that produced more relevant results.

IV. Results

A. Original dataset: 185 intances, 4 classes.

The whole dataset was composed by 185 poems, divided in to four different categories: Love, Songs to Lisi (Lisi for short), Satiric and Philosophical-Moral-Religious (PMR for short). Using this dataset, a classifier tree with 56,22% of accuracy (the accuracy of all the classifiers presented in this paper was estimated using 10-fold cross validation [19]) was built. Even if the classification error is high, at the end of the day it should be considered that the performance of the classifier based on detected emotions is more than twice better than an uninformed selection (25% of chances for choosing the right class for a given poem).

This tree was rather small (13 internal nodes and 14 leaves), as seen at figure 1. Besides, the model built was supported by common sense: for example, poems with high anger, low fear and low sadness were classified as Songs to Lisi.

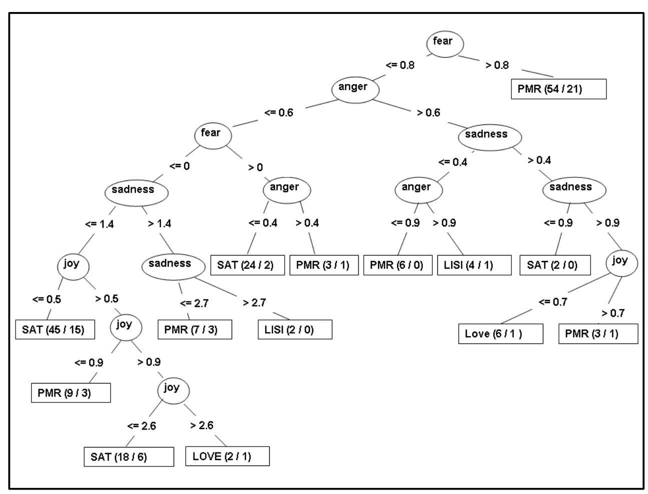

Fig. 1. Classifier tree for the original dataset: 185 instances and 4 classes.

TABLE I. ORIGINAL DISTRIBUTION OF CLASSES

Class	*Number*
Love	21
Lisi	22
Satiric	73
PMR	69

However, this classification was biased because of the dissimilar number of instances on each category. The distribution of each class is shown in Table I. In this type of situations, classes with few instances tend to be ignored. For example, analyzing the confusion matrix (Table II) it is possible to see that most of the Lisi and Love instances are classified as PMR or Satiric. The goal of the confusion matrix is to visualize how many instances of each class are classified correctly and, for the ones bad classified, what classes they are assigned. In this table, the number of correctly classified is shown in the top-left to bottom-right diagonal.

TABLE II. CONFUSION MATRIX FOR CLASSIFIER A

Real Class	**Predicted Class**			
	Lisi	*Love*	*Satiric*	*PMR*
Lisi	5	0	6	11
Love	2	4	7	8
Satiric	1	2	58	12
PMR	10	5	17	37

Furthermore, F-measures are shown at Table III.

TABLE III. F-MEASURES FOR CLASSIFIER A

Class	*F-measure*
Lisi	0,25
Love	0,25
Satiric	0,72
PMR	0,54

B. Resampling: 740 instances, 4 classes

In order to avoid the bias produced by the irregular distribution, a Resample filter [19] was applied. This filter picks up instances of the original dataset at random and creates a new dataset. If a bias is specified, instead of choosing randomly each instance, a given weight is assigned to each class. In that way, the final distribution of the new dataset may be different from the original one. In our case, the bias was configured so the new dataset tends to have a uniform distribution of instances of each class. At the same time, in order to have enough instances for all the classes, the filter was configured to generate a sample 400% larger than the original. Otherwise, the main effect of the resampling would be to remove instances of majority classes. The distribution of the dataset resulting from applying this filter is shown in Table IV.

With this new dataset a new classification tree was built. The accuracy of this tree (again estimated using 10-fold cross validation) was 75,13%. This new classifier not only improved the overall performance of the first one, but it also produced a more “fair” classification of the different classes, as it can be seen in the confusion matrix of table V.

TABLE IV. DISTRIBUTION OF 4 CLASSES WITH RESAMPLING

Class	*Number*
Love	167
Lisi	189
Satiric	169
PMR	215

TABLE V. CONFUSION MATRIX FOR CLASSIFIER B

Real Class	**Predicted Class**			
	Lisi	*Love*	*Satiric*	*PMR*
Lisi	122	16	39	12
Love	14	127	21	5
Satiric	14	11	111	33
PMR	19	24	27	145

Another useful piece of information provided by the confusion matrix is that there is relatively little confusion between classes Love and Lisi. A priori we thought that, as the poems of these two classes are related with the Love theme, it would be difficult to separate one from the other. However the confusion matrix contradicts that a priori presumption.

It is important to highlight that the overfitting effect [27] in this classifier can be too high, as several instances of the low-density classes should be replicated (picked more than once) in order to achieve a uniform distribution. Looking to reduce this effect, another version of the classification tree was built, setting the minimum number of instances per leaf at 16 (default is 2). The resulting tree had an estimated accuracy of 59,86%, what seems a more realistic estimation of accuracy for the classifier.

C. Joining and removing classes

Even if the confusion matrixes do not show any obvious overlapping of classes, it was interesting to test if better classifiers could be obtained by considering only a subset of the original classes.

A first attempt was to join the instances of Lisi and Love classes: as the Songs to Lisi were love poems, it was possible that a class grouping instances of both classes were better classified. The resulting three classes were more balanced, with 43 (Lisi+Love), 73 (Satiric) and 69 (PMR) instances in each class. However, the classifier built with this dataset only had a 52,83% of accuracy. Considering that with a three-class dataset the basic probability of randomly choosing the right class is 33%, this classifier does not provide much improvement.

Afterword the problem of separating pair of classes was considered. The classes analyzed in each case, the number of instances of each class and the accuracy obtained are presented at table VI.

TABLE VI. SEPARATING PAIRS OF CLASSES

Classes considered	Distribution	Accuracy
Love and PMR	21 and 69	61,39%
Satiric and PRM	73 and 69	71,54%
Love and Satiric	21 and 73	73,4%

Even if these results improve the neat accuracy of classifications considering three or four classes, this improvement was expected at least because classifying two classes is easier than classifying four.

D. Other learning techniques

Besides Decision Trees, other learning techniques were tried in order to test whether they were more suitable for the specific dataset. In all the cases, the data set used for training was the one described in section A: 185 instances, classified into 4 categories.

Some of the techniques tested were Naïve Bayes [17] (55,67% of accuracy), Support Vector Machines [18] (53,51% of accuracy), Neural Networks (specifically Multilayer Perceptron [15], with 53,51% of accuracy), K* [7] (52,97% of accuracy), Adaboost M1 [14] (52,43%). Furthermore, confusion matrixes held the same proportions as the ones produced by decision trees.

V. DISCUSSION

The goal of all these experiments was to determine whether a classifier with information about the emotions detected in a given Quevedo's poem was able to reproduce the Blecua's categorization. In that sense, it is possible to conclude that a classifier with that type of information can produce a classification more than twice as good as a random picking would do. In other words, it is clear the sentiment analysis provides valuable information for classifying the poems.

Regarding the results of the different experiments carried out, some conclusions that can be extracted are:

- No combination of less than four classes produces a substantial better classification than classifying four classes: the four-classes classifier got an improvement of 112% over an uninformed selection (56,22% vs. 25% of accuracy), while the best result with two classes only improved the uninformed selection by 46,8% (73,4% vs. 50%). These results imply that, from the sentimental analysis point of view, classes are real different one from the other.

- Experiments based on resampled datasets generate too optimistic results. In the resulting dataset instances of minority classes are replicated, on the average, around 8 times. That is enough to produce a leaf of its own in the classification tree. However, those experiments are useful to show that better results could be achieved if more instances were available from minority classes.

- None of the main pattern recognition techniques produce significant better results than Decision Trees. For this reason, the models produced by Decision Trees are valid and the rules derived can be analyzed to understand the relationships between sentiment values and poem categories.

In that sense, the main patterns that can be extracted observing the trees produced in the different experiments are shown at table VII. In all the cases the terms "high" and "low" are relative and should be interpreted contrasting with other poems and with the values detected for each emotional dimension.

TABLE VII. MAIN PATTERNS FOR EACH CLASS

Class	**Pattern**			
	Joy	***Sadness***	***Anger***	***Fear***
Lisi	-	Low	High	Low
Love	Low	High	-	-
Satiric	-	Low	Low	Mostly Low
PMR	-	High (if Fear=Low)	High	High

VI. CONCLUSION AND FUTURE WORKS

One of the main goals of this paper was to evaluate if our approach for emotion detection was able to identify different emotions for different categories of poems. In other words, whether it was possible to build an automatic classifier using the emotions detected (also automatically). In that sense, Manuel Blecua's classification of Francisco Quevedo poems was used as a target model.

Classifiers built using that approach delivered reasonably good performances. Even if better classifiers would require a larger number of instances (at least from some of the classes), at the end it was clear that the emotional data provided valuable information for predicting the class of a given poem. That is, it is possible to conclude that there exists a relationship among detected emotions and Blecua's categories.

For example, it is easy to see from table VII that Quevedo's love poems are sad ones. In the same line, poems written to the imaginary woman Lisi are high on anger, showing the "frustration of expectancies" (definition of the Anger dimension) expected from an impossible love.

For the future we have planed two research lines: on the one hand, we need to explore why some poems are misclassified. Of course, no automatic classifier is perfect, but it is needed to check whether improving the emotion detection can reduce the classification errors. On the other hand, we will test the approach with other writers and classifications. In addition, we will make use of other emotion identification techniques in order to compare the results obtained in this kind of research studies.

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