

Analyzing the Sentiments of Jordanian Students Towards Online Education in the Higher Education Institutions

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Abstract—Sentiment analysis and opinion polling are two areas that have grown significantly over the past decade. Opinion research and sentiments analysis in the online education environment can truly reflect the learning state of students and educators and experts in the field; providing the theoretical basis needed to further review educational procedure and conduct. This study aims to shed light on identifying and visualizing students' objective feelings based on an exploration of the subject matter and materials of learning and gathering sentiments from university Facebook groups at various levels and layers in detail. The proposed method is a qualitative descriptive research method that includes data pre-processing, subject discovery, sentiment analysis, and visualization. In relative terms, 39.7% of text messages were positive and 52.3% of text messages were negative and understanding the narrative of these feelings and their impact on the online learning environment.

Keywords—Online education; students; sentiment analysis; online education; online environment; online social media

I. INTRODUCTION

With the rapid development of Web 2.0 and online social media, educational institutions are increasingly using online learning environments and online community platforms to create a more convenient learning environment [4]. This is considered an online training in the online environment platform.

Synchronous and asynchronous online education makes virtual reality a social model through teaching, research, other online activities, interactive learning, collaborative learning, and self-directed learning. In a nutshell, online learning consists of three basic components: technology, education, and academic emotional interaction.

The purpose of enhancing academic-emotional interaction is to develop learners' sense of belonging to the community, so that learners remain in the community for a longer period of time, ready to continue learning at a higher level. Academic sentiments are commonly known as records hidden in the text of online activities in the learning community, such as documents, statements, and sentences. The procedures and techniques of Sentiment Analysis, Calculating Weights, and Understanding Meaning allow you to observe and understand the experiences of emotions associated with the learning

process and to account for notes on best practices in future online references of online training.

This paper mainly contributes to the development of new methods and approaches examining the use of online education and other possible explanations. We analyze a collection of 10,000 student messages from university Facebook groups (posts and comments and likes) and explore the potential of automated methods for understanding this data within exploring sentiment in the online educational environment. Although this method presents a combination of text and assessment advocating the use of sentiment analysis techniques to focus on the equivalence of opinions (positive versus negative), it will provide a richer exploration of student experiences related to the emotional aspects of students in an online environment.

The purpose of this study is to find a method and approach that can effectively present best practices from a future perspective by analyzing students' emotions toward the online education environment. Analytical techniques obtain a list of terms related to some topics in learning and visualization that connect and visualize relationships based on sentiment classification in an interactive way that can be illustrated within the online environment of teaching.

The following proposed methods and approaches are presented in the paper:

1) Introduce the hippocampal analysis method to analyze and extract potential topics in the online education environment.

2) Based on the observations of university students, a new methodology was developed to determine the emotions felt by measuring the negative and positive in the online educational environment.

3) In addition, relationships are hierarchical and interconnected to obtain the accuracy of emotional information in an online educational environment.

II. STATE OF THE ART

Online education in the online environment contains a huge amount of information and can be divided into two parts: learning materials and student review information [12]. However, you need to explain how to properly elicit the topic

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of 'attention and performance' from your students; interviews in an online educational environment. Improving emotions based on the sentiment of student feedback, which has become a key factor in improving the quality of community service and improving student learning efficiency. Many scholars have conducted extensive practice and in-depth research, which can be summarized into three main steps: the concept of topic discovery [8], sentiment analysis [11], and sentiment aggregation. In this regard, various investigations and studies have been conducted to improve the quality of data extraction in the online education environment.

In a previous study, an analysis of students' sentiments about online education in Jordan was not covered by all universities, most were a small sample of one university. Our study covered analyzing students' emotions at all universities in Jordan and included many samples without being limited to one university. This article comprehensively explains the proposed method, and focuses on how to find problems and problems in the educational environment of online communities by analyzing the distribution of various emotions and observations on the positive and negative aspects.

III. SENTIMENT ANALYSIS FOR ONLINE STUDENTS

In the process of researching a topic, in addition to analyzing feelings, one can identify emotional changes from online students participating in the online topics within the online educational environment. Therefore, it is imperative to define the distribution of emotions according to the subject in question and the activities conducted in the online education environment platforms.

Sentiment analysis, also known as opinion mining, is the process of analyzing, processing, and classifying subjective texts using sentiment techniques. The methods of analyzing dominant emotions today can be divided into three aspects.

The first aspect is to analyze the text by building a sentiment dictionary that relies primarily on the characteristics of the symbol dictionary with specific semantic rules. PMI (Pointwise Mutual Information) and LDA (Latent Dirichlet Allocation) are frequently used to construct emotional vocabulary, among which PMI is used to determine the emotional disposition of words, and LDA is used to extract emotional words from the corpus. [6, 20]. We developed the PMI algorithm for vocabulary expansion, and propose a semantic polarity algorithm to analyze the emotional tendency of texts to improve the classification accuracy of text data [15]. The author of [18] proposes an LDA-based method to create a domain-specific sentiment dictionary based on the current general sentiment dictionary, which extracts the subject words with the group's prior knowledge. The second aspect focuses on finding emotions in machine learning (ML) based classes such as support vector machines (SVMs) [7] nave bases (NB) [14, 21]. Vinodhini develops a hybrid formulation of SVM and core component PCA analysis to improve the accuracy of sentiment classification by reducing the complexity of the sentiment retrieval model. [13] [16]. We extract the seeds of the term sentiment from Wikipedia using probabilistic latent semantic analysis used as the input matrix for the ME model. Meanwhile, to classify emotions, we use entropy classification theory to determine the properties of

emotions. Also, the last aspect is an approach that relies on focused learning by sending words contained in text vectors to remove the deep emotional features that are mainly associated with confounding neural networks (CNNs) and recurrent neural networks (RNNs). [13] Combines CNN's wedding and meditation techniques to analyze emotions in less loud words. Ethem et. egg. [3] proposes a cross-linguistic sentiment analysis model that can achieve CNN-based sentiment analysis for small groups.

Although many researchers have made great efforts to improve the emotional classification of online communities for practical work, evaluation of the emotional unit composition, especially in the online educational environment, is still insufficient.

Since the emotional analysis of student learning is closely related to the context in which the subject is located, it is necessary to establish the rules of association with context awareness that can be established in the online education environment platform.

This study uses Nvivo tools and Python code to analyze Jordanian students' sentiment towards online education during 2020-2021 to improve the impact and effectiveness of the online education environment platform in higher education institutions.

IV. METHODOLOGICAL ASPECTS

In this section, we discuss how to conduct the fieldwork of this study, suggest methods to identify research problems, and provide a framework for solving these problems step by step. Each step is based on rules and guidelines. According to God et al. [1] research methods are comprehensive methods for studying questions of interest, including specific research methods and tools used to achieve fixed research goals. Al-Dajani [1] believes that this methodology is a procedure for collecting and analyzing the data needed to select appropriate research methods and determine data collection techniques, and the purpose and purpose of the research should be clear.

V. SENTIMENT ANALYSIS

As mentioned above, big data analytics performed on Facebook, students, universities, and active managers have provided insight into the discussion of data science and online learning in the online education environment. Whether its effectiveness and popularity will increase over the next few years. In other words, sentiment analysis allows us to gather information about what other people think [1].

Big data and sentiment analysis are effective ways to capture consumer sentiment. Unlike traditional marketing methods such as focus groups and face-to-face interviews, it has always been very difficult for marketing researchers to gain true consumer opinions, awareness, and preferences. We provide free sentiment analysis service using SNS big data. Also, consumer-generated data available on social media like Facebook doesn't have the bias interviewers might present in their case during a personal interview.

However, according to [2], taking big data out of context can lose its meaning or objectivity. In this case, the data

values can be corrupted as the data can be modeled and reduced to fit a mathematical model [17]. This is where cheating comes in. Netgraphy can be used to explore big data online, so it can be used as a tool to investigate sentiment analysis in an online educational environment, providing more context and deeper insight into the results of sentiment analysis environment, online social networks such as Facebook, Twitter and YouTube [1]. Research provides more information about symbols, meanings and patterns that big data approaches may not take into account [5]. Fig. 1 shows the sentiment analysis method.



Fig. 1. Method of Sentiment Analysis.

VI. DATA COLLECTION

Sentiment analysis was conducted using Facebook's university group data, including online education data. Data was extracted from Facebook pages using Face Pager data extraction software [22]. As mentioned above, analyzing big data trends is an effective way to understand consumer moods, perceptions and preferences. Free access to social media is easy. Additionally, the data is free from potential biases that group interviewers or test takers might encounter in the data [22].

Aggregated data sets extracted from each university group on Facebook were processed, filtered, and analyzed using Microsoft Office Excel. The raw data from this dataset is created in just a few steps [22]:

1) As mentioned above, this study used online sentiment analysis. Therefore, research ignores all other forms of behavior such as likes and reactions, and focuses on the content of posts and comments. This was done because of the size of the data set. No data will be applied unless you remove extraneous data.

2) All duplicate comments have been explicitly removed to prevent unwanted bias, data collection errors or bot activity.

3) This is an Excel file that converts data by date and comment into CSV format. Analyze students' emotions using Nvivo, a qualitative data processing and analysis application.

VII. DATA ANALYSIS

After cleaning and preparing the raw data extracted from the university's Facebook group, the entire dataset consisted of 10,000 text messages, which provided the advantages of big data analysis such as size, speed, and diversity in this study [9]. This study was conducted very recently and contains a large amount of data that can be used to integrate and use various sources of information, such as comments, posts, and responses from various stakeholders. That said datasets are very interesting for doing this type of analysis, i.e. sentiment analysis. Sentiment analysis is performed via CAQCAS, a qualitative content analysis software, a computing subsidiary of Nvivo [22]. CAQCAS uses computer linguistics and text

mining to identify verbal emotions, often in the form of positive, neutral, or negative emotions. In this sense, sentiment analysis can be viewed as an automated knowledge discovery method that aims to find hidden patterns in large amounts of data. When performing sentiment analysis, an important step in the analysis is word classification. There are two general methods available for determining the direction of emotion: the body-based method and the vocabulary-based method [10]. However, the body-based method is rarely used when analyzing emotions. However, both the Modana-based method and the vocabulary-based method require a predefined dictionary or a set of subjective words. Therefore, this research compares the relevant text with a dictionary or dictionary to determine the strength and degree of emotion corresponding to the emotion, so the proposed research compares the relevant text with a dictionary to calculate emotion to determine whether it is done, the degree of emotion, degree of strength and emotion. More specifically, this study uses Pages for nvivo, the Windows search engine, to analyze the collected data. Nvivo can be used to analyze sentiments and texts for online social networks such as Facebook, YouTube, and Twitter [1, 18, 19].

VIII. EXPERIMENTS AND RESULTS

The concerned sentiment about online education was analyzed for a full year, 2020-2021, where it was analyzed from March to December, the period that transformed the learning system in Jordan into a completely online learning system.

As discussed in previous sections, the integration of the resulting data with nvivo and Python code for Windows version 11 describes all the text messages present in the university's Facebook groups, which turned out to be accompanied by emotion whether it is negative, neutral, or with a positive sentiment.

Fig. 2 shows the consequences of emotions. Most text messages were rated negative, with more than a third of text messages rated positively. Relatively few, about 8 percent, text messages were rated as neutral. Overall, out of a total of 10,000 text messages, 3,970 received positive, 800 neutral, and 5,230 negative ratings in Table I. Relatively, this means that 39.7% of text messages were positive and 52.3% negative.

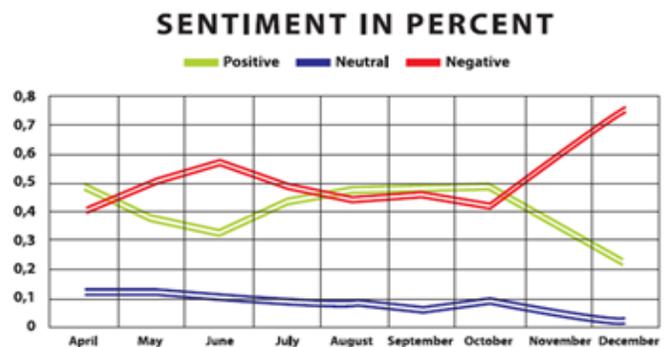


Fig. 2. The Share of the Text Messages Found on the Universities Facebook Group per Month is Either Labelled Positive, Negative, or Neutral.

TABLE I. SHOWS THE AGGREGATE NUMBERS FOR POSITIVE, NEGATIVE, AND NEUTRAL COMMENTS FOR EACH MONTH

	Positive	Neutral	Negative	Total
April	800	100	900	1800
May	500	70	700	1270
June	370	88	550	1008
July	400	60	850	1310
August	650	77	330	1057
September	280	90	500	870
October	450	100	250	800
November	320	65	550	935
December	200	150	600	950
	3,970	800	5,230	10,000
	0,397630831	0,079455154	0,522914015	1

Also, the portion of negative or positive text messages fluctuates a lot over time. For example, as shown in Fig. 2, between March and April, at least 50 percent of text messages are rated negatively. However, less than 50 percent of text messages between the months of May and June are rated negatively. However, the month of July again has a majority of negative comments. As shown, neutral text messages have relatively low volatility, staying within the 2.5 to 12.5 percent range. Positive texting ranges from 22 percent to 48.5 percent. Finally, negative text messages fluctuate between 39.8% and a maximum of 75.2%.

In a nutshell, Table II shows the three major mood swings found in college Facebook groups. First, from March to May, the percentage of negative text messages is increasing. However, a big change occurred in October. It is a sharp trend that turns negative. Texting is increasing rapidly, while Positive opponents are declining at a similar rate. As a result of analyzing the emotions of students in the 2020 school year who started using online education as a basic learning tool as the Corona 19 crisis started in Jordan in March of this year, the emotions of students about online education are contained here.

TABLE II. SHOWS THE OVERALL PERCENTAGE OF POSITIVE, NEGATIVE, AND NEUTRAL COMMENTS FOR EACH MONTH

Percent	Positive	Neutral	Negative
April	0.480812641	0.120767494	0.398419865
May	0.372336758	0.125422326	0.502240916
June	0.323345013	0.105890857	0.57076413
July	0.430826534	0.087619723	0.481553742
August	0.475581934	0.080878947	0.443539119
September	0.479839916	0.063509874	0.456650209
October	0.485078956	0.097711892	0.417209152
November	0.351778987	0.050816241	0.597404772
December	0.221909233	0.025456442	0.752634324

IX. CONCLUSION

This paper described a dataset of assessments and textual responses to student assessments for online education. Sentiment analysis techniques are used to automatically classify text responses as positive, negative, or neutral using student posts and comments.

The outcome of our study highlighted that 52.3% of students feel negative about online education, as one of the main reasons for the student's feeling was the poor connection of the Internet for some students, or the difficulty of electronic exams. Therefore, the reasons must be known by higher education decision makers and work to increase the effectiveness of education via the Internet.

Future work will include expanding the sample with more student assessments and this should provide more reliable results. And also increasing the number of university groups on Facebook to include the largest number of students. Analyzing the sentiment of faculty members and administrators about online education to include all members of the university community and take a sample of students on Twitter to also know how students sentiment about online education.

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