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Research Article

Covid19 Sürecinde Çevrimiçi Eğitim Hakkındaki Toplum Görüşlerinin İncelenmesi: Sentiment Analizi

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Öz

Dünya Sağlık Örgütü'nün (WHO) Mart 2020'de Covid19 salgınını ilan etmesiyle başlayan pandemi süreci, pek çok sektörü olduğu gibi eğitim sektörünü de benzeri görülmemiş bir şekilde etkiledi. Covid19 nedeniyle yaşanan karantina döneminde insanlar duygularını ifade etmek ve kendilerini sakinleştirmenin bir yolunu bulmak için sosyal ağları her zamankinden daha fazla kullandılar. Günümüzde sosyal medya platformları insanların günlük yaşamları için ve politika gündemini belirlemede büyük önem taşımaktadır (Wu ve diğerleri, 2013). Özellikle pandemi dönemi ile birlikte çevrimiçi öğrenmenin artan yaygınlığı ve çevrimiçi öğrenme ile ilgili düzenli olarak sosyal medyada yer alan çok sayıda haber dikkate alındığında, Covid19 Salgını sırasında halkın çevrimiçi eğitime ilişkin görüşlerini öğrenmek için sosyal medya veri kaynaklarını kullanarak duygu analizi yöntemi kullanılmıştır. Veri kaynağı olarak Twitter seçilmiş ve Tweepy kütüphanesi kullanılarak metin madenciliği yapılmıştır. Koronavirüs ve uzaktan eğitimle ilgili gerekli hashtag'ler kullanılarak yalnızca İngilizce tweet'ler veri setinde yer almıştır. Toplanan veriler 03-05-2021 ile 31-05-2021 tarihleri arasındaki 5 haftaya aittir. Duygu analizi sonuçları ile toplumun çevrimiçi öğrenme konusundaki memnuniyetsizliği, beğenisi ve kaygıları yönetim tarafından hızlı bir şekilde öğrenilebilmesi ve eğitim ve öğretim hizmetlerinin kalitesinin artırılmasına yönelik stratejiler geliştirilmesi mümkündür. Bu çalışmada , yapılan duygu analizi sonuçları paylaşılmıştır.

Anahtar Kelimeler: covid-19, duygu analizi, çevrimiçi eğitim, sentiment analizi

Examining Public Opinion Regarding Online Learning during Covid19 Outbreak: Sentiment Analysis

Abstract

The pandemic process, which started with the World Health Organization (WHO) declaring a Covid19 epidemic in March 2020, has affected the education sector in an unprecedented way, as it has many other sectors (World Health Organization, 2020). During the quarantine period due to Covid19, people have used social networks more than ever to express their feelings and find a way to calm themselves. Today, social media platforms are of great importance for their daily lives and in setting policy agenda (Wu et all, 2013). Considering the increasing prevalence of online learning and a large number of items that regularly appear about online learning on social media, especially with the pandemic period, sentiment analysis was used as a method to learn the opinions of the public on online education during Covid19 Outbreak. Twitter has been chosen as a data source and text mining has been conducted using Tweepy library. Only English tweets were mined using necessary hashtags related to coronavirus and distance learning. The collected data is 5 weeks from 03-05-2021 to 31-05-2021. With the results of sentiment analysis, it is possible to quickly learn the dissatisfaction, appreciation and concerns of the society about online learning by the management and to develop strategies to increase the quality of education and training services. In this study, the results of the sentiment analysis are provided.

Keywords: covid-19; sentiment analysis; online learning; emotion analysis

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1. Introduction

At the end of 2019, a deadly virus started to terrorize the whole world and forced countries to lockdown. This virus was later defined by the WHO (World Health Organization) as COVID-19. This new infectious disease spreads so quickly. As of today, confirmed coronavirus cases have reached 219 million with more than 4.5 million deaths. Governments across the world have applied interventions such as face masks, contact tracking, social distancing and quarantine in order to reduce the transmission of COVID-19. Education is one of the elements that suffered from this global pandemic. Especially during the quarantine period, almost all of the educational institutions were able to continue their learning and teaching activities by using online education platforms.

Today, social media platforms are of great importance for their daily lives and in setting policy agenda (Wu et all, 2013). Many individuals and media organizations take social media to express their opinions and feelings about a specific topic (Medhat et all, 2014). Considering the increasing prevalence of online learning and a large number of items that regularly appear about online learning on social media, especially with the pandemic period, sentiment analysis was used as a method to learn the opinions of the public on online education during the pandemic process. Using sentiment analysis on social media like Twitter has proven to provide supportive information for decision making and useful tools for measuring public perception[(Chamlertwat ,2012).

Sentiment analysis can be used to detect patterns in an unstructured text domain such as tweets. Sentiment Analysis (Opining mining) is a text mining method. It uses a natural language processing technique to define the polarity in texts as negative, positive or neutral toward the subject (Nasukawa and Yi, 2003) or or feelings and emotions (angry, happy, sad, etc) of the sentiments (Medhat et all, 2014).

In the literature, many research have used semantic analysis in Covid19. For example, Manguri and his colleagues (2020) has been conducted an analysis to determine the reactions of people about the coronavirus vaccine. They analyzed 500,000 tweets between April 4 and April 15 in 2020. As a result of the research, it shows that 50% of the tweets are neutral about the coronavirus, 36% are positive tweets and 14% are negative.

Dubey (2020) used also sentiment analysis in his research. He examined the subjectivity and polarity of the tweets across various countries. He analysed how the citizens of different countries are dealing with the situation. This analysis has covered 12 countries mainly in Europe and makes a comparison of sentiment between countries. It has included tweeter data between 11-03-2021 and 31-03-2021. As a result of this research, four states especially from the Europe tweeted more than 50% negative and angry, while other countries tweeted more than 50% positive.

In the sentiment analysis made by Drias and his colleague (2020), a data set of 653,996 tweets was used between 23-02-2020 and 03-03-2020. The most frequent patterns were extracted with the aim to grasp social features about the tweets. As a result of this research, negative tweets are more than the positive tweets. And negative tweets contain mostly fear as emotion.

In another sentiment analysis [7], the goal was to analyse tweets containing Canadian-specific social distancing. The tweets included 40% neutral and 35% negative emotions. There are 629 tweets expressing positive emotions to the social format.

In the literature, it is seen that all sentiment analysis studies related to Covid 19 generally reflect the views of the public on covid19. No study is specific to the public's opinions on e-learning during the covid19 outbreak. This study aimed to analyse and understand public opinion around the use and effectiveness of e-learning, as reported in social media from 3 May 2021 to 31 May 2021. This study presents a unique approach to understand public perceptions about online learning during the pandemic.

2. Methodology

Research Design

To analyse the people's opinions, sentiment analysis was conducted in three steps. The first step involved the collection of data from tweeter. Second, the collected data were refined for applying the sentiment analysis. Finally, the refined data were analysed with the three different sentiment analysis techniques which gives information about the polarity, subjectivity and emotion of the tweets. The two most important metrics of sentiment analysis can be defined as polarity and subjectivity. Polarity is a parameter that shows a person's emotional intensity or strength. The relevant behaviour analysis is made from the text that the person has created. On the other hand, with the subjectivity metric, information can be obtained about a person's view on a certain subject. For the polarity analysis, Logistic Regression machine learning model was used with a train dataset which has tweets and their correct polarities. This model returns 1 or 0 only. 1 means positive polarity and 0 means negative polarity. On the other hand, for subjectivity analysis, TextBlob was employed (http://textblob.readthedocs.org/en/dev/) (accessed on 16 August 2021), a framework developed by Loria (Loria, 2018) which has been widely used by the researchers (Onyenwe et all, 2020; Yaqub, 2018) to conduct SA. Subjectivity classifies a text as a fact or opinion. It is an open-source python library which is mostly used for the analysis of textual data. It returns three values (ranges between 0 and +1) here 0 indicates very objective, and +1 indicates very subjective (Yaqub et al., 2018). In order to show emotion in tweets, Logistic regression was used as an emotion classifier. From the experimental results in the literature, it is observed that Logistic Regression has better accuracy compared to the other classifiers (Altawaier & Tiun, 2016). Logistic Regression receives data from the ISEAR(International Survey on Emotion Antecedents and Reactions) emotion dataset, and then emotion classification is performed by applying Logistic Regression classifier. Emotion analysis is similar to polarity analysis because it also uses Logistic Regression machine learning algorithm but uses a different train dataset with texts and their correct emotions in next column such as "anger".

Dataset

Twitter data set was used in this study because it contains a considerable number of personal thoughts with public access (Pak & Paroubek, 2010). It is valuable source to know people's opinions and sentiments towards a variety of topic (Persada et all, 2020). For this study, 33.722 tweets was collected related to online education. In order to extract data from Twitter, Tweepy's python library and the official API which Twitter provided have been used. Tweepy library allows developers to find and gather tweets using some keywords or hashtags and lets developers filter them by date. Since this study is about education and elearning during COVID-19 lockdowns, hashtags such as #covid, #covid19, #distancelearning, #elearning and #education have been used in the data search. Twitter used to allow developers to get datas from years ago but they updated their privacy policies and only a week old data is available. For this reason, related data was retrieved weekly starting from 03-05-2021 to 31-05-2021. (See Table 1)

Table 1. Twitter Data about Covid19 during Five Week

DATE	# of tweets for covid19 AND distancelearning keyword	# of tweets for covid AND education keyword	# of tweets for covid AND elearning keyword	Subtotal Tweets
03.05.2021	49	456	145	650
10.05.2021	47	7560	103	7710
17.05.2021	40	8789	124	8953
24.05.2021	40	11749	111	11900
31.05.2021	17	4369	123	4509
Total Tweets				**33722**

Pre-processing Data

Data pre-processing is a crucial step for sentiment analysis this is to increase accuracy and to reduce error in the data (Nhlabano & Lutu, 2018; Krouska, et all, 2016; Pecar et all, 2018). It involves four steps which are cleaning, normalization, tokenization, and stop word removal. Lots of tweets have unnecessary words, punctuations and writing mistakes. These affect the accuracy of machine learning models and the results of the study as well.

The pre-processing step was started with cleaning step by removing duplicated tweets, unrelated links, URLs, advertisements, and news from the dataset using regular expression. Then, normalization step was applied to the dataset to convert all text to the lower-case characters, eliminating punctuations, converting numbers to words (see Figure 1). In this step of pre-processing, a function named “decontracted” has been created. This function takes each tweet and replaces the shortened negative words with longer versions. As an example, if a tweet with the word “won’t” enters this function, it will be returned as “will not”.

After those previous steps, tokenization step has been applied. Tokenization is splitting each word in a text into smaller units called tokens. After tokenization process, English stop words were removed since they have no importance for our model using this variable. Also, during tokenization process, numbers have been removed from data set as well since they don’t affect the polarity. Finally the stemming process has started. Stem is the part of a word which is stripped from its affixes, also called lemma. NLTK’s Snowball Stemmer algorithm has been used for this process which is the best stemmer algorithm when compared to others (Bounabi et all, 2019)

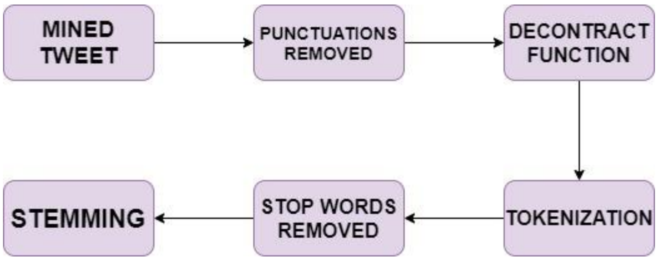

Figure 1. Pre-processing Steps

Polarity Analysis with Logistic Regression

The machine learning part of the algorithm has been handled with the help of Scikit-Learn library.This library offers efficient tools for predictive data analysis.

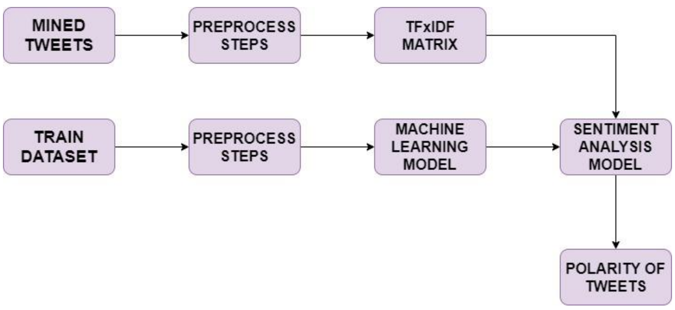

Figure 2. Sentiment Model

In order to make a sentiment analysis program, a prediction model is needed. To create this model, a sample train dataset is needed. 18,000 tweets were downloaded with correct polarities next to them. Many other train datasets were tested and took the one that gives the highest logistic regression model accuracy rate. After testing the accuracy of the model by using “accuracy_score()” function of Scikit-Learn library, the value 88.36% has been found. This accuracy was found high enough to keep the train dataset.

Same preprocessing steps have been applied the train dataset and then sent to the prediction model for training and testing. TFxIDF function has been created to get scores for each different word according to their frequency using TfidfVectorizer function. Preprocessed mined twitter dataset was sent to the TFxIDF function. The frequency scores for each word has been returned. These transformed tweets has been sent to prediction model function. If the prediction model returns 1, the polarity is positive, otherwise it is negative.

3. Results

Results of the Sentiment Analysis with Logistic Regression

In this study, Figure 3 demonstrates sentiment polarity over Twitter for 5 consecutive weeks starting in 5th May 2021. In the total number of collected tweets, it can be seen that negative tweets are twice the amount of positive tweets. In 33,723 tweets, 11,784 are positive while 21,939 are negative (See Figure 3). Overall, more than 35% of people published optimistic views, while only around 65% of the tweets were negative. This result isn’t surprising when we consider that Covid-19 is a deadly virus and distance education isn’t as efficient as face to face education.

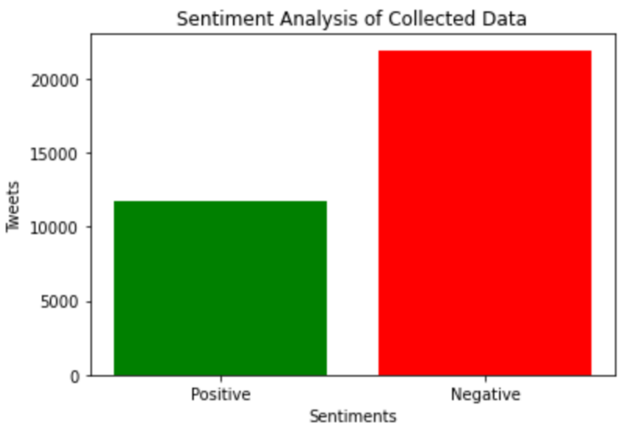

Figure 3. *Sentiment Polarity*

These tweets are also divided into dates (See Figure 4). The data collection program has been executed every 7 days for 5 weeks. In first week of May (03.05.21), 651 total tweets have been fetched. 33% of people (216 tweets) are positive while 67% (435) are negative. Last week of the figures (31.05.2021), shows 37% of tweets positive and 43% of it were negative. The figures of different weeks are relatively similar. Therefore, there is no significant sharp fluctuation in the weeks. Finally, including a large quantity of negative tweets indicates that most of the corpus were facts rather than opinion. Therefore, the next part focuses on subjectivity of the data in detail.

Subjectivity Analysis with TextBlob

In means of the perspective of tweeters, there are subjective, objective and neutral viewpoints. Subjective means that the tweet contains lots of personal opinions of the person who posted it. Objective means that the tweet contains only factual data and no personal opinions nor comments. Neutral means that tweet might include both equally or neither. According to the TextBlob algorithm, 53.6% of the tweets were categorized as objective tweets and only 15.9% were categorized as subjective tweets. These results mean that the twitter users in the dataset mostly shared factual tweets about Covid-19 and distance education.

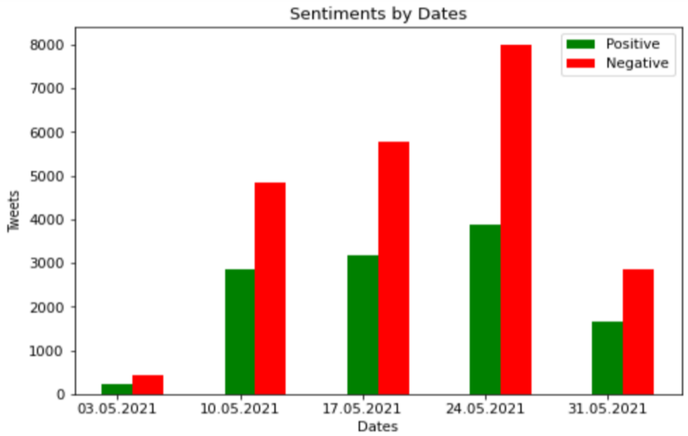

Figure 4. Sentiments by Dates

Table 2. Subjectivity Table

SUBJECTIVITY	***TWEETS***
Subjective	5376
Neutral	10278
Objective	18069

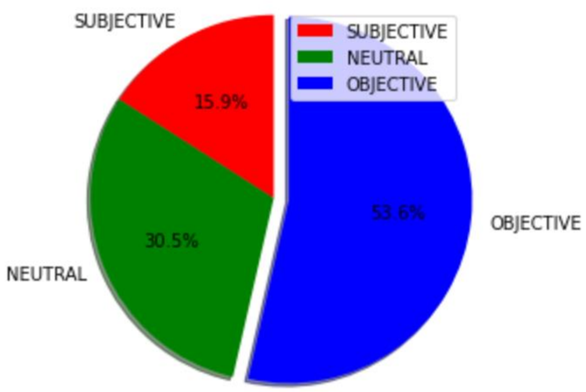

Figure 5. Pie Chart of Subjectivity

Emotion Analysis with Logistic Regression

In the Emotion Analysis with Logistic Regression part, a training dataset was used. Logistic Regression model was trained with this dataset containing 9 basic emotions (sadness, fear, joy, anger, surprise, neutral, love, disgust, shame) tagged to sentences. The aim was to be able to see, check what people feel about e-learning during Covid-19 pandemic process and if we were able to predict their emotions by their tweets. Our Logistic Regression Model performed much better than other classifiers with a score of %72.95. Analysis included two steps which were Cleaning & Balancing Data and Training Model.

Step 1 – Cleaning & Balancing Data

At first, training dataset were over fitting with a certain emotion, which created unwanted results, to prevent this more data was added to other emotions while removing some from the over fitted one. After mostly balanced dataset were acquired, it was started to clean it from its noise (stop words, symbols, repeating words) with NeatText NLP library.

Step 2 – Training Model

It is created a Data Pipeline with ScikitLearn Library, which first creates a matrix of token counts and later fit them to Logistic Regression Model.

Results of the Emotion Analysis with Logistic Regression

The purpose of emotion analysis is to identify the emotional state of public about eLearning during pandemic. As shown in the Figure 6, the majority of the reactions, nearly 26%, toward this health problem were anger.

Table 3. Number of Emotions

EMOTIONS	TWEETS	%
Anger	8775	26.02
Fear	8265	24.51
Neutral	5293	15.70
Joy	4006	11.88
Sadness	3947	11.70
Surprise	2505	7.43
Disgust	888	2.63
Love	36	0.11
Shame	7	0.02

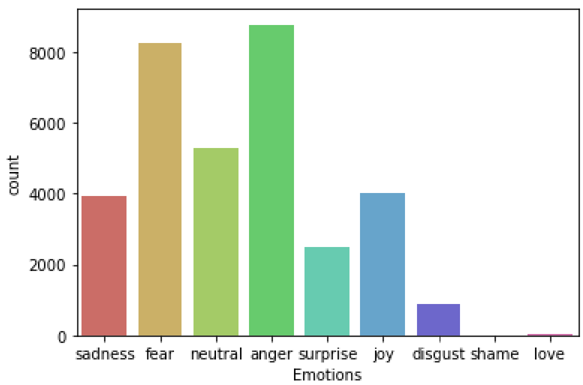

Figure 6 Graph of Emotions

Here, it can be seen the “Anger” emotion has the most tweet count followed by “Fear” and the “Shame” emotion has the least. These results are not surprising at all. It is so natural for people to feel anger and fear against this deadly virus and how it affects the education. This model has 2.95% accuracy rating while TextBlob has only 56%.

Here are some sentences gathered from Twitter and categorized by our machine learning model.

Anger:

“Teachers don’t get paid enough; not all our schools have adequate ventilation; and in the midst of an ongoing pandemic we cut funding for so we cannot offer any either”

Sadness:

“Covid-19 means that the many children living in conflict right now are doubly at risk of missing out on an education will you support to help all kids”

Joy:

“As state universities plan to return to 'pre-covid operations' Florida State University eliminates mask requirement indoors”

Neutral:

“Expert says vaccinating children for covid-19 key for schools this fall”

Disgust:

“its not acceptable that we have a two-tier education system where white kids go to school in person disproportionately and students of colour disproportionately go to school online”

Fear:

“covid brought in additional problems not replaced the existing ones one such is child labour witnesses million child labourers worldwide”

4. Discussion and Conclusion

In this article, it was tried to understand the public opinions towards online learning on Twitter during the pandemic process by using Logistic regression with the TextBlob algorithm. The architecture and method used in this article are generic and can be easily adapted and extended to other fields (for example, same method can be used to analyse sentiment for a brand, product or situation using another social media environment). When the results were examined, most tweets have negative opinions about online education during Covid19 outbreak. Number of people who are not happy with online learning is almost twice the size of people who are happy with it. It can be seen that many countries are not prepared to carry education online during the rapidly developing pandemic process. This study shows that current online education environment isn’t enough and it should be improved in order to make people more satisfied and happier. This result is consistent with many research (Nartiningrum & Nugroho, 2020; Asare, 2020; Chakraborty, 2021) where they highlighted the challenges of online learning during pandemic.

Online education, which has become more widespread with the covid19 process, will change according to public opinions and will take its real form over time, which will enable it to be more effective and efficient. It can be seen from many studies that show how effective the social media on the public, interest group leaders, policy makers, and policy is(Protes& McCombs, 2016; Feezell, 2018). Online media will play a critical role not only in identifying problems, but also in triggering positive changes that will help the adoption of online learning in the international domain.

5. Limitations and Recommendations

In this study, a small 5-week dataset was used due to various limitations of the twitter platform and leaving out other social media platforms such as Facebook, Instagram, and YouTube. However, as the pandemic continues, different feelings may arise as people become more experienced in using online learning in more diverse, innovative and more diverse ways. This type of analysis will help with improvements to deployed systems and better dissemination of online learning. Therefore, it is planned to validate the relevant approach on larger datasets in future studies.

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