The Anxieties Detection from Tweets about Distance Learning with Negative Sentiments

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Abstract— **The study of the mental health of society and the automatic detection of various types of disorders based on text analysis is one of the priority areas of e-health. The empirical investigation of the various anxieties and their causes in the pandemic period connecting with distance learning introduction based on an analysis of 71475 tweets is performed in the paper. The analysis of hashtags of tweets with negative sentiment and proposed patterns based on part of speech recognition allows us to extract regularities that describe sensations and causes of emotions associated with the appearance of the affective state. We created a dictionary of terms describing affective states based on the most frequent words with negative sentiment. Particular attention was paid to feature engineering using positive words from positive tweets and negative words from negative tweets, taking into account parts of speech. The proposed approach to feature engineering made it possible to reduce the dimension of the feature space while maintaining the quality of the classification (84%).**

Keywords—**mental health, POS-tagging, random forest, sentiment analysis, TF-IDF**

I. INTRODUCTION

The forced transition to distance learning during the COVID-19 pandemic gave rise to new challenges for studying the media data, in particular, students' feedback on the quality of teaching, used distance technologies, and studying the impact of students' feedback on the reputation formation of the teachers and Universities [1]. There are many investigations that are aimed at the extraction of the social average opinion and moods from comments on social media platforms. The most studied social media platform is Twitter where people in short messages called tweets can express their feelings, emotions, and relationship to events in their own lives and society. The limited number of characters in messages gave birth to a special manner of communication expressed in emoticons, abbreviations, scraps of words, words with grammatical errors, slang, etc. [2]. These peculiar properties of tweets require special methods of text preprocessing, vectorization, and recognition. Natural Language Processing (NLP) methods together with machine learning opened new perspectives for social media data mining and some success was achieved. For example, opinion mining of political leaders based on sentiment analysis with extraction of the most influenced words on sentiments and entities [3]; the learning of social moods and dynamics of opinions changing about vaccination and COVID-19 vaccines with the extraction of frequency words, n-grams [4] and topics detection with extraction such interesting regularities from tweets as the trust prevailed over negative emotions associated with fear, anticipation, etc [5]; the investigation of dependencies between tweets (quantity, polarity) and prices of cryptocurrencies [6]; the detection and understanding of toxic behavior of users through tweets analysis [7]; considering the tweets as data for the development of recommendation systems with personalized propositions for users [8]. So, tweets are a powerful resource for understanding society's relationship to different social events and a platform for tools development that are aimed at managing people's opinions, for example, through liars and fakes. The scholars used extraction of parts of speech, frequencies of words, most influenced opinion words, and the different levels of sentiment analysis detailed sentiments by words, sentences, documents, and features for tweets investigation [9].

Analyzing the students' feedback based on tweets and sentiment analysis techniques using the lexicon-based approaches is the most investigated direction in educational data mining. The mining of tweets allows for characterizing the quality of education. Oyekunle and Abdulkareem revealed the students' dissatisfaction with CDT exams and the causes of their negative emotions such as high-level stress, feeling of unwellness, waiting time for results, presence of queues, and people who made it difficult to concentrate [10]. Such regularities extracted from tweets can be used for exams organization improvement next time and developing strategies to reduce stressing states of students. Clustering of students' opinions and their causes can be aimed at detecting target groups with personalized methods of psychological assistance and training. The grouping of students' tweets based on vectorization (n-grams, BOW) and clustering methods (k-Means, Brown clustering algorithm) are considered in [11], [12].

Special interests of social media mining are the understanding of students' problems during learning in universities or colleges such as adaptation problems, the causes of stress, and anxieties. Chen et al. proposed the methodology for mining tweets for students problems detection such as learning difficulties and high academic workload, lack of sleep, social adaptation, etc, and used the Naive Bayes algorithm for effective classification of students' problems [13]. Mujahid et al. investigated the tweets about online learning during Covid-19 with the help of sentiment analysis based on TextBlob, VADER, and SentiWordNet, classification by sentiments based on such vectorization of tweets as BoW, TF-IDF, and classification techniques such as random forest, SVM, AdaBoost, different deep learning models and SMOTE algorithm usage for solving the problem with unbalanced data. LSA usage allowed us to understand the causes of students' and parents' dissatisfaction with online education during Covid-19. Primarily, it was technical problems connecting with networks and the perception of online classes as boring [14]. The tendencies of the positive relationship between pupils and negative relationship between students from universities to distance learning during Covid-19 were demonstrated in [15]. Authors used unigrams and TF-IDF for tweets vector representation and logistic regression for the classification of Arabic tweets by sentiments and achieved 89.9 % of accuracy. The investigation of tweets about distance learning and their distribution in countries by sentiments based on TF-IDF and TextBlob is presented in [16]. The extraction of the different behavioral patterns of students according to their roles in the Twitter community through their activities is considered in [17].

The research of tweets in the education field contains many open questions that are required a comprehensive study. For example, how to extract and evaluate the fear and anxieties of students, how to define criteria for evaluation of the quality of education technologies usage, teachers' competencies, and universities status based on tweets, and how to extract advantages and disadvantages of distance learning and different teaching techniques with the help of tweets, how to evaluate the involvement of students in the learning process and factors that are most influenced on involvement and academic performance.

The goal of the paper is the extraction of regularities connecting with anxieties, worries, stresses, and their causes etc based on tweets analysis during the pandemic period when distance learning was introduced.

II. RELATED WORKS

Nowadays, the most investigated are the sentiment analysis of tweets, especially, the sentiments of tweets about Covid-19 and the vaccine relationship. The preprocessing stage includes cleaning up tweets from messages by bots, removing noisy data and insignificant words, punctuation, etc, and usage of Porter stemming for stems extraction, the extraction of patterns from tweets based on association rule, and understanding of emotions of tweets about Covid-19 with the help of NRC are described in [18]. The choice of the feature set is very important for the solving of classification problem by sentiments. There are many approaches for feature set construction for tweets classification and clustering. Chikersal et al. used a feature set based on TF-IDF for N-grams, frequencies of part of speech contained in tweets, and the usage of different emotion lexicon calculations (Sentiment140 Lexicon, Bing Liu Lexicon, NRC Lexicon, SentiWordNet, etc), and classification algorithm such as SVM together with rule-based approach [19]. The effectiveness of BERT deep model usage with self-attention and transformers architecture together with a fully connected layer for decision making about sentiments of tweets is described in [20].

A. The Tweets Classification by Sentiments with Deep Learning

For deep learning leveraging to classify tweets by emotion classes, researchers use various pre-trained models for word embedding and emoticons processing. The analysis of emoticons and emojis can provide additional insight into the emotional inflection of tweets. Wolny described main types of emoticons that were used typically in tweets and matched them to emotion words [21]. Khalil et al. performed the investigation of Arabic dialects in tweets and handling of emoticons with manually created lexicons, special stemming algorithm ARLSTEM, BiLSTM architecture with 3 BiLSTM layers and 3 Dropout layers between them with Relu activation function and final Dense layer with sigmoid activation function for detection of probabilities of 11 classes of emotions classes and achieved 61.5% (micro F1). Tam et al. [23] used word2vec embeddings and hybrid architecture of neural network such as ConvBiLSTM: CNN layer with Relu activation function, Max-pooling layer, BiLSTM layer, Dense layer with sigmoid activation function and achieved 91.82% (F1). Mujahid et al. [14] used sentiments evaluation based on TextBlob, VADER, SentiWordNet, and SMOTE technique for tweets sentiments balancing, realized CNN with embedding layer, Conv1D, MaxPooling1D, Flatten, Dense layers and softmax activation function, LSTM-CNN with embedding, Conv1D, MaxPooling1D, LSTM and Dense layer with softmax activation function, LSTM with embedding, dropout, LSTM and Denses layers with softmax activation function, Bi-LSTM with embedding, Dropout, Bidirectional, Dense, Dropout and Dense layer with softmax activation function for decision making and achieved 94% (accuracy) and 93% (F1). Das S. and Kolya A.K. [24] performed the analysis of sentiments of unigrams, bigrams, trigrams, word2vec embeddings, and sequential LSTM architecture and achieved 58.5% (F1). Situla et al. [25] constructed the domain-specific feature sets, FastText, ensemble of Convolutional Neural Networks and achieved 84.46% (validation accuracy).

B. The Web-services for Tweets Analysis

We used the visualizing of the Twitter sentiment tool from Healey and Ramaswamy and extracted 246 tweets with the keyword "distance learning" from 23 October 2021 to 25 October 2021 [26]. The results of automated analysis of tweets such as the distribution of tweets according to Russell's model of emotional states and tag clouds connected with distance learning in such a period of time are presented in Figure 1 and Figure 2 respectively.

Such web tool allows us to analyze emotions from tweets based on their sentiments according to Russell's model of emotions, consider the cluster of topics and tag clouds, evaluate the frequencies of tweets with the help of heatmap, and investigate the location of authors of tweets and their activities. Each tweet is represented as a circle with such characteristics as color, brightness, size, and transparency that are meant pleasure of tweets (more pleasant tweets are represented with the help of warm colors such as green and its shades, the presentation of unpleasant tweets is presented with blue color and its shades), reliable and confidence of tweet.

Rusell's model of emotions includes a big circle with 8 sectors: from aroused to excited (or synonymously as in our research we consider emotions from active to excited), from excited to pleased (from excited to pleasant), from pleased to relaxed (from pleasant to relaxed), from relaxed to sleepy (from relaxed to subdued), from sleepy to de- pressed (subdued to depressed), from depressed to miserable (from depressed to unpleasant), from miserable to distressed (from unpleasant to stressed), from distressed to aroused (from stressed to active). As you can see from Figure 1 most part of the tweets with high confidence are located in the pleasant-subdued sector and describe such emotions as pleasant, contented, serene, relaxed, calm, and subdued. Cloud of words from tweets in Figure 2 demonstrated the satisfaction of distance learning support and free access to learning resources.

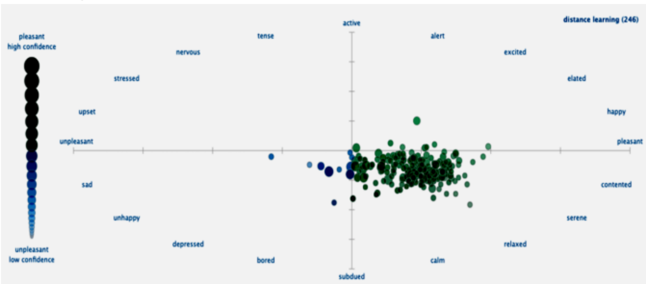

Figure 1. Tweets analysis according to Rusell's model of emotional states

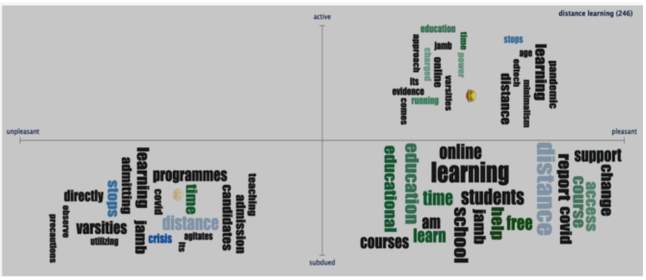

Figure 2. Tag clouds based on tweets

Unfortunately, such web-service don't allow us to extract the regularities connection with the mental health of students.

III. DATASET AND METHODOLOGY

A. Dataset Description

We used a dataset with 187052 unique tweets about distance learning during Covid-19 from Kaggle platform sharing with license CC0: Public Domain [27] and extracted from it the balanced data with 2 types of sentiments (positive, and negative) based on the VADER lexicon-based approach corrected manually. So, we extracted 37950 positive tweets, and 33525 negative tweets for our research.

The fundamental paper for our research was [28]. Baris Hasdemir scrapped tweets and performed sentiment analysis of tweets about distance learning based on lexicon-based TextBlob. He noted the prevalence of tweets with positive sentiments, and also extracted the adjective for the description of tweets about distance learning with negative sentiments such as boring, terrible, horrible, etc. The classification of tweets by sentiments was performed with the help of Bernoulli Naive Bayes with the best accuracy of 83.21 %.

B. Methodology of Research

At first, we labeled tweets as positive and negative using VADER lexicon-based algorithm based on compound score value [29]. The analysis of tweets include the following steps: 1) the hashtag extraction from tweets with negative sentiments based on regular expressions; 2) the extraction of nouns, adjectives, and verbs with negative sentiment from tweets and word clouds construction based on the most frequent of them; 3) the construction of the dictionary of the words with the most negative sentiment taking into account their frequencies; 4) the construction of the patterns based on part of speech for extraction the description and causes of affective states; 5) the feature engineering based on the most positive and negative words of various part of speech from the most positive and negative tweets (the feature sets based on the most frequent positive and negative nouns, adjectives, verbs from positive and negative tweets respectively); 6) the vectorization of tweets based on TF-IDF with the help of different custom vocabularies constructed based on proposed feature engineering, where TF-IDF is computed as

$$TF-IDF = TF_d^i * \log(N/DF^i),$$

where TF_d^i is the number of times term i occurred in tweet d, N is the total number of tweets in corpus, DF^i is the number of tweets in which term i occurred [30]; 7) the random forest construction for classification tweets by sentiments; 8) the comparison the results of the approaches for feature engineering for classification tweets by sentiments based on Accuracy, Recall, Precision and F1-score [31]:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 - score = 2\frac{Precision * Recall}{Precision + Recall},$$

where TP, TN – number of true positive and true negative values respectively, FP, FN – number of false positive and false negative values respectively.

IV. EXPERIMENTS AND RESULTS

Sentiment analysis of students' feedback is a very important direction in learning analytics as it is connected with the detection of students' negative emotions and anxieties that have a strong influence on students' engagements and forming of their relationships with disciplines, teachers, and universities, etc.

A. The most frequent hashtags from Negative Tweets

We used VADER lexicon-based approach to detect tweets with negative sentiments. The most frequent hashtags from distance learning tweets with negative sentiments after stopwords removing are presented in Figure 3. The most frequent hashtags from tweets with negative sentiments connected with questions about pay, essay, homework and assignment, and problems with biology, maths, statistics, chemistry, and calculus.

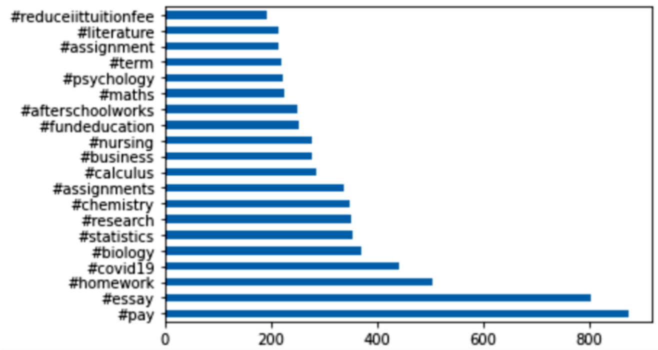

Figure 3. The most frequent hashtags from negative tweets about distance learning

B. The Analysis of Negative Words from Tweets with Negative Sentiments

We elicited the negative words from 33525 negative tweets with the help of part of speech recognition using spacy and word cloud python-libraries as shown in Figure 4.

Figure 4. The clouds of the most negative nouns, adjectives, verbs

The most frequently negative words connecting with various affective states such as nouns danger, anxiety, crisis, hate, worry, defeat, stress, woe, fear, fault, accusation, offense, harm, disgust; adjectives hellish, disastrous, dead, awful, fearful, stressful, eerie and verbs hate, offend, defeat, suffer, complain, threat, kill, condemn, etc. were used for the creation of dictionary with this kind of words.

C. The Patterns Construction based on POS-tagging for Extraction the Description and Causes of Anxieties

We constructed the patterns with the help of part of speech recognition. The pattern based on the investigation of the left and right surroundings of the target word "anxiety" is presented in Figure 5.

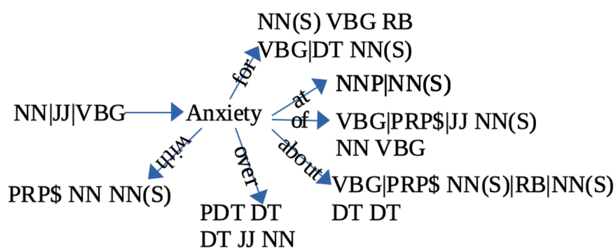

Figure 5. The patterns based on part of speech recognition for target word "anxiety"

For example, the pattern noun NN(S) + gerund or present participle (VBG) + adverb (RB) or the pattern gerund or present participle (VBG) or determiner (DT) + noun (NN) allow us get anxieties causes connecting with the kids staying home or coming school in pandemic period or problems with some students.

The similar patterns were generated for target words "fear" and "worry" presented in Table 1.

Table 1. The extracted descriptions and causes of the mental disorders connected with distance learning

The target word	The number of tweets	The description of target word	The causes of of target word
anxiety	177	awful, social, parental, storm, major, zoom, crippling, real, overcome, constant, debilitating, extreme experiencing	for kids staying home/coming school/ some students, at bay/ thought, of my kid/life changing/digital connection/ engaging their kids, about this all/weighing our schooling/being in online, teaching in person/my fall class, distance learning, over all this/this stupid online, with our new workshop
fear	167	teachers, nagging, big(est), constant, learning, crippling	of death/immigration/ young child/ infection/ being hurt / contagion/ being judged/disease/ corona virus (covid-19)/ intrusion, in anxious educators/ all this/ speaking up, for adverse effect
worry	185	parents, experts, some	about distance learning/ quality/ domestic violence / virtual learning/ mana-ging decision/ your child / their mental health / losing kid / online education / hateful self / internet costs / conflicting schedules / teaching online/ writing notes / my friends

As shown in Table 1, people describe anxiety as awful, debilitating, social, extreme and connecting with kids engaging and staying at home, the changing of their life, being online/distance learning. They describe fear as nagging, crippling, constant, and fear of teachers. Their states are caused by fear of death, infection, contagion, being judged, and dealing with anxious teachers. We extracted the parents' and experts' worry about connecting with distance or virtual learning, domestic violence, internet costs, problems with mental health, schedules, communication with friends and writing notes in online mode.

D. The Classification of Tweets about Distance Learning

For the classification of 71475 tweets about distance learning by positive and negative sentiments, we used different approaches for feature engineering. We realized vectorization of tweets based on TF-IDF with different vocabularies such as all words (vocabulary contains 41376 feature names (words)), positive nouns among positive tweets with negative nouns among negative tweets (nouns based sentiment vocabulary (sentiment_nouns) with 1766 words), positive adjectives among positive tweets with negative adjectives among negative tweets (adjectives based sentiment vocabulary (sentiment_adjs) with 636 words) positive verbs among positive tweets with negative verbs among negative tweets (verbs based sentiment vocabulary (sentiment_verbs) with 791 words) and random forest was used for classification by sentiments.

Table 2. The average score of classification metrics for 10-fold cross validation

Approach	Accuracy	Recall	Precision	F1
TF-IDF+RF	0.84±0.01	0.72±0.03	0.91±0.01	0.80±0.01
TF-IDF (vocabulary = sentiment_nouns)+RF	0.84±0.01	0.74±0.02	0.90±0.01	0.81±0.01
TF-IDF (vocabulary = sentiment_adjs)+RF	0.82±0.01	0.71±0.02	0.87±0.01	0.78±0.01
TF-IDF (vocabulary = sentiment_verbs)+RF	0.82±0.01	0.73±0.02	0.87±0.01	0.79±0.01

As can be seen from the Table 2, the use of words, taking into account sentiment and parts of speech, can significantly reduce the dimension of the feature space with a slight change in the quality (accuracy, recall precision, f1-score) of the classification, which is extremely important when classifying big data.

V. CONCLUSION

Sentiment analysis is a very important direction in data analysis. It allows extracting polarities from social media data and a better understanding of the mood of society and individuals. Sentiment analysis in education opens perspectives in the field of the students' emotions understanding that are connected with their engagement in the learning process and academic performance. We considered tweets with negative sentiments about distance learning and found the absence of sharply negative emotions. The anxieties were connected with homework, zoom usage, increased payment to people who can help with assignments on exact sciences, fear of infection and death, worrying about domestic violence, internet costs, and problems with mental health.

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