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ANALYSIS OF TEXTS' EMOTIONAL CONTENT IN A MULTIDIMENSIONAL SPACE

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ABSTRACT

In this paper we focus on the task of detecting emotion in texts. Among the most employed approaches, categorical ones are mainly used for their simplicity and intuitiveness while dimensional ones, although less common, may provide more objective and accurate results. In current works, both methods often result in tagging texts with emotion labels (resulting from a segmentation of the emotional space into regions for the dimensional case). In this paper, we propose to consider another point of view: we analyse texts as point sets in an emotional multidimensional space. To that aim, we exploit a norm built up of 3000 French terms established on the basis of a psychological experience, mapping terms in a 3 dimensional space constituted of valence, activation and emotionality. Our experiments on lyrics and film dialogues show promising results despite the lack of any linguistic pre-processing. We hope this approach will lead to new ways of identifying and discriminating emotional content from texts.

Keywords: emotion mining, text analysis, affect curves, computational intelligence

1. INTRODUCTION

Identifying and discriminating emotions in text corpora has recently been subject of great interest over the scientific community [1]. The complexity of this task arises from the multiplicity of words used to express feelings, the influence of the context on their meaning but also from the personal nature of emotions and their expression which for instance depend on cultures, languages, ages or personal experiences.

To tackle this problem, it is necessary to define what an emotion is. From a psychological point of view, two approaches are mainly adopted. On one hand, categorical models define a set of basic

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emotions, sometimes declined into a hierarchy of different intensity levels. On the other hand dimensional models represent emotions as vectors in a multidimensional continuous space usually composed of three axes, namely valence, activation and potency. This space can be segmented in predefined basic emotions. When considering their application to emotion detection from texts, these approaches give rise to dictionaries that list terms to be extracted from texts and associate them with emotion labels or coordinates in a multidimensional space.

Instead of labeling a text with an emotion, we propose a representation that relies on the dimensional approach of emotion. Our method consists in exploiting a dictionary that maps words to coordinates in the space in order to analyse a text as the projection of the words it is composed of. Our experiments rely on a norm built up of 3000 terms in French, obtained as a result of a psychological experience [2]. An emotional characterization of a text is thus attained in such a way that it remains free of any prior emotional labeling resulting from basic emotion labels or from a segmentation of the space into emotions. Our method opens the way to new approaches for discriminating emotions from text corpora.

This paper is organized as follow. In Section 2 we discuss how both categorical and dimensional models can be exploited to detect emotions from texts. In particular, we underline that the categorical approach appears to be well suited because of its intuitiveness and simplicity, while the dimensional approach provides a continuous scale which increases the model's accuracy and objectiveness. In Section 3, we present our method and study the relevance of the norm we base our work on for emotion detection in textual documents. Applications of our method are provided in Section 4: in a first experiment we study and compare two songs' lyrics overall emotional content while in a second one, we analyse the emotional content of a movie's French subtitles over time. Conclusions and future works are given in Section 5.

2. PSYCHOLOGICAL MODELS AND THEIR APPLICATION TO TEXTS

In this section, we present two psychological models of emotion mainly used in computational intelligence, namely categorical and dimensional models. We first give their general principle before reviewing their application to texts.

2.1. Categorical models

2.1.1. In psychology

Emotions are structured as a set of basic elements and subelements declined as a hierarchy. Depending on authors, they may vary in number and nature. The relationship between basic emotions and subemotions may as well differ, for instance some authors might consider intensity or inheritance hierarchies. The interested author might refer to [3, 4, 5]. Despite the lack of consensus, many authors agree on six emotions [6]: *joy, surprise, fear, anger, sadness and disgust*. Each of them may be declined as a hierarchy of subemotions, for example, Plutchik [4] considers three intensity levels and proposes a declination of *joy* as *ecstasy* $\triangleright$ *joy* $\triangleright$ *serenity* or of *surprise* as *amazement* $\triangleright$ *surprise* $\triangleright$ *distraction*. Complex emotions can then be defined as mixes of these independent basic emotions, e.g contempt as a mix of *anger* and *disgust* [4].

2.1.2. Application to texts

Detecting emotion in texts Emotions and subemotions may be regarded as labels to be recognised in texts. To that aim, it is considered that an emotional vocabulary exists and each emotion is assigned words denoting it. This approach is mainly adopted due to its intuitiveness and simplicity. Put that way, the detection problem is indeed similar to classical text classification tasks where a corpus is segmented into categories and sub categories through its vocabulary, emotion labels here playing the role of categories. The widely addressed *opinion mining* task [1] can be regarded as a particular case of emotion mining where the set of identifiable label is brought down to a couple, to discriminate positive vs. negative emotions.

In order to handle text-based information, dictionaries that list terms to be extracted from texts and associate them with emotion labels are mainly employed. Generally speaking, the detection process consists in counting occurrences of the dictionary's terms extracted from the texts being studied. The system then delivers a classification decision corresponding to the emotion with the highest count. Since texts may express one leading emotion attenuated by multitude of annexed emotions, some authors have tackled the problem with fuzzy logic and considered degrees of belonging to emotion categories: the system not only outputs all the emotions recognized in texts but it also gives information on their presence levels [7].

Automatic vs. manual dictionaries There are different ways of constituting the dictionary. Individuals being the ones experiencing emotions, it does make sense to make them tag lists of terms with emotion labels. However, as no good agreement exists between individuals when it comes to emotions, some authors refer to experts for mapping terms to emotion labels [7, 8]. Others work on automatic dictionaries expansion: in the case of models constituted only of two categories, positive and negative, terms are extended through their distance in a semantic graph such as WordNet [9]. When dealing with complex models, emotion labels are employed as seeds to traverse the semantic graph and gather emotional vocabulary [10].

Denotative vs. connotative dictionaries Another distinction may be made regarding the collected vocabulary: denotative terms directly express emotions while connotative terms call emotions through among others, personal experiences and established consensuses in a more implicit and latent way. Thus, while denotative vocabulary usually expresses one and unique emotion, connotative vocabulary may call different emotions depending on the person interpreting it. For emotional classification, using only denotative vocabulary results in poor information on the texts being studied, nevertheless adding connotative vocabulary must be taken carefully as it might end up adding uncertainty with respect to the detected emotions. This difference is extremely important: words like *weapon* may be regarded as more emotional and negative in a context of energy than for video games.

Generic vs. contextual dictionaries While denotative dictionaries always lead to generic dictionaries (the mapping between terms and labels is absolute and irrevocable), connotative dictionaries may lead to contextual dictionaries. Many authors have focused on constituting dictionaries from manually labelled corpora. Resulting dictionaries are then relevant but specific to the corpora being studied. Some authors have also combined the two for constituting hybrid dictionaries [11].

2.2. The dimensional approach

2.2.1. In psychology

Dimensional emotion models [12, 13] make use of descriptive features to characterize emotions, consequently they hold an interesting abstraction power. The main motivation behind the choice of the features defined in the many different models relies in their capacity to describe the phenomena experienced by individuals when confronted to emotional situations. From a psychological point of view, if individuals were able to rate these phenomena, then it would become possible to discriminate emotions using values on objective and absolute scales rather than using subjective and language dependent labels. Dimensional models depict features as axes describing emotions in continuous spaces. Among the most studied axes, valence represents the pleasure procured by a situation, activation measures the physical excitation caused by a situation and potency portrays the capacity of a subject to take over a situation. There is no real consensus regarding the number of axes or their nature: some authors advocate that a bi-dimensional model dealing with valence and activation holds the best relevance [12], while for others potency is essential for instance to differentiate fear and anger [13].

2.2.2. Application to texts

Dimensional models have a strong background in psychology and are widely employed in computational fields such as speech recognition or video annotation. Compared to other models, their continuous nature offers a solid basis for deep statistical analysis of the data. Furthermore, they are well suited for studying continuous phenomena such as voice's pitch, video sequences' color or motion information [14, 15, 16]. However when dealing with texts, there are much fewer works that make full use of the dimensional model [1]. Text processing is indeed a special case where objects are described by discrete descriptors: the terms extracted from texts. The lack of relevant continuous descriptive features stands in the way of approaches based on dimensional models. Furthermore, going from the discrete linguistic space to the continuous dimensional space causes problem as no order relation exists when dealing with linguistic terms. The solution is to ask individuals to rate lists of words on emotional descriptive features [17, 2]. Their corresponding vectors may lead to the analysis of texts' emotional content, yet they are usually brought to categorical spaces by segmenting the continuous space into basic emotions [18]. Finally, the several ways of constituting and extending the dictionary recalled in Section 2.1.2 are well extensible to dimensional approaches.

3. PROPOSED METHOD

In this section, we describe our proposal. We give our method's general principle, then we discuss the choice of a norm adapted to French corpora.

3.1. Principle

Relying on the dimensional approach of emotion, instead of assigning an emotion label to a text, we propose to study the text as a point set. To that aim, we exploit a dictionary that maps words to coordinates in the space and we interpret texts as the projection of the words they are composed

Table 1: Sample of Leleu's terms [2]

Terms	Activation	Emotionality	Valence
amour (love)	61	68	68
haine (hatred)	58	59	20
confiance (trust)	44	53	59
mépris (contempt)	35	46	16
mort (death)	13	56	16
arme (weapon)	45	45	25
fromage (cheese)	11	13	45

of: they are thus represented as point distributions in a multidimensional space. Observing and analysing their properties may lead to novel methods for discriminating emotions in texts: in Section 4.1 we compute and compare point sets' five-number summaries along each dimension in order to discriminate their emotional content. In Section 4.2, instead of considering the overall information contained in a text at the same time, we view it as an information stream and analyse its emotional content sequentially along each dimension.

Our method to process texts can be decomposed into three steps: the first one consists in choosing a dictionary that maps words to emotional descriptive features, see Section 2.1.2 for further details. In a second step, the dictionary's terms are extracted from texts by regular keyword spotting, it is possible here to make use of further elaborated linguistic methods. Finally, the resulting point sets can be analysed, along several lines, as detailed in Section 4.

3.2. Selection of a norm for the French language

3.2.1. Norm choice

Many norms exist for the English language: [17, 19, 20, 21]. However, when it comes to French, finding such resources becomes rather problematic. Some authors have addressed the problem through cross-language processing techniques by employing translate/back-translate procedures [13]. In the following, we focus on the norm established on an experimental process in [2] that contains 3000 frequent French terms: the vocabulary expressed in it ranges from truly emotional terms like *love* or *sadness* to very low emotional terms like *chair* or *table*. It makes use of three dimensional vectors in a space defined by valence, activation and emotionality, where emotionality measures terms' subjectivity. Subjects were asked to rate different terms on different features, results were then averaged on integer scales between 10 and 70 (see Table 1).

According to the description of dictionaries' different natures given in Section 2.1.2, we may qualify this norm as being manual and generic.

3.2.2. Study of the norm's properties

In order to value the relevance and the expressive power of the norm, we first study the independence of its axes. Since they represent descriptive features, it is desirable that the information carried over remains unique and useful, thus independent. Figure 1 shows the norm along each 2D combination of axes. From the left graph, valence seems to divide the data distribution into two distinctive groups around the value 40 that corresponds to the middle value of its domain. It goes

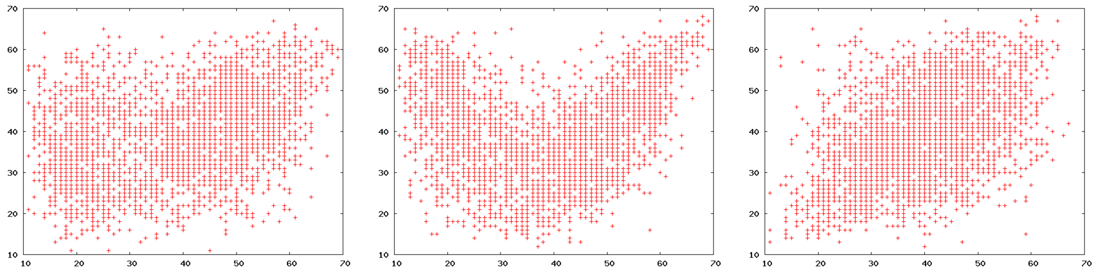

Figure 1: Visualisation of the norm on: (left) valence/activation, (middle) valence/emotionality and (right) activation/emotionality

along with psychologists' work where valence is often found out to be the most descriptive feature when dealing with emotions. Except for the bottom right region where the space seems rather sparse, the data distribution covers the whole plan, which may involve some kind of independence between the two axes. On the middle graph, a V-shape pattern is identifiable, it may put in relief some association between the emotionality and valence.

These observations are confirmed by linear correlation analyses on the activation/valence and the emotionality/valence graphs, computed for two regions characterized by valence values inferior (resp. superior) to 40. As reported in Table 2, the correlation coefficients show that emotionality is strongly associated to valence values higher than 40 and to a lesser degree to values lower than 40. Regarding activation/valence, while coefficients indicate the independence of the axes in the left region, they report a low dependence in the right region.

Among the axes defined in the norm, *emotionality* does not hold much information with respect to *valence*. In fact it seems to play as an intensity measure for *valence*, a possible explanation may consist in the interpretation of emotionality as an intensity descriptor by subjects of Leleu's experiment. However, *emotionality* may lead to interesting applications when it comes to subjective vs. objective classification tasks.

4. APPLICATIONS AND DISCUSSION

In this section, we apply the methodology described in the previous section on two experiments: songs' lyrics and film subtitles. No linguistic preprocessing (for instance, negation or linguistic intensity modifiers) was performed, except to take into account exclamation marks. Indeed, these punctuation marks absent from the norm provide precious information especially regarding texts' activation. Consequently, we incorporate an additional configurable entry whose valence and emotionality are set to the neutral value 40 and whose activation is empirically set to 75% of the scale, i.e. 60.

4.1. Experiment on song lyrics emotional content

A first experiment has been conducted on lyrics' French translations from the songs *Ode to joy* (the song the UE anthem drew its inspiration from) and *You are not alone* featured by Michael Jackson. While the former contains really enthusiastic and joyful vocabulary attenuated with darker

Table 2: Linear correlation coefficients

	Activation/Valence	**Emotionality/Valence**
Valence < 40	-0.03	-0.5
Valence ≥ 40	0.36	0.67

passages in the middle of the song, the latter expresses truly sad and melancholic thoughts on love. For each feature, Figure 2 displays box plots of the lyrics emotional content for both songs. A box plot efficiently displays a data distribution over one dimension by plotting the distribution's median value inside a box defined by the distribution's lower and upper quartiles. The position of the median inside the box is usually thought of as an indicator of skewness while the height of the box as an indicator of dispersion. Furthermore, outliers are defined as observations superior to 150% of the inter quartile range, these points are usually considered as being accidentally too extreme with respect to the overall data distribution. Minimum and maximum values that are not outliers are plotted outside the box so that it is visually identifiable where the distribution lies between its extrema.

The distribution associated to *Ode to joy* appears as being clearly positive with 75% of the data located in the upper part of the valence axis and 50% spanning high values, from 53 to 65 (left graph). Furthermore, we observe that the distribution is spread along the activation axis with a tendency for high values as 50% of the data ranges from 43 to 58 and only 25% remain below the value 35 (middle).

Regarding *You are not alone*, the distribution appears more positive than expected (the median value on the valence axis being 40), however, only 25% of the data possesses very high valence, above 51 (left). The dispersion of the observations along the valence axis seems to indicate a combination of positive and negative vocabulary in the lyrics, it may be caused by the song theme, love. On activation, observations are concentrated on rather low values, lower than 42 with the presence of outliers on high values that underline the overall unactivated state of the song (middle).

For both song, emotionality plots (right) reminds of the valence plots (left): indeed both distributions seem to be distanced from their respective extrema, lower and upper quartiles in the same proportions. It goes along with our previous observations of the norm where we found out emotionality to be associated with valence.

Even if the differences between the two song are not appealing, our method captures the overall positive and active state of *Ode to joy* with respect to *You are not alone*.

4.2. A movie emotional content

The second experiment aims at performing an analysis of the temporal variation of a text's emotional content. It is based on the French subtitles of the movie *Little miss sunshine*[1].

[1] Available on http://www.opensubtitles.org/fr/subtitles/3091817/little-miss-sunshine-fr

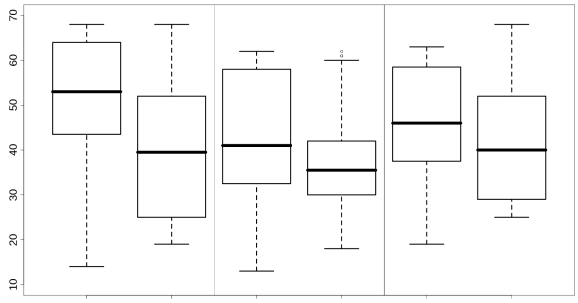

Figure 2: Emotional box plots of the lyrics (left) Ode to joy and (right) You are not alone along (left) valence, (middle) activation and (right) emotionality

In order to analyse the movie emotional content over time, dialogues have been segmented as per the 24 DVD's scenes. For each scene, Figure 3 displays smoothed version of valence, activation and emotionality curves over time. Smoothing has been achieved through exponential moving average, around 20 words. Even though the curves obtained in this experiment may be associated to the *affect curves* proposed in [15], our work is specifically based on words thus on linguistic information while *affect curves* are computed on the basis of pure visual information.

It can be observed that the overall enthusiasm carried over the scene of *Little miss sunshine* is well depicted by the valence curve's overall high values. Besides, segments below the neutral value 40 and in particular low points on valence do systematically correspond to scenes involving arguments, fights or confrontation between characters (scenes 3, 5, 8, 15, 16). Peaks reveal enthusiastic or affective passages like in the middle of scene 3 where a love story is depicted by one of the character, or in scene 13 where a mother explains to her children how much their recently lost grand father loved them and how family is important. Regarding activation, peaks reveal intense passages as in the final scene which constitutes the movie's high point or in scene 7 where the family breaks their van's gearbox and has to push behind it to make it start. On the contrary, low points appear to be associated with heavy atmospheres in particular in scene 9 the brother meets his ex-lover and the father loses his business hopes. Finally, emotionality is, according to our former consideration, somewhat associated to peaks and low points in valence, however, it seems to hold some kind of precious information. For instance, in scene 3 two successive peaks occur in valence and activation while emotion raises up only with the latter which corresponds to the earlier described narration of the love story.

The global relevance of these curves is encouraging and promising in the meantime, difficulties can be identified: in scene 12, a couple has a serious argument concerning their financial situation, while our method captures the global slope in valence, the relating curve remains abnormally high due to the use of terms like *trust*, *family*, *love* by the characters. On the other hand, the peak in activation well depicts the situation. Furthermore, in scene 6 where a father tells his daughter how ice cream does not fit to modelling, we observe an abnormally deep low point in activation. As mentioned earlier in Section 3.2.1, the dictionary we used is manual and generic. Apparently, terms like *gras* (*fat*) or *grosse* (*fatty*) were judged as extremely low activated and their repetition in this scene causes the huge slope in activation.

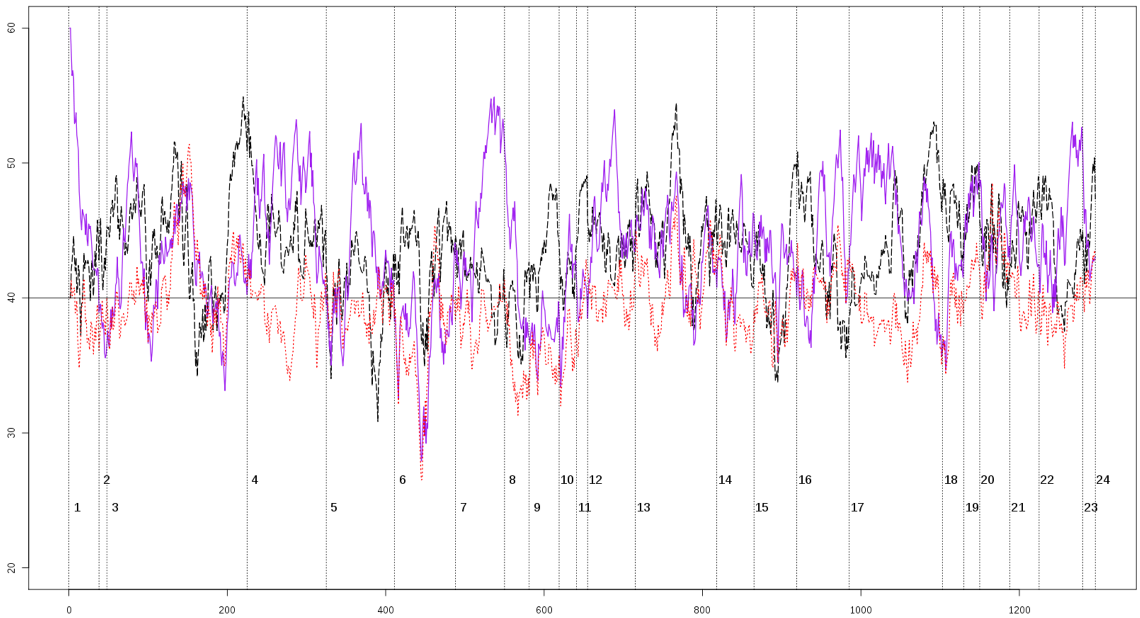

Figure 3: Emotional curves of the movie Little miss sunshine: (dashed) valence, (solid) activation and (dotted) emotionality, plotted sequentially on the horizontal axis.

5. CONCLUSIONS AND FUTURE WORKS

Although categorical models of emotions are more frequently used to detect the emotional content of texts, due to their intuitiveness and simplicity, dimensional approaches can lead to more objective and accurate results. In this paper, we proposed a novel approach based on the latter, that represents a text as a set of points in the emotional space and analyses its emotional content through the properties of these points' distribution. We illustrated this approach in two different frameworks, to assess a text globally, or to study the emotion evolution along the text and the emotion dynamics. The experiments performed on lyrics and film dialogues show promising results, that can be further improved in particular by taking into account the difference between connotative and denotative vocabulary in the norm, as well as integrating linguistic pre-processing steps.

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