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Sifting French Tweets to Investigate the Impact of Covid-19 in Triggering Intense Anxiety

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RÉSUMÉ

Les réseaux sociaux peuvent être exploités pour comprendre les sentiments et les émotions des personnes en temps réel et cibler les messages de santé publique en fonction de l'intérêt et des émotions des utilisateurs. Dans cet article, nous étudions l'impact de la pandémie COVID-19 dans le déclenchement des crises d'angoisse, en nous appuyant sur les messages échangés sur Twitter. Plus précisément, nous fournissons : *i)* une analyse quantitative et qualitative d'un corpus de tweets en français liés au coronavirus, et *ii)* une approche en pipeline (un mécanisme de filtrage suivi par des méthodes de réseaux de neurones) pour classer de manière satisfaisante les messages exprimant de l'anxiété sur les médias sociaux, en considérant le rôle joué par les émotions.

ABSTRACT

Sifting French Tweets to Investigate the Impact of Covid-19 in Triggering Intense Anxiety.

Social media can be leveraged to understand public sentiment and feelings in real-time, and target public health messages based on user interests and emotions. In this paper, we investigate the impact of the COVID-19 pandemic in triggering intense anxiety, relying on messages exchanged on Twitter. More specifically, we provide : *i)* a quantitative and qualitative analysis of a corpus of tweets in French related to coronavirus, and *ii)* a pipeline approach (a filtering mechanism followed by Neural Network methods) to satisfactory classify messages expressing intense anxiety on social media, considering the role played by emotions.

MOTS-CLÉS : détection de l'anxiété, COVID-19, données Twitter, apprentissage automatique, apprentissage profond.

KEYWORDS: intense anxiety detection, COVID-19, Twitter data, machine learning, deep learning.

1 Introduction

The COVID-19 pandemic - that overtook most of the world's countries - is forcing government-issued lockdowns, strict hygiene regulations and is ultimately causing global panic, uncertainty and fear. During this crisis, social media are representing a valuable source of news and a medium for expressing people's opinions and sentiment about the emergency [1] and the restrictive measures deployed by the different countries to fight COVID-19 spread. Given that social media are proving instrumental in keeping people connected during the crisis, they turned out to be beneficial for mental

1. https://www.medrxiv.org/content/10.1101/2020.04.03.20052936v1

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health, in helping to combat widespread feelings of loneliness stemming from extended periods of isolation and social distancing. However, panic attacks are reported to be increasing during COVID-19, as people are increasingly worried about their health [2]. Panic attacks are characterized by an intense fear and sense of feeling overwhelmed, according to the National Institutes of Mental Health. Fear of contamination, sleep disturbance and probability of an economic slowdown with potential job losses are among the major factors leading to depression and anxiety among people (as emerges from the following tweets : *"Coucou...insomnie depuis 15 jours....merci corona."(EN : "Hi... insomnia since 15 days... thanks corona"* ; *"Coronavirus au début jmen foutai de oufff mais mntn vazy y commence a être chaud" (EN : Coronavirus at the beginning I was not caring but now it's heated)*). Despite how scary they can feel, anxiety attacks are relatively common, and in most of the cases feelings are manageable. However, if multiple anxiety attacks happen, or fear over having a panic attack gets in the way, this may be a sign of anxiety disorder and a person should seek help from a mental health professional.

Starting from these considerations and from the observation that people are heavily using social media to express - among others - their feelings about the current sanitary situation, the goal of the current work is to investigate the impact of the COVID-19 pandemic in triggering intense anxiety, relying on messages exchanged on Twitter. Such research issue breaks down into the following research questions : *Can we automatically distinguish tweets expressing a person's intense anxiety status from tweets that are more factual or expressing general feelings on COVID-19 ?* and *Does emotion detection in tweets help improving such task ?* To address such research questions, we analyse a corpus of tweets in French, with the goal of delivering automated methods to detect severe anxiety in social media messages. As a first step, we propose a qualitative and quantitative study on a subset of French tweets of the multilingual Twitter COVID-19 Dataset (Chen *et al.*, 2020). We carried out an annotation process to classify such tweets as expressing severe anxiety, or not. Moreover, we also annotated each tweets with one (or more) emotion(s) (Ekman, 1992) and their intensity, to investigate the correlations between emotions and anxiety. We then propose and experiment with a pipeline approach (keyword-based filtering + Neural Network models) to classify such tweets as containing or not severe anxiety, relying on a set of features including emotions, obtaining satisfactory results. Our findings, together with other analysis as the monitoring of Google Trends can provide continued surveillance and guide public mental health initiatives to mitigate the psychological toll of COVID-19.

2 Anxiety-COVID19 Dataset

For our study we rely on a subset of the French tweets of the multilingual Twitter COVID-19 Dataset (Chen *et al.*, 2020), a large-scale public Twitter dataset. Such ongoing data collection started in January 2020 by tracking COVID-19-related keywords and accounts [3] in multiple languages.

Data collection and annotation. From the COVID-19 Dataset, we extract only the tweets in French posted from March to May 2020 (2.7 million tweets). As only a very small percentage of tweets is actually written by people expressing severe anxiety, we decided to apply a filtering strategy to narrow down our search space to those tweets in the corpus expressing worries and troubles related to coronavirus. As a first step, a linguist helped us in compiling a list of keywords, i.e., unigrams

2. Since the beginning of the pandemics, Google Trends has revealed a massive uptick in the rise of searches related to anxiety, panic attacks, and treatments for panic attacks `https://www.weforum.org/agenda/2020/09/google-trends-panic-attack-anxiety-self-help-rise-covid`

3. `https://github.com/echen102/COVID-19-TweetIDs`

Formal language	Colloquialism
inquiet, inquietant, inquietude ; stress, stressé, stressant ; anxieux, anxiété ; angoisse, angoissé, angoissant ; terrifié, terrifiant, terrible ; pleure, pleurer ; crier ; hurler ; triste ; tristesse ; pessimiste ; tourmenté ; soucieux, soucis ; craintes, craindre ; malaise ; trouble ; frayeur ; terreur ; peur, peurs ; panique, paniquer ; redouter ; agité ; larmes	*trac ; flipper, flippant ; je suis pas bien, jsuis pas bien, chui pas bien ; c'est chaud, c chaud ; jsuis en pls, chui en pls ; ça craint ; je suis en pls, c'est éclaté, c éclaté, eclate ; c'est claqué, claque ; je suis mort, jsuis mort, chui mort*
EN : worried ; stress, stressed out, stressful ; freaking out ; freaking out, I'm not well ; it's heated ; I am not well ; I am not anxious, anxious ; anguish, distressing ; terrified ; well, not well ; it's heated ; terrifying, terrible ; cry ; yell ; sad ; feel down ; it sucks ; sadness ; pessimistic ; tormented ; worried, worries ; fears, fear ; discomfort ; trouble ; fright ; terror ; I am dead ; afraid ; panic ; restless ; tears	

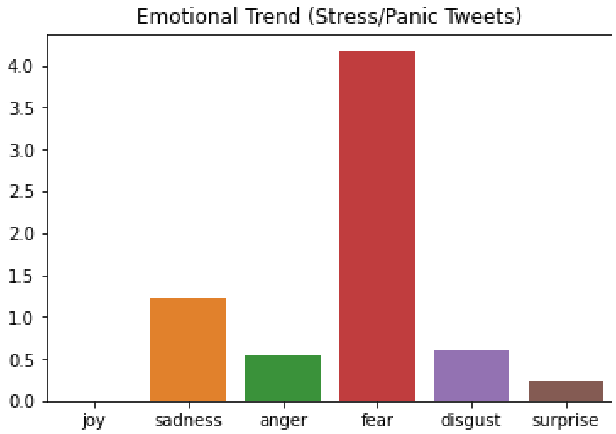
TABLE 1: Examples of panic-related keywords

or n-grams, that frequently occur in messages expressing anxiety or stress, considering both formal language and colloquialism (see Table 1). We then apply a string matching algorithm to extract only the tweets containing one or more of those keywords, reducing the initial dataset to ~33 000 tweets.

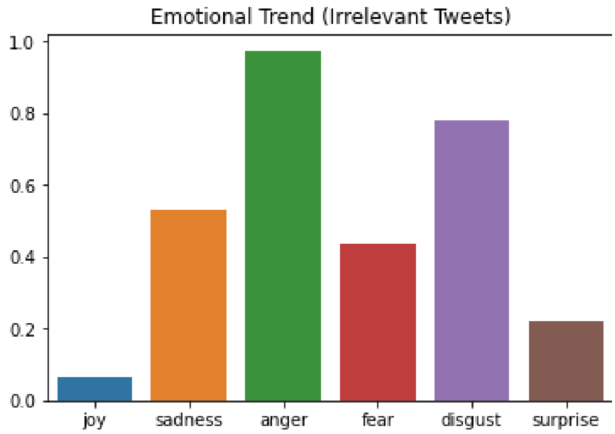
As a pilot study, we carry out an annotation process of a sample of 1032 keyword-filtered tweets, to check how many are actually expressing severe anxiety. To create such sample, we selected ~50 tweets per day starting from the beginning of the lockdown in France in March 2020, till May. We selected this period of time as we aim to study also the correlation between the pandemic evolution and the increase/decrease of messages expressing anxiety about the sanitary situation. Out of the 1032 keyword-filtered and annotated tweets, 114 have been labeled as positive instances of the "anxiety" class (e.g., *"Y'a trop de gens qui je connais qui commencent à mourir du Corona là comment c'est angoissant" (EN : "There are too many people that I know that are dying because of Corona that's frightening")*, *"Le coronavirus il me fait flipper, maintenant tu es enrhumé tu as peur..." (EN : "Coronavirus is driving me crazy now you have a flu and you are scared"))*, while the rest of the tweets is labeled as "non anxiety". In the latter category there are general or factual tweets referring to some news as in *"l'#OMS demande aux personnes de plus de 60 ans et à ceux souffrant d'une maladie respiratoire d'éviter le plus possible de se rendre partout où il y a de la foule." (EN : "The OMS calls on people over 60 and those with respiratory illnesses to avoid traveling to crowded places as much as possible."))*, or tweets containing sarcasm (e.g., *"Maintenant que l'on vas tous mourir du coronavirus mdr il est temps de m'avouer vos sentiments après c'est trop tard" (EN : "Now that all of us will be dying of coronavirus lol I should confess my feelings, after it will be too late"))*. To verify the reliability of our annotation, we calculated the inter-annotator agreement (IAA) on a reserved and previously unseen subset of 100 keyword-filtered tweets, sampled randomly from the collected data. Three raters annotated the data independently, resulting in a Fleiss' kappa of 0.67 (meaning substantial agreement).

Following (Li *et al.*, 2020b), we also annotate the same sample of 1032 keyword-filtered tweets with one (or more) emotion(s) (the 6 basic emotions : joy, sadness, anger, fear, disgust and surprise (Ekman, 1992)), and the emotion intensity (a score between 0 and 5), to investigate the correlations between emotions and severe anxiety.

Labels correlation. We calculated the emotions distribution over the keyword-filtered tweets. The emotions of anger, disgust, sadness and fear are the most intense in the keyword-filtered dataset, while joy and surprise have very little to no presence. Anger and disgust arise for unfavourable opinions about the government decisions, e.g., underestimating the scale of the outbreak. The more active cases and deaths were reported in the news, the more the frequency of panic tweets increased. Sadness generally refers to losses, both in terms of lack of mobility freedom due to lockdown and death tolls.



(a) "Panic" class



(b) "Non panic" class

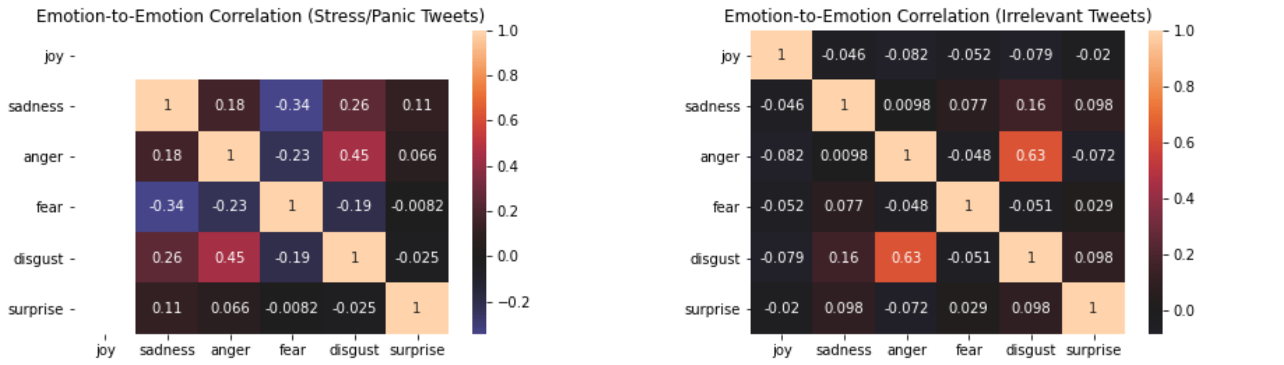
FIGURE 1: Emotions distribution over the keyword-filtered tweets by class

Figures 1a and 1b report on the emotions distribution over the two classes of keyword-filtered tweets. As introduced before, an emotion intensity score ranging from 0 to 5 is provided for the annotated tweets, for each of the 6 basic emotions. Such emotional intensities have been normalized and the average intensity of each emotion is calculated and plotted (Y-axis). Fear is the predominant emotion in the "anxiety" tweets, followed by the other negative emotions and the absence of joy. Anger and disgust dominate the other tweets, followed by sadness. We calculated the emotion-to-emotion correlation using the Pearson correlation coefficient (Figures 2a and 2b). The emotions of anger, disgust and sadness positively correlate to each other, especially due to a person's general feeling of anger or sadness for a particular "disgusting" message or news. The correlation between anger and disgust also seems to occur more in "non anxiety" tweets ; the same positive correlation is found in the "anxiety" tweets coupled with disgust and surprise emotions. Fear has a negative correlation to anger as one overwhelms the other in a given tweet. Moreover, we calculated the correlation between the emotional intensities of a given tweet and the following features : the number of uppercase words, the number of adverbs, the number of unidentified words by the spaCy's PoS Tagger [4], the number of emojis related to each emotion, and the number of retweets. Results on our dataset show that fear positively correlates with the number of emojis expressing it or sadness. Anger is also correlated to the number of adverbs, uppercase words and mentions. Joy, sadness and anger emojis are also present in their respective emotions. As for the tweets expressing anxiety, sadness, anger and disgust positively correlate with a high number of adverbs in the tweet (see Figures 3a and 3b).

3 Classification of intense anxiety messages

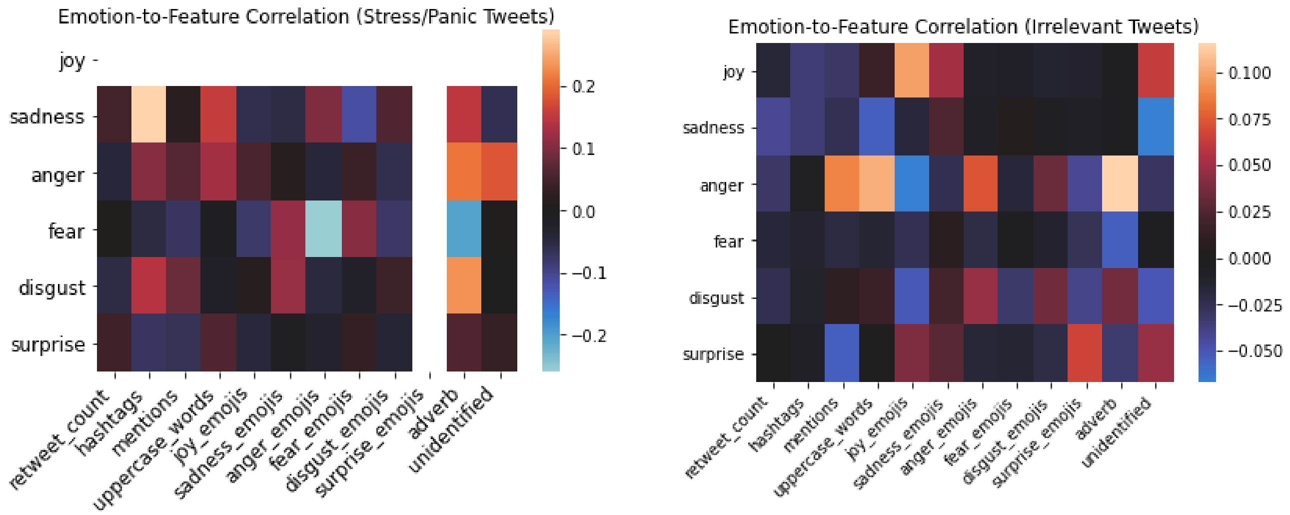
As our goal is to automatically detect messages expressing severe anxiety, we propose a pipeline approach that after employing the filtering mechanisms we described to Twitter messages, applies supervised methods to classify tweets as expressing or not anxiety. We cast this second step as a binary classification task (anxiety tweet / irrelevant), and we experiment over our dataset of 1000 keyword-filtered tweets.

4. https://spacy.io/



(a) "Panic" class (b) "Non panic" class

FIGURE 2: Emotion-to-emotion correlation



(a) "Panic" class (b) "Non panic" class

FIGURE 3: Emotion-to-features correlation

Classification methods. We test the following supervised methods and features :

1. *Bag-of-Words + SVM Classifier*. Baseline method relying on Bag-of-Words, TF-IDF and features from spaCy as input to a Support Vector Machine. Grid Search is performed on the hyperparameters to get the better combination of N-grams, learning rate and loss function.
2. *CamemBERT Embedding + GRU Classifier* : CamemBERT (Martin *et al.*, 2020) is a state-of-the-art language model for French based on the RoBERTa architecture (ready-to-use module in HuggingFace's (Wolf *et al.*, 2020) "transformers" library).
3. *CamemBERT Embedding + CamemBERT Sequence Classifier* : This model uses a RoBERTa classification head consisting of 2 dense Linear NN layers with a dropout rate of 10%. It is the default Sequence Classifier of CamemBERT.
4. *CamemBERT Embedding (w/ Emotional Embedding) + GRU Classifier* : This model is based on the same CamemBERT model described above (point 2), enhanced by emotion intensities (manually annotated) as features. This combination is made in a rather simple manner where instead of returning the output of the previous model, such output gets fed into a final dense layer where it is processed with the 6 emotion intensities of the current tweet batches.

5. *CamemBERT Embedding (w/ Emotional Embedding) + CamemBERT Sequence Classifier* : same CamemBERT model as described in point 3, plus emotional embeddings as in point 4.

Given the small dataset at our disposal, the evaluation is reported over a 10-Fold Cross-validation (train/validation on 80% of the data, the rest for testing). For the last four models, we perform 10-Fold Cross-validation during a 50 epochs training with early stopping. As a preprocessing step, we get rid of mentions and hashtags at the beginning and end of the tweets. For the last 4 models, we use HuggingFace's CamemBERT Tokenizer to encode tweet token ids and attention masks.

Results and error analysis. Table 2 reports on the obtained results for the binary classification task over the keyword-filtered dataset. Even with a small and unbalanced dataset as ours, state-of-the-art deep neural network models such as CamemBERT obtain promising results (avg. F-measure 0.72), outperforming standard approaches like SVMs. Note that those results are obtained over the keyword-filtered dataset, meaning that if on the one side the minority class ("panic") is more represented than in the COVID-19 dataset thanks to the filtering mechanism, still it represents only the 11% of the dataset. Moreover, all the keyword-filtered messages contain similar terms making it pretty challenging to separate an alarm message from a person (e.g., *"Et mais jvais creuver si j'ai le coronavirus deja jcours 2 mètres au foot je suffoque j'ai besoin de ma ventoline" (EN : "If I have coronavirus I will die, already now when I run 2 meters when playing football I suffocate I need my ventoline")*) from a tweet expressing general worries on the sanitary situation (e.g., *"mais stop créer de la fausse panique y'a déja assez de gens qui over-react avec le Coronavirus" ("EN : Stop generating fake panic there are already too many people that overreact with Coronavirus")*). Therefore, including emotion features helps in improving classification performances on the minority class (for both models). We employed gold-standard emotions as features, but we plan to implement an emotion classifier to extract them automatically.

	Precision		**Recall**		**F-measure**	
Models	**Panic**	**Non-Panic**	**Panic**	**Non-Panic**	**Panic**	**Non-Panic**
BOW + SVM	0.40	0.92	0.35	0.93	0.37	0.93
CamemBERT + GRU Classifier	**0.52**	0.94	0.48	**0.95**	0.50	**0.94**
CamemBERT + Sequence Classifier	0.43	0.94	0.52	0.91	0.47	0.93
CamemBERT (w/ Emotional Embedding) + GRU Classifier	0.46	0.94	0.57	0.92	**0.51**	0.93
CamemBERT (w/ Emotional Embedding) + Sequence Classifier	0.39	**0.95**	**0.65**	0.88	0.49	0.91

TABLE 2: Obtained results on the panic messages classification

Concerning the classification errors, for the CamemBERT + GRU Classifier model, tweets such as *"Wallah : Jamais je fais le teste pour le covid en faite :joy_emoji :" (EN : "I will never do the covid test actually :joy_emoji :")* have been annotated as "no anxiety" but predicted otherwise. This may be explained with the model not learning that joy emojis may counter the content of a panic message. Looking to misclassified "anxiety" tweets, tweets like *"J'ai appelé mes parents aujourd'hui. Je suis dépité. [...] Je me suis énervé. Ils n'ont rien compris. Une fois raccroché, j'ai pleurer de colère." (EN : I called my parents today. I'm disappointed. I got angry. They didn't understand anything. When I hung up, I cried in anger.")* are hard for a model with limited anxiety-labeled samples.

Related work. (CALVO *et al.*, 2017; Coppersmith *et al.*, 2018) investigated NLP methods to identify people who may be in need of psychological assistance. (Medford *et al.*, 2020) extract a sample of tweets matching hashtags related to COVID-19 and measure frequency of keywords related to infection prevention practices, vaccination, and racial prejudice. They perform sentiment analysis to identify emotional valence and predominant emotions, and topic modeling to explore discussion topics over time. Similarly, (Xue *et al.*, 2020) and (Sengupta *et al.*, 2020) analyze Twitter messages related to the COVID-19 pandemic, and apply LDA to identify popular unigrams and bigrams, salient topics and themes, and sentiments in tweets. (Li *et al.*, 2020a) train deep models that classify each tweet into 8 emotions, and build the Emotion-Covid19-Tweet dataset. They investigate the reasons that are causing sadness and fear, and study the emotion trend in both keyword and topic level. While we share the same objective, to the best of our knowledge ours is the first study for French that investigates Twitter messages to unveil the impact of COVID-19 in triggering severe anxiety.

4 Conclusions and Future Work

The main contributions of the paper are *i)* a dataset of 1032 tweets in French annotated with the "anxiety" label and six emotions (despite the small size of the minority class, the collected data are representative, as most of the tweets mention or are related to the major factors mentioned by the medical literature to lead to depression and anxiety among people) ; *ii)* a corpus-based analysis of the correlations between panic messages and emotions, and other linguistic features ; *iii)* a pipeline approach (keyword-based filtering + supervised model) to classify tweets containing panic. As future work, we plan to extend the Anxiety-COVID19 dataset, and to test alternative methods to deal with class imbalance. Moreover, we plan to carry out a study on the impact of the pandemic evolution in time with respect to messages expressing intense anxiety.

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