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Patient's rationale: Patient Knowledge retrieval from health forums

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***Abstract*— Online health forums are areas of exchange where patients, on condition of anonymity, can speak freely on their personal experiences. These resources are a gold mine for health professionals—giving them access to patient to patient, patient to health professional and even health professional to health professional exchanges. In this study, we used text mining techniques to analyse health forums in order to extract emotions (e.g., joy, anger, surprise, etc.) expressed by patients. After a study of real messages, we demonstrate the difficulty of manual annotation due to the low level of agreement between humans. We propose a method to identify the polarity of a message and extract one or several emotions. This method was validated on a substantial real dataset.**

Keywords*— *Health forum analysis, emotion analysis

I. INTRODUCTION

Online health forums are areas of exchange where patients, on condition of anonymity, can speak freely about their personal experiences. Some examples are the very active forums, including healthforum.com[1], ehealthforum [2], which allow internet users (often non-health professionals) to exchange opinions on their health situation. Hancock [3] demonstrated that the ability to communicate anonymously via computers facilitates the expression of affective states such as emotions, opinions, doubts, risk fears, etc. These affective states are generally repressed in more traditional communication contexts, such as face to face interviews or when responding to surveys. These resources are a gold mine for health professionals—giving them access to patient to patient, patient to health professional and even health professional to health professional exchanges. For example, recently, the effects of new generation pills have been widely debated in French forums. This prompted some women to stop taking contraceptive pills, with a concomitant increase in abortions. Even if all patients do not use health forums, they represent a large and varied database of knowledge and patients' perceptions on their illnesses and any healthcare they have received. In this highly subjective setting, the characterization and understanding of these perceptions is difficult but nevertheless particularly relevant for complementing and improving public health programs.

As part of the French project called "*Parlons de nous*" ("Let's talk about us"), we tried to combine different markers (emotions, risk fears, uncertainty, etc.) with respect to medical items (drugs, treatments, etc.) in order to identify common collocations (e.g., between mediator and fear). In this article, we focus on the identification of emotions as a specific sentiment analysis task. While many approaches have been proposed for the analysis of text polarity (positive and negative), few approaches focus on the analysis of feelings (joy, anger, sadness, etc.). From a corpus of messages collected on the English-language Spine Health website, we used the vocabulary of emotions of Mohammad and Turney [4] to automatically annotate messages. A part of the corpus was manually annotated by 60 annotators. Based on a study of the agreement between annotators, we were able to show that it was difficult, even for humans, to associate a particular emotion to a message. We decided to give two information items to health professionals: the polarity of the text (positive or negative) and associated emotions (e.g., joy). We looked for the best descriptors for these two items. Experiments on real datasets revealed the effectiveness of this approach and discussions with health professionals have shown the medical importance of identifying such information.

The rest of this paper is organized as follows: in Section 2, we identify the medical issues. In Section 3, we propose a first sentiment analysis categorization and recent methods. In Section 4, we describe the corpus used in our approach. The method we used is described in Section 5. In Section 6, we describe the main results. Finally, in Section 7, we conclude and give the main prospects.

II. MOTIVATIONS

As pointed out by Siegrist [5], one of the great challenges for health professionals is to capture patients' satisfaction to answer the question "How can we improve our practice?". With this objective, Siegrist studied patients' feedbacks after their stay in large American hospitals and turned them into raw data that could be tapped by the medical authorities for decision making. Using the forums as an object of study, we are getting closer to the patient private sphere. Indeed, patients express things in posts, they does not express in comments (even anonymous). However, precisely identifying the emotional state of patients through these messages is a difficult objective task and not always verifiable, as discussed by Quirk [6]. However, we could consider using these large amounts of emotionally-charged texts to construct indicators that are relevant for health professionals. An example of such an application is "We feel fine" [7]. This tool queries the web with the aim of assessing users' moods. Every 10 minutes, the application considers

sentences with emotional words and performs statistical calculations based on the type of feelings, age, gender, etc. An example of application is dedicated to pharmaceutical companies. They monitor the social web in general to identify texts in which patients talk about their medications and measure the associated emotional states. This feedback can help them improve their products or their communication about these products. Another example concerns the physicians who want to know the patients fears about the prescribed treatments. This feedback can help them to improve their communications to patients.

The (semi-)automatic analysis of forums is difficult from a technological standpoint. Most (semi)-automatic methods used in the health domain are applied to publications and hospital reports. Adapting these methods to messages from social media like forums is not simple at all. Such messages are written by patients in rather a loose style. They vary in size (between a hundred and a thousand characters). They contain non-standard grammatical structures, many misspellings, abbreviations, emotion-rich expressions as well as emotion-rich words (I love, I hate), unconventional lay-out, e.g., repeated use of capital letters (TIRED), unconventional spelling (enoooooough), and punctuation repetition (!!!!!!!!), slang words that are (or not) specific to the forum or the topic (LOL vs. IVF) and emoticons (:-)). Message volumes are generally very high (in the French forum dedicated to breast cancer on the Doctissimo site, there are more than 3,300 threads, some of which contain more than 2,000 replies). Finally, the processing of health forum data based on semi-automatic information extraction methods is a significant technological challenge.

III. State of the art

Sentiment analysis has been widely studied since the early 2000s. Many communities are interested in this area and their definitions and interpretations are highly varied (e.g., psychology, social sciences, computational linguistics, natural language processing, data mining, etc.). Sentiment analysis involves the extraction of emotional states expressed or implied in texts [8]. It includes the following tasks:

1. Subjectivity analysis [9] focuses on the detection of feelings based on subjective expressions or words;
2. Polarity analysis [10] focuses on the detection of positive and negative polarity of texts;
3. Emotional analysis [11] focuses on the emotional category of texts (e.g., anger, disgust, fear, etc.)
4. Intensity analysis [12] focuses on different levels of polarity or emotion intensity (e.g., very positive, very sad, etc.). These approaches offer a more precise granularity of expressed opinions and emotions.

We focus on the third task. Like most semi-automatic methods in the literature, we use the typology of emotions defined by Ekman [13], which describes six emotions, but many other typologies also exist ([14]; [15]; [16]).

The methods used to analyse feelings are numerous and generally specific to the text type, e.g., tweets [17], press titles [18], *etc*., and application areas, e.g., social media analysis [19], gender impact in negotiations [20], identification of suicidal emails [21].

For all studied sentiment analysis tasks (polarity and emotions), most previous studies focus either on the creation of resources to describe feelings or on the use of these resources to classify texts according to sentiments. In the first category, most methods associate texts with emotional word resources. Most of these resources have been compiled for English texts and polarity analysis, e.g., General Inquirer [22], Linguistic Inquiry and Word count [23], MicroWNOp [24], sentiwordnet [25]. More specific resources, such as the DAL dictionary [26], Wordnet affect [27] or the lexicon of Mohammad and Turney [4] were created for emotional words. There are also approaches for extending these vocabularies for specific application domains by building manual rules [28], or identifying co-occurring words with words already identified as denoting emotions through large corpora [29] or the web [30]. For classification, most approaches use machine learning techniques based on specific attributes, including emotion words ([31]; [18]) to build a statistical model from a corpus of texts and use it to detect feelings in other texts.

While many of these methods are effective on large text corpora, they are limited in the case of short texts such as tweets or specific texts as in health forums. In our study, these limitations were mainly due to the subjectivity of the annotation task, as we describe in Section 4.2.

IV. Corpus

A. Data collection and annotation

We built a corpus from 17,000 messages collected in the English-language Spine-health forum. We automatically annotated the corpus with the vocabulary of emotions of Mohammad and Turney [4]. This lexicon consists of more than 14,000 entries characterized by their polarity and associated with 8 emotions. In this work, we consider only 6 emotions (Ekman, 1992): anger, disgust, fear, joy, sadness and surprise.

Each word in the lexicon could be associated with several emotions (e.g., the word abandoned was associated with the emotions fear, anger and sadness). This automatic annotation enabled us to filter 22% of the messages (not containing emotion words). In order to focus only on emotions associated with medical items, we used MeSH to identify medical units in the text, which allowed us to filter messages without any medical references (6% of messages). In a message, many emotions were usually expressed because the messages were relatively long. We therefore chose to segment the messages in sentences. We finally kept 3,000 sentences to constitute an Automatically Annotated Corpus (AAC) and labelled sentences with several emotions by the most frequent one (re-annotation step).

A subset of this corpus (600 sentences) was manually annotated by 60 non-health professionals, i.e. basically Master's students and computer science researchers from our lab. We called this the Manually Annotated Corpus (MAC). We thus set up a web-based platform. Unlike Strapparava and Mihalcea [18] who used an interface to annotate and capture many emotions through an emotion-intensity cursor, we decided to simplify the task and asked the annotators to

identify only the presence of emotions expressed in the texts. Each sentence was pre-labelled automatically via the lexicon, the corresponding emotion was shown by default but could be unchecked if the annotator believed that it was not expressed in the sentence. If the sentence did not express any emotion, all emotions were to be unchecked. Finally, if the annotator could not decide, "I do not know" was selected.

Table 1 shows the distribution of sentences in both corpora according to six emotional categories. The AAC corpus was clearly unbalanced and both fear and sadness emotions were best represented. In the MAC corpus, 45% of the sentences were annotated as neutral (no emotion) and 9% were undecidable. We also noted after the re-annotation that the MAC corpus was better balanced than the AAC corpus. However, surprise was very poorly represented.

TABLE I. PERCENTAGE OF SENTENCES IN BOTH AAC AND MAC CORPORA ACCORDING TO 8 CATEGORIES (J – JOY, SU - SURPRISE, F - FEAR, A - ANGER SA - SADNESS, D - DISGUST, N - NEUTRAL, DK - DO NOT KNOW) BEFORE AND AFTER RE-ANNOTATION.

AAC	J	Su	F	A	Sa	D	N	DK
Before	22	14	39	22	39	18	/	/
After	13	4	33	9	35	6	/	/
MAC	J	Su	F	A	Sa	D	N	DK
Before	10	4	17	13	19	14	45	9
After	14	6	23	14	25	18	0	0

B. *Between-annotator agreement*

We used the Kappa measure to assess the between-annotator agreement. For this, 150 sentences from the MAC were annotated by two non-professional annotators. We got a Kappa of 0.26, which clearly shows that the agreement between annotators was very low. In addition, we measured the agreement between health professional annotators and non-professionals for the same 150 sentences and obtained a moderate agreement of 0.46. This preliminary experiment highlighted the difficulty of the manual annotation task. Moreover, the disagreement between annotators was mainly due to the variability between people and not their sensitivity to health (professional vs. non-professional).

A first bias, already identified by [32], was in considering the perspective of the annotator/reader likely differed markedly from that of the author of the message. Indeed, health forum posts treat topics such as disease, treatment, etc. This information is negative by nature and most of the annotators, by empathy, associated an emotion such as sadness to factual information such as the description of a diagnosis. For example, the sentence "I am also HLA-B27 negative, so was diagnosed with a spondyloarthropathy" was annotated as sad in our corpus, although it contained a factual diagnosis. A second bias concerned the fact that the corpus was in English, while the annotators were native French-speakers. Furthermore, by studying sentences with gaps in the annotations, we noticed that it was easier to identify the polarity than the emotion. It was also easier to predict positive emotions than negative emotions because negative emotions share very similar vocabulary. We also noted that surprise was the hardest emotion to identify, as also noted by Strapparava and Mihalcea [18] who argue that surprise is not often taken into account in studies of emotions as it is neutral in nature. For example, the sentence "I discovered its effect on me the hard way, hugging the toilet after a painful back procedure, ugh!" None of our annotators considered the emotion surprise, despite the presence of the word "discover".

The quality of our annotated corpus was actually quite questionable. Indeed, the annotators were not sufficiently coached with specific instructions to avoid the biases mentioned above. Tests of internal consistency (inter-individual reproducibility) would have to be done to assess if the annotators were consistent over time. Another possibility would be to get several annotators to annotate sentences and choose labels by majority vote. Finally, even with its drawbacks, this study gave a relatively clear picture of the difficulties involved in obtaining a qualitative corpus and the methodology to improve its quality. Based on these findings, we then decided to compare the results obtained with the AAC and MAC corpus, knowing that most of the methods of the state of the art only use AAC corpus. We evaluate different methods to characterize forum texts based on: 1) a two-category classification to identify the polarity of emotions; 2) a multi-category classification for six emotions: a sentence could only be associated with a single emotion class. Surprise was eliminated because of its neutrality. This typology is similar to that described by Roberts [17]; 3) a multi-label classification allowed us to associate a sentence to several emotion classes.

V. EXPERIMENTAL PROCEDURE

Our approach relies on a classification method based on attributes such as unigrams, bigrams and specific attributes, defined to capture traces of emotions in messages. It consists of two steps: 1) pre-processing of sentences from messages, and 2) classification of these sentences. Evaluation of the results depends on the classification performed.

Pre-treatments: forum posts are specific in the sense that the words used are not necessarily found in conventional dictionaries (slang, special formatting, abbreviations, emoticons, etc.). It is therefore necessary to standardize them by generalizing their content. To do this, we applied the pre-processing procedure outlined in Table 2 and corresponding to the chain set up by (Balahur, 2013) for tweets.

TABLE II. APPLIED PRE-PROCESSING

Pre-processing	Example	Resource
Repeated punctuation	!!!!	/
Specific layout	TIRED	/
Emoticon	:-)	/
Slang	2mr > Tomorrow	Chatslang.com
Emotional words	Fear	Mohammad's lexicon [4]

Classification: We used the following attributes in order to find the best emotion descriptors:

– Attributes based on N-Grams (U, U+B): Unigrams, Unigrams and Bigrams;

– Emotion words (EW): if a sentence contains two words corresponding to the emotion joy, it takes the value 2 for the corresponding attribute;

– Smileys (SMI): all emoticons (:-):-(...) were classified according to the six emotions. If a sentence contains a smiley related to joy, it takes the value 1 for the corresponding attribute;

- Amplifiers (AM): These attributes correspond to punctuation (!,?...), repeated letters (looool) and capitalized words (HATE). If a sentence contains such elements, it takes the value 1 for the corresponding attribute;

- The emotion context (CONT): we used two attributes that we call neighbour emotion and overall emotion. The first attribute is true if the sentence that precedes or follows the sentence expresses the same emotion and the overall feeling is the true value if there is another sentence in the message that expresses the same emotion.

Like Bechet [33], we enriched the attributes with patterns obtained using a sequential pattern algorithm (PAT). For this, we used the MeSH medical thesaurus to identify medical words (labelled MW), the lexicon of emotion words (labelled EW) to identify traces of emotions and a lemmatizer for grammatical category words (labelled JJ, NN, VV, MD, etc.). Each sentence was then considered as a sequence of itemsets corresponding to a combination of these three labels. We then used the GSP algorithm [34] to obtain frequent patterns, i.e. frequent sequences. We used only those containing at least one label for a medical entity and another label for an emotion word. These patterns were then used as attributes. A sentence was labelled true for a pattern if its syntactic form fit the pattern. Figure 1 summarizes the protocol for obtaining patterns.

Initial sentence:
Chronic pain may cause secondary depression

Emotional and Medical word tagging:
Chronic/MW pain/EW/MW may cause secondary depression/EW/MW

Grammatical tagging:
Chronic/MW/JJ pain/EW/MW/NN may/MD cause/VV secondary/JJ depression/EW/MW/NN

Sequence:
MW/JJ EW/MW/NN MD VV JJ EW/MW/NN

Figure 1. Sequence definition

Evaluation: The quality of the two-class classification was evaluated using the standard precision measurements *P* (percentage of correct predictions), recall *R* (percentage of correct labels found by the system) and F-measure *F* (harmonic mean of precision and recall). For multi-class classification, we calculate both the average *Fmi* at a micro level (*R* and *P* were calculated by constructing the overall contingency table) and *Fma* at a macro level (*R* and *P* were calculated for each class and averaged). For multi-label classification, other metrics were needed. Indeed, if we took, for example, a sentence belonging to both classes sadness and anger, the system could predict: sadness and anger (the prediction was correct), sadness (the prediction was partially correct) and disgust (the prediction was wrong). So there were degrees of possible misclassification. Other measures [35] were then used such as the Hamming loss *HL* (accuracy for each class averaged per class), accuracy *A* (averaged for all examples) and macro F-measure *Fma.*

VI. Results and Discussion

We used implementations of Weka for bi-class and multi-class classification and Meka for multi-label classification. We used the SMO implementation of the SVM classifier of Weka with default settings. We used the CC chain classification implemented in Meka for multi-label classification. We used two datasets: MAC and AAC corpora (considering that the majority emotion label set after automatic annotation was the class to predict). We carried out a cross-validation (10-fold) and used the attributes described in Section 5. Table 3 presents the AAC corpus results. We do not present the MAC corpus results which were similar that seems to suggest that even with the previsous limitations mentioned in Section IV.B, the MAC corpus has at least the same quality as the corpus used in the literature and obtained automatically from emotional word ressources.

TABLE III. Comparison of results obtained according to a set of attributes using the AAC corpus

	Bi-class			M-class		M-labels		
Attributes	R	P	F	F_{mi}	F_{ma}	HL	A	F_{ma}
U	62.7	57.8	60.1	24.4	23.2	0.24	51.5	58.2
U+B	65.9	61.5	63.6	24.8	22.3	0.14	58.3	59.3
U+B+EW	66.3	64.1	65.1	**27.3**	25.1	**0.12**	**61.4**	61.8
U+B+EW+SM+AM	53.4	52.4	52.9	23.4	20.7	0.25	55.5	55.8
U+B+EW+CONT	53.6	45.5	49.2	25.2	22.5	0.22	55.4	57.6
U+B+EW+PAT	66.2	65.2	**65.7**	26.1	**25.8**	0.15	58.2	**62.4**

The bi-class classification gave the best results, which seemed fairly consistent because the two classes were better represented. This task was also easier for human annotators. Multi-label classification gave better results than the multi-class classification because one example could be associated with multiple classes. Moreover, we detected only little differences between the micro and macro F-measures for multi-class classifications, which suggests that all classes were hard to identify. These results should be compared with the inter-annotator agreement (see section 4.2). In both cases, the task was difficult, but the semi-automatic method seemed to detect patterns more systematically, except in specific cases such as irony.

We could also conclude that the best descriptors were a combination of unigram and bigram with emotion words (U + B + EW). Taking smileys and amplifiers into account did not improve the classification. Indeed, smileys were often used for irony, which was not captured by considering their presence in the sentence. For example, the sentence "I stopped working in 1/09 and kind a thought that at some point I would get better, in hindsight, also rather dumb:-) instead of picking up the pace of getting worse significantly" was automatically associated with the label joy because of the smiley:-), even though it was used by the patient to indicate his bitterness. A simple improvement consists in changing the polarity of the smiley if in the near context there is a contradictory polarity.

Similarly, the context was not an attractive attribute. Indeed, messages were often long (7 sentences on average in our corpus) and contained many feelings (more than 6 emotions in 41% of the messages). Two consecutive sentences often contained different uncorrelated emotions. Finally, patterns were also ineffective because they were too general. They could easily be used to improve the accuracy if we define them by class of emotion.

Note that when the classifiers were wrong, they often placed the sample in a "close" class, with the same polarity. These incorrect predictions were due to the fact that the classes shared many words (such as anger, disgust and sadness). Dictionaries and lemmatizers are used as resources, so the method could easily be applied for other languages using similar resources.

VII. Conclusions and perspectives

Here we describe a method for analysing emotions in health forums. The main challenge was the acquisition of annotated data, and this step will be further improved. For the extraction of emotions, we compared different attributes for different classification tasks (two-class, multi-class and multilabel) and showed that the most effective were a combination of unigrams and bigrams and emotion words for classification bi-classes. However, suggesting a precise label, despite the precision obtained, could be relevant for the health care professionals involved in such studies.

[36]Prospects associated with this work are numerous. From the emotion analysis standpoint, we will apply our method on larger datasets not specific to health, such as the SemEval challenge [37] and compare our method with other published methods such as SWAT [38], uPAR [31] and UA [30]. We will also take shifters into account. Indeed, Smith and Lee [36] showed that the polarity of a term is often modified by the context surrounding it, including markers of negation. In the sentence "This treatment does not make her happy", the negation changes the polarity of the sentence from positive to negative. In the case of emotions, it is harder to understand the impact of these shifters because there are close links between emotions, such as between the failure to be happy and to be sad. For this, more complex emotion models should be used, such as SentiSens [39] which takes the relationship between emotions into account (e.g., hate vs. love). In addition, we will build a lexicon of emotion words specific to our area, as proposed by Carrillo de Albornoz [39]. For this, several options are considered. Smith and Lee [36] used Wordnet [40] to associate new words with words already associated with an emotion based on the relationship *"similar to"* for adjectives and hyponymy for nouns and verbs. Inspired by the Turney and Littman approach [41], it is also possible to search for frequently co-occurring adjectives (or other grammatical forms) using the web or large corpora [30]. We will also validate the genericity of our approach on a French corpus. Indeed, our method relies solely on lexicons and a stemming tool. Finally, the attributes used in our study are focused on the expression of emotions through the lexicon and not through the syntax or through other discourse markers. An improvement would be to integrate these aspects, although complex rhetorical constructions are not frequent in the studied forums.

We also identified issues related to the field of application. The spine-health forum is specialised in the topic of "pain" and discusses a pathology which is a disease of the elderly. The nature of the text message is closely related to these two factors (little smileys or slang, little expressions of joy, etc.). To explore other feelings, we need to diversify the themes of the studied forums. Once the emotions are identified, many applications can be envisaged. The discovery of novelties such as medical associations between medical entities and emotional markers can be used for informational searches by laboratories (e.g., what patients think of this medicine?), physicians (e.g., what patients think of this operation?), patients, etc. More generally, emotion searches could be used to model variations in emotions over time. For example, over time we frequently observed changes in the emotions of patients, e.g., "fear and surprise", "surprised and angry", etc. Furthermore, we could study the influence of the media on the patients' emotion changes, e.g., the case of the third generation pill. Another application might be to identify patients communities based on the expressed emotions. For example, in the debate about the effects of new generation pills, it was noticed that many of the comments were related to religious beliefs. This information is essential for moderators. This applications list is not exhaustive. Identification of emotions is a step toward these applications.

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