

Sentiment Analysis on Massive Open Online Courses (MOOCs): Multi-Factor Analysis, and Machine Learning Approach

Abdessamad Chanaa, Mohammadia School of Engineers (EMI), Mohammed V University in Rabat, Morocco*

Nour-eddine El Faddouli, Mohammadia School of Engineers (EMI), Mohammed V University in Rabat, Morocco

ABSTRACT

Massive open online courses (MOOCs) have evolved rapidly in recent years due to their open and massive nature. However, MOOCs suffer from a high dropout rate, since learners struggle to stay cognitively and emotionally engaged. Learner feedback is an excellent way to understand learner behaviour and model early decision making. In the presented study, the authors aim to explore learner sentiment expressed in their comments using machine learning and multi-factor analysis methods. They address several research questions on sentiment analysis on educational data. A total of 3311 messages, posted on a MOOC discussion forum, were analysed and categorized using machine learning and data analysis. The results obtained in this study show that it is possible to perform sentiment analysis with very high accuracy (94.1%), and it is also possible to periodically supervise the variations in learners' sentiments. The results of this study are very useful. In the context of online learning, it is very beneficial to have information about learner sentiment.

KEYWORDS

Decision-Making, Online Discussion Forums, Online Learning, Sentiment

INTRODUCTION

E-learning is the process of learning, educating, or training using digital or electronic based technologies. E-learning permits learners to build up and develop their knowledge independently of time and place. Recently, Massive Open Online Courses (MOOCs) are changing the way of online learning. MOOCs break the limitations of traditional online courses as they provide more flexibility in terms of when and where to take the courses through many features and components. MOOCs platforms generally use video lectures, reading texts, online assessments, quizzes and collaborative projects (Pursel et al. 2016; Pappano 2012). Moreover, MOOCs are usually supported by discussion forums to reinforce the interactions between different learning process actors.

DOI: 10.4018/IJICTE.310004

*Corresponding Author

This article published as an Open Access article distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0/>) which permits unrestricted use, distribution, and production in any medium, provided the author of the original work and original publication source are properly credited.

Although the many advantages and available features that MOOCs provide, they encounter very serious problems such as the high dropout rate (Parr 2013). For instance, Amnueypornsakul et al. (2014) declare that MOOCs have less than 13% as a passing rate. Similarly, Breslow et al. (2013) determine a completion rate of 15% in MOOCs. In addition, Ho et al. (2014) affirm that only 5% of learners received the course certificate. Reich & Ruipérez-Valiente (2019), confirm a retention rate of 7% in the 2016–2017 cohort on all MOOCs taught on edX. Also, studies prove that MOOCs lack interaction between learners and instructors comparing to other educational approaches such as blended learning (Jia et al. 2019). Most students who dropout are not able to engage determinedly in the course materials, as many learners endure to stay cognitively and emotionally engaged. One way to increase learners-instructors interactions and to supervise learners' progression during courseware is to analyse discussion forums. Discussion forums are a crucial part of the learning process, they provide students and instructors with an interactive collaborative environment for exchanging ideas and sharing opinions (Andresen 2009). Learners in the discussion forums come from different backgrounds; sharing textually their ideas, thoughts, feelings, knowledge and struggles toward different learning objects. Discussion forums are free open platforms where learners can explicitly express whatever cross their minds. Discussion forums open a great opportunity for tutors and the course's instructors to analyse those textual data and extract knowledge about each individual learner during the learning process.

Sentiments are thoughts, attitudes, or mental perceptions. Sentiment analysis is commonly used as a general term related to extracting subjective information related to human opinions and emotions from texts (Pang & Lee 2008; Gilbert & Hutto 2014). Sentiment analysis is also associated with different research fields such as natural language processing, machine learning and data mining (Hailong et al. 2014). The sentiment is widely associated with affections, emotions, and feelings, and it profoundly affects learning. It may be defined as a determined opinion reflective of one's feelings (Pang & Lee 2008). The use of sentiment analysis can shed the light on relevant knowledge obtained from unstructured text, which can be useful for decision-making (Phan et al. 2019). In the education domain, learning is not a cold mental activity. It is interspersed with different kind of emotions and sentiments. Sentiment analysis can show an individual's inner cognitive development (Imai 2010), analyse students' feedback in real-time (Altrabsheh et al. 2013), affect students' subjective perceptions and judgement, individually (Molinari et al. 2013) or in collaborative groups (Zheng & Huang 2016). There are three techniques for conducting a sentiment analysis study; lexicon-based approach, machine learning-based approach and hybrid. The lexicon-based approach is based on creating a manual sentiment lexicon dictionary (Ahire 2014). As for the machine learning-based approach, it uses supervised machine learning algorithms and linguistic features (Medhat et al. 2014). The hybrid approach is a combination of both lexicon-based approaches and machine learning approach.

Analysing learner's sentiments is very beneficial to determine the users' sentimental state (positive or negative) at a certain period, in order to appropriately provide each of them with personalized aid. Furthermore, it is important to know whether this sentiment state corresponds to their previous state or, on the contrary, an alteration has taken place. Sentiment variations can indicate changes (especially negative ones) in the learner's behaviours and attitudes toward learning objects. Therefore, specific interference could be taken by tutors. In order to take those measures, a multi-factor analysis is important to understand all features that may affect learners' acquisition from different perspectives during their learning process.

In this work, we have collected 3311 learners' posted messages in MOOCs discussion forums. We present a text mining and machine learning approach to analyze those messages. The approach has been evaluated using six supervised machine learning algorithms: Support Vector Machines (SVM), Naïve Bayes (NB), Logistic Regression (LR), Gradient Boosting (GB), Random Forest (RF) and Neural Network (NN). The study also uses empirical multi-factor analysis to compare different features that contribute to the learner's sentiment state during the learning process. In this analysis, the following research questions have been addressed:

- RQ1:** What is the difference in sentiment analysis between the predictive performance of different machine learning algorithms on MOOCs reviews?
- RQ2:** What is the impact of multi-factor sentiment analysis in online education, and what are the factors that most affect learner's sentiment polarity?
- RQ3:** What is the role of supervising learners' periodic sentiment variations?
- RQ4:** How our model could enhance learners' learning process?

The rest of the paper is organized as follows. Section 2 introduces a theoretical background that highlights the importance of sentiment analysis in education. Section 3 gives an overview of recent works on sentiment analysis in MOOCs. Section 4 describes the method and features for text-based sentiment analysis. We establish the experiment as well as the analysis of the results in section 5. Section 6 puts into words some technical limitations of the study. Finally, section 7 highlights conclusion and discusses future works.

BACKGROUND

Difference Between Emotion and Sentiment

Emotion is a complicated character that indicates the behavioural and personality traits of humans. Emotion is defined as a strong feeling deriving from one's circumstances, mood, or relationships with others (Hornby 2000). Emotion is a short and intense affect caused by a specific object or event (Scherer 2005). Theories of emotion can be grouped into three categories (Cherry 2019): neurological, physiological, and cognitive. First, the neurological theory design the emotional responses as results of brain activities (e.g., Evolutionary Theory of Emotion (Darwin 2015)). Second, the physiological theory proposes the emotional responses as results of body responses (e.g., The James-Lange theory of emotions (Cannon 1927)). Last, the cognitive theory suggests that physiological arousal and thoughts identify emotions (e.g., The Schachter-Singer Theory of emotion (Schachter & Singer 1962)). Two major theories exist to measure emotions. First, the dimensional approach. It represents affect states using a continuous numerical value for different dimensions, one well-established dimensional model is Russell's circumplex model of affect, where emotions are seen as combinations of valence and arousal (Russell 1980). In this model, emotions are dispersed in a system of coordinates where the x-axis measures the valence and the y-axis expresses the degree of arousal. Alternatively, the categorical approach is another effective approach that describes affective states as discrete classes such as the six basic emotions: surprise, anger, sadness, disgust, fear, and happiness (Ekman 1992).

On the other hand, sentiment can be defined as a positive or negative feeling that determines a human's opinion (Kim & Klinger 2018). Sentiments indicate a combination of social emotions, cognitive and behaviours (DeLamater & Ward 2006). Unlike emotions, sentiments are built and maintained for a longer period. Although the literature usually considers 'Emotion' and 'Sentiment' as replaceable terms, they are actually two separate problems. A sentence may consist of multiple emotions but only a single sentiment (positive or negative). For example, if someone writes «I am sad and confused», then it is understood that the emotions expressed by that person are 'sadness' and 'confusion' but the sentiment associated with those emotions is 'negative'. Most sentiment analysis systems use the information (explicitly or implicitly) obtained from emotion analysis (Sailunaz & Alhajj 2019; Kumar et al. 2019).

The Importance of Sentiment Analysis in E-Learning

The subjective nature of humans is one of their principal characteristics. Subjectivity is linked to the persons' feeling and thus, affecting their actions and behaviours, including their learning conducts during the learning process. The capability of tracking and analysing an individual's change in sentiment behaviour could certainly enhance learning decision making.

In the education context, the ability to know the learner's sentiment opens new possibilities for e-learning. Sentiment analysis in e-learning goes beyond just only knowing learner's sentiment polarity (positive/negative). It presents many benefits to learners, tutors and educational institutions, which lead to improving teaching/learning effectiveness (Zhou & Ye 2020; Archana Rao & Baglodi 2017). In the next subsections, we will discuss the importance of sentiment analysis in e-learning from different perspectives.

The Importance of Sentiment Analysis for Learners

Learner's feedbacks during learning are a powerful tool that could reveal meaningful information about each learner and understand their learning behaviour. Likert-type questionnaires, Surveys, open-ended questions or students' rating are forms of direct feedback that could expose learner's sentiment. In this direction, many researchers have applied sentiment analysis techniques to analyse student's feedback. For example, Altrabsheh et al. (2013) propose a Sentiment Analysis for Education (SA-E) to analyse student's feedback in real-time during lectures where tutors are able to follow learners and provide them with necessary assistance. Also, sentiment analysis may be used for evaluating learners' performance quality (Burstein et al. 2013). Student's feedback is also used to rate professors performances and hence understand learner's sentiment toward tutors and not only the course materials (Azab et al. 2016). Also, learner's feedbacks are employed to examine users' sentiment to address problems like boredom and confusion which influence students' satisfaction toward the course (Altrabsheh et al. 2014). Therefore, encourage their active engagement with the learning process. Visualising collected feedbacks can axiomatically show learner's satisfaction and then provide them with guidance, suggestions or adjustment of their current emotional/sentimental state (Cunningham-Nelson et al. 2019; Pong-Inwong & Songpan 2019).

Understanding the sentiment of students implicitly expressed in messages posted on forums can aid in identifying learners' sentiment. For example, analysis of MOOCs discussion forums can efficiently help tutors and course designer to rearrange curriculum and increase student's completion rate (Crossley et al. 2015), to model timely intervention triggered by detection of negative sentiment (Liu et al. 2019), to measure learner's satisfaction with the course (Altrabsheh et al. 2014). Or, to improve learners' performance during their learning process (Tucker et al. 2014).

The Importance of Sentiment Analysis for Tutors

Tutors' tasks have remarkably changed over the years with the development of distance education. Tutors' duty does not rely only on delivering their knowledge and learning via technology, but also on effectively committed and dedicated to improving teaching methodologies and materials. One way to achieve this is to analyse the learner's feedback. Sentiment analysis extracted from learners' feedback can play an important role in understanding learners' need, predict future performance and thus making more efficient teaching activities (Yu & Wu 2015, Rani & Kumar 2017). Using sentiment analysis on discussion forums, the instructor could identify if there is any pattern associated with the social variables which could increase the understanding of learner's behaviours (Moreno Marcos et al. 2018a). It can also aid administrators and tutors to perform timely teaching interventions at the right time (Liu et al. 2019). Sentiment analysis can also help to evaluate teacher's performance (Nimala & Jebakumar 2021), and therefore, to select the outstanding teachers (Tseng et al. 2018).

Employee's satisfaction, recognition and appreciation have a very essential impact on the development of any system. In this conduct, using sentiment analysis, the teachers' satisfaction can positively affect their own behaviours in the classroom and boost their teaching abilities (Mishra & Rinsangi 2020).

The Importance of Sentiment Analysis for Educational Institutions

Without a doubt, learners and teachers are the principal actors of any learning systems. However, despite their importance, the educational system/institution plays also an important role. Using

sentiment analysis, collecting users' feedback towards universities can be used as a complementary source for evaluating universities (Abdelrazeq et al. 2016). Sentiment analysis can also be used on parent feedback to provide knowledge about the institution's functioning (Patel et al. 2015). Also, it can aid to improve e-learning services and components via understanding users (teachers and learners) feedbacks (Kechaou et al. 2011). It could also extract the meaningful information of course reviews to assist in the enhancement of the e-learning platform construction (Liu et al. 2019).

RELATED WORKS

In this section, we aim to present some of the meaningful recent works that assess sentiment analysis in MOOCs discussion forums. First, recent reviews on the application of sentiment analysis on education affirm that the most used supervised classification techniques are Support vector machine (SVM) and Naive Bayes (NB) and MOOCs discussion forums are the most used resources to analyse learners' sentiment (Mite-Baidal et al. 2018). Khan et al. (2019), provide a ranking of students based on their participation in the online discussion forums, by applying text analytics along with the lexicon-based approach of sentiment analysis to evaluate the importance of each student's communication. Kastrati et al. (2020), proposed a framework for aspect-based sentiment analysis of students' feedback of MOOCs; using a supervised neural network, this framework can help learners to identify the most important aspects of the course based on their feedback. Cobos et al. (2019), propose a content analyser system using NLP and opinion mining. This tool extracts and analyses the opinion about the learning material of online courses on Small Private Open Courses (SPOCs) and MOOCs. Onan (2020), evaluated the efficiency of text representation schemes and word-embedding schemes for sentiment analysis in MOOCs. This work presents an efficient comprehensive empirical study on sentiment analysis of MOOCs reviews, in which the predictive performances of ensemble learning methods, conventional classification algorithms, and deep learning algorithms have been reported. Hew et al. (2020), build a predictive model of MOOCs learner's satisfaction using text mining, sentiment analysis, supervised machine learning and hierarchical linear modelling. This study discusses learner level sentiment factors and course-related factors that affect directly learner's satisfaction. Moreno-Marcos et al. (2018b), used supervised learning while presenting empirical results for lexicon-based and machine learning-based approaches for sentiment classification on MOOCs forum posts, in order to extract patterns of learners' sentiment behaviour. Using machine learning and semantic analysis, Wang et al. (2018) propose to classify the learners into four sentimental categories (Active & Negative, Active & Positive, Touring and Sampling) according to course participation, time series and emotional states in MOOCs environment.

Most of the previous works take into consideration only the text polarity and ignore other data and factors (direct rating, posted emoticons, etc) that can affect the sentimental state of the learner during the learning period. Further, many researchers take sentiment state statically and then omit its dynamical aspect. The sentiment state can change multiple time during the same learning process. In the next sections, we built our sentiment analysis model while taking into consideration those multiple elements.

CONTRIBUTION

Most work reported in the education domain is realized using only text data and NLP techniques without taking into consideration different features (learning aspects). Our paper differs from existing works in the following aspects:

- We present a framework for multi-factor sentiment analysis of real educational dataset.
- In addition to posted messages and text analysis identification, we studied the polarity of other features that affect the educational domain.

- As far as we are concerned, this is the first study that takes into consideration the dynamic aspect of the sentiment that changes continuously and examines the supervision of learners' sentiment state at each step of their learning stage.
- We propose a supervised learning machine learning approach to manage a large amount of students' textual and non-textual feedback.
- We propose a framework that can be used to evaluate students' feedback with high precision and can easily gauge the learning process and course different learning objects related aspects.

METHODOLOGY

The proposed architecture of the methodology is presented in Figure 1. A more comprehensive description of each step (Data collection, machine learning & data analysis and decision-making) is given in the coming sections.

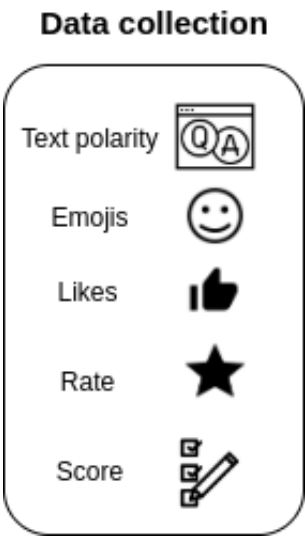
Data Collection

Our methodology is based on MOOCs data, more precisely the interactions between learners in the discussion forums. As explained in Figure 2, the MOOC provides multiple metadata and variables that could determine student's sentiment state toward learning materials. The included variables details are given in the next subsections.

Figure 1. Methodology steps



Figure 2. Data variables



Posts Polarity

This is the most important variable that could determine student's sentiment. As already stated in the previous sections, online discussion forums plays a crucial role as they allow the student to liberally share ideas and opinions. Each message posted by learner reflects a sentimental state, either positive, negative or neutral. For identifying post's sentiment polarity, we conduct three steps: text pre-processing, word embedding based feature, and neural network-based text sentiment classification:

- **Text pre-processing:** A important step for text classification applications. This step consists of removing noise, cleaning data and normalise text. Noise removal and text cleaning comprise removing special characters, digits and pieces of text that interfere (e.g., links and tags). For text normalisation, it allows transforming the text into a consistent form using stemming and lemmatization techniques.
- **Word embedding based feature:** Word embedding based feature is a technique in which each word from the vocabulary is mapped into an N dimensions vector of real numbers. Several word embedding methods have been proposed to transform the text into a structured input vector. The most common methods for features word embedding are Word2Vec, FastText, Latent Semantic Analysis (LSA) and Glove. Glove creates explicit word to word co-occurrence statistics across the text corpus, we opted for Glove algorithm in our work (Pennington et al. 2014).
- **Neural network-based text sentiment classification:** Using the artificial neural network we aim to establish the message into numerical vector representation by aggregating relevant words in their sentiment context into the sentence vectors and next aggregating important sentences vectors to the final message vector. This method can capture significant words/sentences to the sentimental context and hence, classify the message into positive, negative or neutral category.

After classifying each message according to its category, we count the number of messages in each class in a predetermined period of the learning process. This variable will keep track of learners' sentiment interactions on discussion forums based on number of posted messages of each category.

Emojis and Emoticons

Lately, to address the challenge of sentiment analysis, researchers analyzed emoticons and emojis on online discussion forums. The sentiment information comprised in the emoticons data can supplement the text polarity for better sentiment understanding. Emoticons and emojis are usually expressed in the shape of faces that represent happy or sad feelings, although there is a wide range of non-facial variations. Accordingly, emoticons can be a powerful tool in sentiment analysis to reveal the individuals' thoughts and perceptions.

Textual sentiment analysis has been well studied on online discussion forums, the use of emojis and emoticons have been studied in multiple fields (Fernández-Gavilanes et al. 2018; Hu et al. 2017; Bosch Jover & Revilla 2018; Chen et al. 2018). However, there are only a few researchers that examine the role of emotions used in educational sentiment analysis (Doiron 2018). In our method, we explore the importance of emojis and emoticons in MOOCs discussion forums as an important variable that can determine student's sentiment. We assume that the number of used emoticons have strong sentimental meanings.

For this study, similar to posts polarity count, we aim to count the number of positive, negative and neutral emoticons used by each learner. Based on the conducted study in (Kralj Novak et al. 2015), we adopt manual labelling of frequently used emoticons as explained in Table 1.

Like

For a better understanding of learner's sentiment state in the discussion forums, we examine the "Like" feature of messages. The Like or Dislike option/button can express the emotions of like,

Table 1. Examples of emoticons and their categories

Sentiment	Emoticons examples
Positive	    
Negative	    
Neutral	    

interest, support or agreement toward a specific message. “Like” is considered as the lowest level category feedback on content that a user can provide in social networks (Dedić & Stanier 2016). However, it has a significant impact on analysing user’s opinion. It is also a suitable and easy mean for critically evaluating other posts. Generally, in formal discussion forums like the case of MOOCs, “Like” is expressed with a “Thumbs up” icon. Nonetheless, it can still be expressed with “Heart” or “Star” icons. In our paper, we also consider the number of likes given by each learner in a pre-defined period. In that way, we can collect additional information from the discussion forums that expresses the learner’s sentiment toward the posted messages. In other words, the number of likes is a supplementary, yet important information that expresses the general sentiment about the presented learning materials in this period.

We consider that information extracted from discussion forums are not always enough to fully analyse learners’ sentiment toward learning materials. Therefore, we consider “Rating” as a variable in our sentiment vector. Rating the effectiveness and quality of the course reflects the sentiment that learner acquires for this learning materiel. Generally, using a range of rating scale from 1 to 5. Users’ rating is an effective indicator to determine user’s satisfaction in many fields (Ögüt & Onur Tas 2012). The sentiment extracted from rating has an important role in the educational system and in our approach as it determines how learners act to different learning objects or learning sequences during their learning process.

Score

In order to draw a clear sentiment state regarding the utility of discussion forums, it was necessary to take into consideration a more direct factor that reflects learner’s state like scores. It is clear that cognitive and affective systems are working independently, but they impact one another. It goes without saying that every gained score affects the sentimental state of learner either positively in the case of good performance results or negatively on the opposite side. Scores are one of the important keys in education. In MOOCs, we generally use assessments to evaluate student’s performance. Assessment is defined as a measurement of the learner’s achievement and acquisition in the learning process (Reeves & Hedberg 2007). Two main types of assessment exist, formative and summative assessments. We are interested in this study in the summative assessment which measures what learners have gained at the end of an instructional chapter, end of a learning sequence, or a defined period (Dixon & Worrell 2016). In our study, we take into consideration the summative assessment as an additional factor to the sentiment analysis as we presume that scores directly affect the sentiment state of learners.

Machine Learning and Data Analytics

Machine Learning (ML) is a key part of artificial intelligence. Samuel (1959), defines ML as “the field of study that gives computers the ability to learn without being explicitly programmed”. It is a system of learning by examples. To perform specific tasks, ML aims for a machine to deal with new situations through observations, self-training and experiences. Machine Learning is widely used now in daily life in many areas such as Image processing (Liu et al. 2015), finance (Heaton et al. 2016), agriculture (Kamilaris & Prenafeta-Boldú 2018), healthcare (Esteva et al. 2019) and e-learning (Chanaa & El Faddouli 2018). We distinguish three main types of machine learning: supervised learning, unsupervised learning and reinforcement learning. The supervised learning uses input data X to predict label output data Y , unsupervised learning analyses X without supervision from Y , while reinforcement learning makes a sequence of decisions over time to maximise the performance.

After creating data vectors representing each learner's sentiment state at each period. We aim to perform a supervised machine learning analysis to identify sentiment classes of learners and grouping data based on their attributes and aspects. More specifically, our goal is to create groups of elements “classes” so that the affinity within each group is as high as possible. We first code those learners' data vectors into three groups: negative, neutral and positive. On the other hand, a dimensionality reduction is necessary in our case to better visualise and analyse learners' distribution based on their sentiment state. This explicit data representation will aid to better understand and interpret data distribution. After applying the machine learning technique, we can examine the multi-factor analysis impact on the dataset. We measure the collinearity between vectors' features by using the correlation measure. To perform that, we use a statistical correlation method. In this way, we can measure the level of collinearity between our features while performing the machine learning process. This can highlight the empirical impact of each factor/feature on the prediction of the sentimental state of learners. Also, a statistical study of the sentimental distribution of different learners through different time steps is necessary, as it could clarify to the system the changes of sentimental state during the learning process and distinguish which period the overall positive/negative sentiment is higher.

Since it is not likely possible to identify the best performing classification model in advance, it was important that we first conduct a guided study to examine a set of well known classification models to determine the best operating one. We aim to investigate many machine learning models and chose the best models among them based on the accuracy and the precision of results.

After choosing the best classification model, we aim to integrate it into the MOOC platform for best usability of it. This model will help to detect the sentimental polarity of learners during each period of the learning process.

Decision Making

After extracting sentiment polarity of each learner during the learning process. The sentiment classification model provided can facilitate the supervision process. In fact, integrating the ML model into MOOCs platform can strikingly increase the decision-making quality and learning options in decision systems.

This approach aims to ease the entire learning process by making the automatization of logical decision-making tasks adequately without requiring a costly teaching intervention. Recent researches in the area of sentiment analysis in MOOCs are trying to take advantage of the ability of automatizing decisions given by machine learning techniques. This leads to multiple research topics already explored in the literature such as predicting MOOCs satisfaction (Hew et al. 2020), student's attrition (Chaplot et al. 2015), MOOCs dropout prediction (Dmoshinskaia 2016; Xing & Du 2019) and learning objects recommendation (Chanaa & El Faddouli 2019; 2020; Hilmy et al. 2019).

In our approach, we aim to adopt the recommendation system approach to personalize the need of each learner in the platform. This recommendation system will be implemented in the second phase of the research, which is not stated in this paper. Phase two will be based on creating a recommendation approach that provides a mean of improving and validating the courseware and supporting personalized

learning in the evolving learning process. This system will be based essentially on the sentimental state of each learner while taking into consideration other cognitive and social metrics as well.

EXPERIMENT

In this section, we conduct an extensive experiment to provide concrete details about our approach and verify its feasibility.

Dataset

The corpus used in this study is collected from a MOOC online discussions forum in our university. A login and password are required for any user to write posts and interact with other learners. This discussion forum is a free platform where any learner is free to create threads, post questions, express thoughts, expose difficulties or struggles and share knowledge through text and different kind of emoticons. Learners have also the possibility to like any chosen post in the forum. For this study, we adopt discussion related to an university course: “Artificial Intelligence” as our data source. The collected dataset contains 3311 messages posted by 1862 different learners (university learners). This corpus contains also 92 used emojis and 416 “Like” on different posts.

The text polarity was classified using a pre-trained model dedicated to the educational field, that model was trained based on Stanford MOOCPosts dataset that contains 29604 forum posts from eleven Stanford University public online classes (Agrawal et al. 2015). This sub-study detail was elaborated in a separate paper.

The annotation of the most used emojis was performed by two expert coders (a senior PhD student and a full professor). Before the coding process, the coders introduced the annotation procedure and guidelines based on the study presented in (Kralj Novak et al. 2015). The inter-rater agreement was calculated using Cohen’s kappa (Sim & Wright 2005) as a measure for corpus annotated by the two coders. According to (McHugh 2012), we got an almost perfect inter-rater agreement for emojis sentiment polarity (Cohen’s kappa = 0.91). The disagreement was generally due to the right modulation of each emoji in the educational field. For example, the raised hand “👋”, is an emoji presenting an open hand showing its palm. It may be utilized to mean “Stop”, which has a negative sentiment polarity, and it may also be used as a “High-five” gesture, which has a positive sentiment orientation. Generally, in the educational field, this specific emoji has a positive sentiment polarity. At the end, the two coders agreed on the totality of emojis polarity while opting for a middle ground.

The second phase consists of coding each learners’ sentiment polarity according to the number of features and the coded emojis. The same two annotators have coded the final dataset corpus according to the sentiment polarity of each entry. The inter-rater agreement was also calculated using Cohen’s kappa metric. According to (McHugh 2012), we got a strong inter-rater agreement for learner’s sentiment polarity (Cohen’s kappa = 0.84). The reason behind the disagreement was the neutral polarity, it was sometimes confusing to distinguish whether the learner has a neutral sentiment polarity or not. The two coders then discussed entries where they had different opinions. Finally, the two coders adopted a midway agreement. Each entry receives the label “0” to present negative sentiment, “1” to present neutral sentiment and “2” to present the positive sentiment. From the selected 1862 learners, 505 entries present negative sentiment, 432 present neutral sentiment, and 925 present positive sentiment. Table 2 exhibits examples of entries from the dataset.

Experiment Settings

The data was collected using Python3 programming language and SQLITE3 as a database for storage. Text data were cleaned and pre-processed using the Gensim library (Noise removal, normalization, stemming, lemmatization, etc).

For data analysis, we also examined features correlation using Spearman correlation. It is a non-parametric correlation test that measures the grade of association between two variables (Spearman

Table 2. Examples of entries from database

Name	Neg posts	Neut posts	Pos posts	likes	Neg emo	Neut emo	Pos emo	First active	Last active	Label
id523	6	5	20	0	0	0	0	Jun 2014	Jan 2015	2
id388	0	2	0	0	0	0	0	Jan 2017	Feb 2017	1
id406	1	0	0	0	1	0	1	Jul 2017	Jul 2017	0

1907). Spearman correlation is the pertinent correlation analysis when the variables are measured on an ordinal scale, which is the case in our data. Technically, we used the statistical library “Scipy” to perform our test. As for data visualisation, we used the Matplotlib library.

After removing duplicates, 169 unique entries remained for analysing and performing machine learning algorithms. The core data set contains 169 entries, the training set and the test set are divided randomly according to 80:20, that is 135 entries for the training set and 24 entries for the test set. The data analysis, dimensionality reduction, and classification tasks were performed using Scikit-learn. Scikit-learn is an open-source machine learning library in python (Pedregosa et al. 2011). It contains a wide range of regression, classification and clustering algorithms for machine learning.

For dimensionality reduction, we considered the Linear Discriminant Analysis (LDA) algorithm. It is a supervised algorithm that maximizes the interclass separability among known categories while simultaneously minimizing the intra-class compactness (Martínez & Kak 2001). LDA is like Principal Component Analysis (PCA). However, LDA doesn’t look for the principal component, it works on discovering features that give more discrimination to separate the data.

We investigated the following candidate machine learning models: Logistic Regression (Cox 1958), Support Vector Machines (Cortes & Vapnik 1995), Gradient Boosting Trees (Friedman 2001), Naïve Bayesian (Lewis 1998), Random Forest (Breiman 2001) and Neural Network (Dayhoff 1990). We embraced the following five specific metrics to check the efficiency of the candidate machine learning models: the accuracy, the precision, the recall, the F1 score and Cohen’s kappa. The first four metrics measure the percentage of correct predictions from different perspectives, while Cohen’s kappa expresses the degree of classification compatibility between the machine learning model and the coders.

RESULTS AND DISCUSSION

To give a better overview of our results, we represent our dataset in a two-dimensional graph using Linear Discriminant Analysis (LDA). Figure 3 presents a maximization of the components axes for the three classes. We note a good separation between negatives and positives data. However, a poor separability between them and the neutral data, this comes from the difficulty to distinguish the neutral class from positive/negative classes.

We conduct many empirical experiments to demonstrate the efficiency of multi-factor analysis in sentiment analysis. In particular, we aim to answer the following Research Questions (RQs):

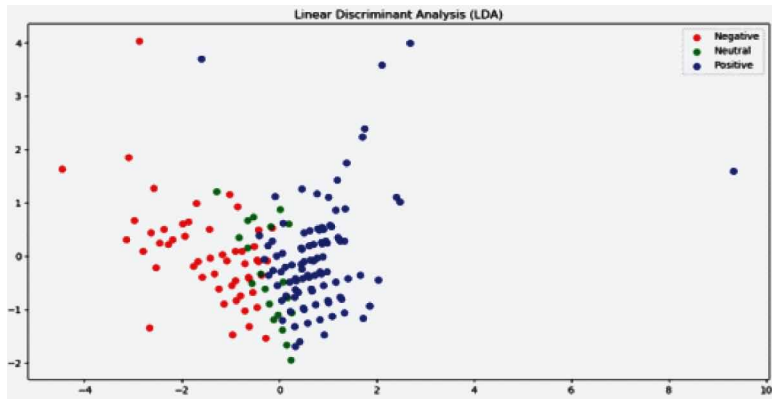
RQ1: What is the difference in sentiment analysis between the predictive performance of different machine learning algorithms on MOOCs reviews ?

RQ2: What is the impact of multi-factor sentiment analysis in online education, and what are the factors that most affect learner’s sentiment polarity ?

RQ3: What is the role of supervising learners’ periodic sentiment variations ?

RQ4: How our model could enhance learners’ learning process ?

Figure 3. Linear Discriminant Analysis (LDA)



(RQ1) What is the Difference in Sentiment Analysis Between the Predictive Performance of Different Machine Learning Algorithms on MOOCs Reviews?

To evaluate the predictive performance of machine learning models, Table 3 presents the classification results obtained by considered six widely used supervised learning classification algorithms: Support Vector Machines (SVM), Naïve Bayes (NB), Logistic Regression (LR), Gradient Boosting (GB), Random Forest (RF) and Neural Network (NN). Regarding the predictive performance of classification models, the highest predictive performance in terms of classification is obtained by Logistic Regression. The second-best predictive performance is obtained by the Support Vector Machines algorithm. Random Forest and Naïve Bayes algorithm have very poor performances compared to other models.

Overall, we achieved very good classification results above 94%, which proves the effectiveness of the model to predict the sentiment state of new learners based on their interaction in the discussion forums. This model will help the system and tutors to early predict with very high precision, learners with negative sentimental orientation, and interfere with the best decision to enhance their engagement.

One related work that uses multi-factor analysis for sentiment extraction and change detection is the study presented in (Ortigosa et al., 2014). It presents a high accuracy performance of 83.2% on the educational online discussion of Facebook. However, Facebook does not provide a reliable source of data due to its messages' nature (informal, spontaneous, sarcastic and unserious). Beside, it is hard to empirically compare the two approaches since the other work is used on different data that we do not have access, and it uses different models/settings.

Table 3. Results of the predictive analysis

	Accuracy	Precision	Recall	F1 score	Kappa
SVM	0.941	0.942	0.941	0.939	0.896
NB	0.205	0.897	0.205	0.187	0.067
GB	0.852	0.9	0.852	0.869	0.759
LR	0.941	0.948	0.941	0.94	0.899
RF	0.764	0.694	0.764	0.712	0.545
NN	0.781	0.779	0.882	0.882	0.827

(RQ2) What is the Impact of Multi-Factor Sentiment Analysis in Online Education, and What are the Factors that Most Affect Learner's Sentiment Polarity?

We examined the correlation of the features using Spearman's rank correlation. Table 4 highlights the results of the analysis; it shows the correlations between the output variable (the class label) and the various input features.

By setting $\alpha = 0.05$, we accepted the strong correlation between the output label and the following features: the number of negative posts, the number of positive posts, and the number of "likes". This means that these three specific features have a high linear association with the output variable. We notice that the correlation between positive posts ($r = 0.346$, $\rho = 0$) and the number of "likes" ($r = 0.227$, $\rho = 0.003$) are positively related to the sentiment state. This implies that the more learners post positive messages and react with the "like" feature, the more their sentiment state increases towards a positive polarity. On the other hand, the number of negative posts is negatively related to the sentiment state of learners ($r = -0.573$, $\rho = 0$). This indicates that the more negative posts learners make, the more their sentiment state decreases towards a negative polarity. Therefore, all three features contribute at a high level and have a direct influence on the final sentiment state of each learner.

Table 5 explains different comparative model for multi-factor analysis and the impact of each factor individually and in combination with others in predicting learner's sentiment. We note that "Messages" has the best predictive performance among all features separated (accuracy = 0.911) comparing to "Emojis" (accuracy = 0.705) and "Likes" (accuracy = 0.617). In addition, combining "Emojis" and "Likes" decrease the accuracy results (accuracy = 0.558). On the other hand, combining "Messages" with "Emojis" (accuracy = 0.882) and with like (accuracy = 0.911) significantly increases these performance results.

Combining the three features gives the best predictive performance as stated in table 3 (accuracy = 0.941). This proves that all those features combined have a beneficial effect in analysing learner's sentiment state during learning. Therefore, this combination noteworthy affects the predictive performance of this model in sentiment analysis.

Kastrati et al. (2020), is a recent literature study that examines multifactor analysis. It inspects many factors about tutors, learners and learning objects and the chosen technology. It performs an accuracy of 81%. However, this study does not include a clear empirical comparison of each (or combined) feature in the multi-factor analysis.

(RQ3) What is the Role of Supervising Learners' Periodic Sentiment Variations?

To give more insight about supervising the sentiment state of learners during the learning process, Figure 4 visualizes statistics about the student's sentiment state in the period from January 2017 to

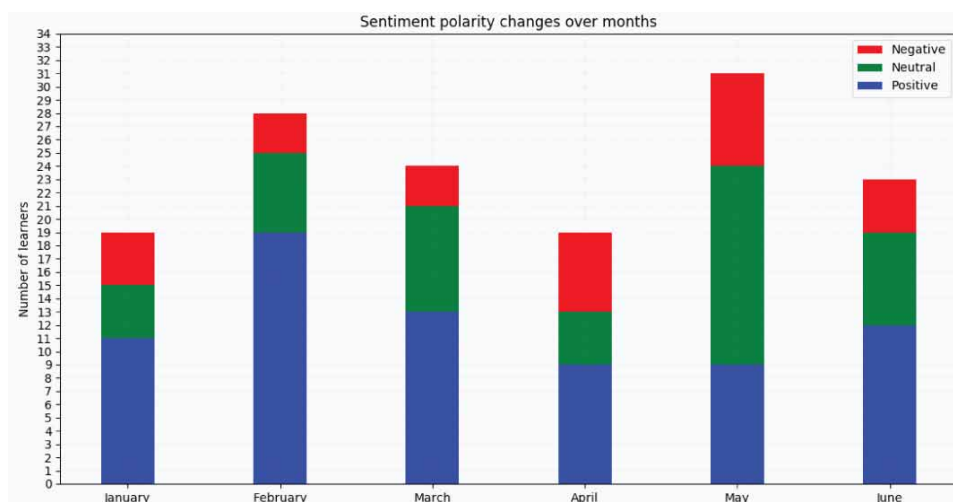
Table 4. Spearman rank correlation of input features with output feature (label)

Feature	Spearman's correlation coefficient r	Spearman rank correlation ρ	Decision with $\alpha = 0.05$
Negative messages	-0.573	0	High correlation
Neutral messages	-0.059	0.443	Low correlation
Positive messages	0.346	0	High correlation
Likes	0.227	0.003	High correlation
Negative emo	-0.149	0.054	Low correlation
Neutral emo	-0.029	0.705	Low correlation
Positive emo	0.03	0.702	Low correlation

Table 5. Results of multi-factor sentiment analysis

Features	Metrics	Accuracy	Precision	Recall	F1 score	Kappa
Only messages	SVM	0.911	0.831	0.911	0.869	0.818
	NB	0.794	0.904	0.794	0.830	0.658
	GB	0.794	0.904	0.794	0.830	0.658
	LR	0.911	0.831	0.911	0.869	0.818
	RF	0.882	0.890	0.882	0.868	0.756
	NN	0.823	0.774	0.823	0.782	0.606
Only likes	SVM	0.617	0.381	0.617	0.471	0
	NB	0.5	0.692	0.5	0.484	0.246
	GB	0.617	0.381	0.617	0.471	0
	LR	0.617	0.381	0.617	0.471	0
	RF	0.617	0.381	0.617	0.471	0
	NN	0.617	0.381	0.617	0.471	0
Only emojis	SVM	0.705	0.498	0.705	0.584	0
	NB	0.705	0.625	0.705	0.626	0.086
	GB	0.676	0.491	0.676	0.569	0.05
	LR	0.705	0.498	0.705	0.584	0
	RF	0.676	0.491	0.676	0.569	0.05
	NN	0.705	0.498	0.705	0.584	0
Messages & Emojis	SVM	0.882	0.779	0.882	0.827	0.775
	NB	0.529	0.314	0.529	0.394	0.02
	GB	0.882	0.877	0.882	0.877	0.791
	LR	0.882	0.858	0.882	0.864	0.783
	RF	0.823	0.733	0.823	0.771	0.654
	NN	0.711	0.765	0.852	0.852	0.801
Messages & Likes	SVM	0.911	0.831	0.911	0.869	0.825
	NB	0.647	0.7	0.647	0.62	0.394
	GB	0.852	0.905	0.852	0.871	0.742
	LR	0.882	0.882	0.882	0.882	0.782
	RF	0.794	0.721	0.794	0.755	0.586
	NN	0.633	0.758	0.823	0.823	0.781
Emojis & Likes	SVM	0.558	0.312	0.558	0.400	0
	NB	0.529	0.304	0.529	0.386	0.05
	GB	0.5	0.296	0.5	0.372	0.09
	LR	0.558	0.312	0.558	0.4	0
	RF	0.558	0.312	0.558	0.4	0
	NN	0.558	0.312	0.558	0.4	0

Figure 4. Statistics about learner's sentiment state in the period from January 2017 to June 2017



June 2017. We chose in this example to track monthly the global sentiment changes of learners. For example, from the period February to March, we remark a decreasing number of learners with positive state and decreasing of the total number of active learners. If we shed the light on the learners of these periods, for example, the learner “id250” has a positive polarity in February, while in March, it has shifted to a negative polarity. As for April, this learner is not active any more on the platform. This change in learner’s sentiment state becomes easy to detect while defining the time interval. In this specific example of learner “id250”, the system or the educators could automatically interfere with a recommendation process or a personalized aid at the end of March. This will keep the learner active, and he/she can recover his/her positive sentiment state and more importantly, his/her motivation to keep going with the course materials.

Moreover, we can examine the changes of learner’s sentiment in a time period detected from the number of messages/emojis he/she writes, this could be associated with changes in that learner’s behaviour. In other words, a learner defined with a negative sentiment posts more negative messages/emojis than usual. Therefore, a sentiment change is identified. We can also observe learners’ increase/decrease of activities in that period of time (number of comments, number of likes, etc).

The analysis of sentiment will shed the light on the most active and less active students at each defined period. Also, this will give an automatic overview of learner with negative sentiment states and comparing them with their score results. This will help the system to intervene with the best possible decision (recommendation, personalization, etc) suitable for each learner. This approach is different from other states-of-the-art approaches that analyse polarity at the end of the course, which makes it too late for tutors or system to interpose.

(RQ4) How our model could enhance Learners’ Learning Process?

Sentiment analysis is important in the educational field. However, asking learners directly about their sentiments is usually un-welcomed and can be considered as intruding. Furthermore, learners tend to not reveal their true sentiments/emotions, especially negative sentiments due to their cultural background or fear of the tutor’s misjudging. Automatic sentiment analysis and extraction with high accuracy and without learners’ direct recall reveal their true sentiments that they are not able to explicitly express.

Our main objective of this analysis is to gather features that show the learner's sentimental state (messages, likes, emojis, rates and scores). Those features are explicitly extracted without a direct demand for learners. The advantage of this study is to use the strength of machine learning algorithms in combination with the Natural Language Processing (NLP) techniques to build a new system that is capable of extracting and defining learners' sentiment polarity with very high accuracy (94%).

Also, since learners nowadays are more familiar with expressing their opinion, mood and struggles through messages and posts in online discussion forums. As stated in table 4, posted messages (positive and negative) contribute highly to the sentiment state of learners. This helps our model with the ease of determination of the sentiment state of learners through only their posted messages. Also, it will help to achieve that without a heavy intervention of the tutor, or instructional designers to supervise each message of each learner in the system.

As previously indicated, since sentiments and emotions are not stable through time, one of the principal aims of this study is to investigate the supervision of sentiment variation of learners during the learning process. The goal of periodic monitoring of learner's sentiment is to automatically alert the system or the tutor of any noticeable sentiment variation as soon as possible, especially negative ones. This can give an insight into whom to individually track, examine behavioural changes, analyse those patterns, predict future conducts and then propose motivational supportive tasks. This can also help early detecting drop out. This step is very important to both tutors and learners.

One other application of the sentiment analysis model is adaptive e-learning systems. Any adaptive system needs useful data about the user in order to provide relevant adaptation. Adaptive systems can take advantage of knowing the users' sentiments at a certain time compared to their usual state. Therefore, building adaptive e-learning system that personalize educational activities based on learner's sentiment state.

One other possibility is to use e-learning recommender systems, more precisely context aware recommender system (CARS) that are more sensitive to the user's context variations (Adomavicius & Tuzhilin 2011). CARS was used widely in many fields using sentiment as the main context that could define the user state. Since learning is not a cold mental activity and the sentiment state of the learner was proved important, we believe that a sentiment based Context-Aware Recommender System could be an effective mean to recommend relevant learning objects to learners while taking into consideration their emotional and sentimental activities.

One other application of this study is to apply it into collaborative groups, where learning behaviours differ from one learning group to another. Group members usually manage their behaviour by planning, monitoring, and evaluating cognition and sentiments (Järvenoja & Järvelä 2009). Therefore, sentiment information in the learning group can aid in evaluating learners as a group, oversee individual's behavioural changes, and then assess individual's impact on the group performance. It will be also helpful to control the groups in which all their learners have negative sentiments towards the subject/learning objects.

From another perspective, learner's sentiment can also be beneficial to tutors and course designers. Learner's sentiment can highlight the general feedback of learners for each time step of the ongoing course. This can create the emotion of satisfaction and recognition for the tutor or, on the other side, it can be taken as self-evaluation and thus, taking personalized measures toward learners or group of learners and thus, monitoring their sentiment change at the next time period for any potential improvement.

As many studies show, only a minority of learners participate in active postings (Chua et al. 2017). However, meaningful information can still be gathered from these data. Certainly, sentiment analysis is not enough to fully define learner's behaviour. Nevertheless, using sentiment analysis might be one important step (of many others) to address the dropout issue in MOOCs and make a better decision to enhance learning. The combination of automatic sentiment analysis processed from discussion forums along with the direct questionnaire, achievements and summative assessment could better explain patterns of learner's behaviour. The combination with other non-sentimental factors like cognitive

presence, learning style and competency level can shed the light on a more accurate predictive model that better models learner's learning acquisition. It can also help tutor and educational designers to properly adapt learning materials and platforms.

LIMITATIONS

The empirical results reported here should be considered in light of some limitations. Due to the lack of data resources, we could not experimentally prove the influence of learners' rating and scores mentioned in the methodology. Theoretically, their importance in defining learners' sentiment state is unquestionable. However, empirical studies should give more insight into those two other features. On the other hand, the data we collected belongs to one course since our goal is to analyse the interactions of learners on only one specific course and provide a recommendation according to these course components. The sample size of 1862 different learners and 3311 posted messages needs a little more improvement (in the size aspect) since machine learning methods require a large training dataset to make a better prediction. An other limitation to be considered, is that within a single post/message, students exhibit contradicting perspectives/opinion toward various problems. Thus, the models should be fine-tuned to identify learners' precise sentiments/emotions.

CONCLUSION AND FUTURE WORK

Unlike face-to-face learning environments, analysing the sentiment state of the learner is a challenging task in e-learning. Affective and sentimental factors have a big effect on students' motivation and, in general, on the outcome of the learning process. Online discussion forums are an essential tool that permits educators to overview the sentiment state of each learner. The main motivation behind our research is to examine different factors that affect sentiment state in MOOCs, more precisely on online discussion forums to acquire judgement of students' expressed thought and feeling during the learning process. Also, our main objective is to investigate an efficient practical means to early predict student's sentiment state and overview their changes over different learning process time-scale.

In this work, we examined differences in sentiment analysis between different machine learning model, and we acquired a precision of 94.1%. Then, we examined different data analysis methods to understand the impact of multi-factor analysis on sentiment analysis in MOOCs. Next, we used this model to periodically supervise the change in learner's sentiment. Last, we discussed the importance of this model in e-learning systems with different possible applications to enhance learning quality. This model will assist educators and instructional designers to automatically keep a judging eye over each individual learner at any time of his/her learning, then come up with the best solution through rising the course delivery quality; thus, efficiency enhance the learner's cognitive and sentimental engagement. This model is suitable to any online learning platform, more especially in MOOCs where learners on discussion forums are active, and the dropout rate is very high.

In future works, we intend to technically integrate this model into a real MOOC discussion forum and give control to the tutor to analyse and supervise the learner's sentiment at every step of the learning process.

REFERENCES

- Abdelrazeq, A., Janßen, D., Tummel, C., Jeschke, S., & Richert, A. (2016). Sentiment analysis of social media for evaluating universities. In *Automation, Communication and Cybernetics in Science and Engineering 2015/2016* (pp. 233–251). Springer. doi:10.1007/978-3-319-42620-4_19
- Adomavicius, G., & Tuzhilin, A. (2011). Context-aware recommender systems. In *Recommender systems handbook* (pp. 217–253). Springer. doi:10.1007/978-0-387-85820-3_7
- Agrawal, A., Venkatraman, J., Leonard, S. & Paepcke, A. (2015). *Youedu: Addressing confusion in mooc discussion forums by recommending instructional video clips*. Academic Press.
- Ahire, S. (2014). *A survey of sentiment lexicons*. Academic Press.
- Altrabsheh, N., Cocea, M., & Fallahkhair, S. (2014). Learning sentiment from students' feedback for real-time interventions in classrooms. In *International conference on adaptive and intelligent systems*. Springer.
- Altrabsheh, N., Gaber, M. M., & Cocea, M. (2013). Sa-e: Sentiment analysis for education. *Frontiers in Artificial Intelligence and Applications*, 255, 353–362.
- Amnueyopornsakul, B., Bhat, S., & Chinprutthiwong, P. (2014). Predicting attrition along the way: The uiuc model. *Proceedings of the EMNLP 2014 Workshop on Analysis of Large Scale Social Interaction in MOOCs*, 55–59. doi:10.3115/v1/W14-4110
- Andresen, M. A. (2009). Asynchronous discussion forums: Success factors, outcomes, assessments, and limitations. *Journal of Educational Technology & Society*, 12(1), 249–257.
- Archana Rao, P. & Baglodi, K. (2017). Role of sentiment analysis in education sector in the era of big data: a survey. *International Journal of Latest Trends in Engineering and Technology*, 22–24.
- Azab, M., Mihalcea, R., & Abernethy, J. (2016). Analysing ratemyprofessors evaluations across institutions, disciplines, and cultures: The tell-tale signs of a good professor. In *International Conference on Social Informatics*. Springer. doi:10.1007/978-3-319-47880-7_27
- Bosch Jover, O., & Revilla, M. A. (2018). *The use of emojis by millennials*. Academic Press.
- Breiman, L. (2001). Random forests. *Machine Learning*, 45(1), 5–32.
- Breslow, L., Pritchard, D. E., DeBoer, J., Stump, G. S., Ho, A. D., & Seaton, D. T. (2013). Studying learning in the worldwide classroom research into edx's first mooc. *Research & Practice in Assessment*, 8, 13–25.
- Burstein, J., Beigman-Klebanov, B., Madnani, N., & Faulkner, A. (2013). 17 automated sentiment analysis for essay evaluation. In *Handbook of Automated Essay Evaluation: Current Applications and New Directions* (p. 281). Routledge.
- Cannon, W. B. (1927). The James-Lange theory of emotions: A critical examination and an alternative theory. *The American Journal of Psychology*, 39(1/4), 106–124. doi:10.2307/1415404 PMID:3322057
- Chanaa, A., & El Faddouli, N.-E. (2018). Deep learning for a smart e-learning system. *Proceedings of the 2nd International Conference on Smart Digital Environment*, 197–202.
- Chanaa, A., & El Faddouli, N.-E. (2019). Context-aware factorization machine for recommendation in massive open online courses (moocs). In *2019 International Conference on Wireless Technologies, Embedded and Intelligent Systems (WITS)*. IEEE.
- Chanaa, A., & El Faddouli, N.-E. (2020). Predicting learners need for recommendation using dynamic graph-based knowledge tracing. In *International Conference on Artificial Intelligence in Education*. Springer. doi:10.1007/978-3-030-52240-7_9
- Chaplot, D. S., Rhim, E., & Kim, J. (2015). Predicting student attrition in moocs using sentiment analysis and neural networks. *AIED Workshops*, 53, 54–57.
- Chen, Y., Yuan, J., You, Q., & Luo, J. (2018). Twitter sentiment analysis via bi-sense emoji embedding and attention-based lstm. *Proceedings of the 26th ACM international conference on Multimedia*, 117–125. doi:10.1145/3240508.3240533

- Cherry, K. (2019). *Overview of the 6 major theories of emotion*. Verywell Mind. <https://www.verywellmind.com/theories-of-emotion-2795717>
- Chua, S.-M., Tagg, C., Sharples, M., & Rienties, B. (2017). Discussion analytics: Identifying conversations and social learners in futurelearn moocs. MOOC analytics: Live dashboards, post-hoc analytics and the long-term effects, 36–62.
- Cobos, R., Jurado, F., & Villén, Á. (2019). Moods in moocs: Analyzing emotions in the content of online courses with edx-cas. In *2019 IEEE Global Engineering Education Conference (EDUCON)*. IEEE. doi:10.1109/EDUCON.2019.8725107
- Cortes, C., & Vapnik, V. (1995). Support vector machine. *Machine Learning*, 20(3), 273–297. doi:10.1007/BF00994018
- Cox, D. R. (1958). The regression analysis of binary sequences. *Journal of the Royal Statistical Society. Series B. Methodological*, 20(2), 215–232. doi:10.1111/j.2517-6161.1958.tb00292.x
- Crossley, S., McNamara, D. S., Baker, R., Wang, Y., Paquette, L., Barnes, T., & Bergner, Y. (2015). Language to completion: Success in an educational data mining massive open online class. International Educational Data Mining Society.
- Cunningham-Nelson, S., Baktashmotlagh, M., & Boles, W. (2019). Visualizing student opinion through text analysis. *IEEE Transactions on Education*, 62(4), 305–311. doi:10.1109/TE.2019.2924385
- Darwin, C. (2015). *The expression of the emotions in man and animals*. University of Chicago Press.
- Dayhoff, J. E. (1990). *Neural network architectures: an introduction*. Van Nostrand Reinhold Co.
- Dedi'c, N., & Stanier, C. (2016). Towards differentiating business intelligence, big data, data analytics and knowledge discovery. In *International Conference on Enterprise Resource Planning Systems*. Springer.
- DeLamater, J., & Ward, A. (2006). *Handbook of social psychology*. Springer. doi:10.1007/0-387-36921-X
- Dixon, D. D., & Worrell, F. C. (2016). Formative and summative assessment in the classroom. *Theory into Practice*, 55(2), 153–159. doi:10.1080/00405841.2016.1148989
- Dmoshinskaia, N. (2016). *Dropout prediction in moocs: using sentiment analysis of users' comments to predict engagement* [Master's thesis]. University of Twente.
- Doiron, J. G. (2018). Emojis: visual communication in higher education. *PUPIL: International Journal of Teaching, Education and Learning*, 2(2).
- Ekman, P. (1992). An argument for basic emotions. *Cognition and Emotion*, 6(3-4), 169–200. doi:10.1080/02699939208411068
- Esteva, A., Robicquet, A., Ramsundar, B., Kuleshov, V., DePristo, M., Chou, K., Cui, C., Corrado, G., Thrun, S., & Dean, J. (2019). A guide to deep learning in healthcare. *Nature Medicine*, 25(1), 24–29. doi:10.1038/s41591-018-0316-z PMID:30617335
- Fernández-Gavilanes, M., Juncal-Martínez, J., García-Méndez, S., Costa-Montenegro, E., & González-Castaño, F. J. (2018). Creating emoji lexica from unsupervised sentiment analysis of their descriptions. *Expert Systems with Applications*, 103, 74–91. doi:10.1016/j.eswa.2018.02.043
- Friedman, J. H. (2001). Greedy function approximation: a gradient boosting machine. *Annals of Statistics*, 1189–1232.
- Gilbert, C., & Hutto, E. (2014). Vader: A parsimonious rule-based model for sentiment analysis of social media text. *Eighth International Conference on Weblogs and Social Media (ICWSM-14)*. <http://comp.social.gatech.edu/papers/icwsm14.vader.hutto.pdf>
- Hailong, Z., Wenyan, G., & Bo, J. (2014). Machine learning and lexicon based methods for sentiment classification: A survey. In *2014 11th web information system and application conference*. IEEE.
- Heaton, J., Polson, N. G., & Witte, J. H. (2016). *Deep learning in finance*. arXiv preprint arXiv:1602.06561.

- Hew, K. F., Hu, X., Qiao, C., & Tang, Y. (2020). What predicts student satisfaction with moocs: A gradient boosting trees supervised machine learning and sentiment analysis approach. *Computers & Education*, 145, 103724. doi:10.1016/j.compedu.2019.103724
- Hilmy, S., De Silva, T., Pathirana, S., Kodagoda, N., & Suriyawansa, K. (2019). Moocs recommender based on user preference, learning styles and forum activity. In *2019 International Conference on Advancements in Computing (ICAC)*. IEEE. doi:10.1109/ICAC49085.2019.9103376
- Ho, A., Reich, J., Nesterko, S., Seaton, D., Mullaney, T., Waldo, J., & Chuang, I. (2014). *Harvardx and MITx: The first year of open online courses, Fall 2012-Summer 2013* (HarvardX and MITx Working Paper No. 1). Academic Press.
- Hornby, A. S. (2000). *Oxford Advanced Learner's Dictionary. Emotion*. Oxford University Press. <https://en.oxforddictionaries.com/definition/emotion>
- Hu, T., Guo, H., Sun, H., Nguyen, T.-T., & Luo, J. (2017). *Spice up your chat: The intentions and sentiment effects of using emoji*. arXiv preprint arXiv:1703.02860.
- Imai, Y. (2010). Emotions in sla: New insights from collaborative learning for an efl classroom. *Modern Language Journal*, 94(2), 278–292. doi:10.1111/j.1540-4781.2010.01021.x
- Järvenoja, H., & Järvelä, S. (2009). Emotion control in collaborative learning situations: Do students regulate emotions evoked by social challenges. *The British Journal of Educational Psychology*, 79(3), 463–481. doi:10.1348/000709909X402811 PMID:19208290
- Jia, M., Gong, D., Luo, J., Zhao, J., Zheng, J., & Li, K. (2019). Who can benefit more from massive open online courses? a prospective cohort study. *Nurse Education Today*, 76, 96–102. doi:10.1016/j.nedt.2019.02.004 PMID:30776535
- Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, 147, 70–90. doi:10.1016/j.compag.2018.02.016
- Kastrati, Z., Imran, A. S., & Kurti, A. (2020). Weakly supervised framework for aspect based sentiment analysis on students' reviews of moocs. *IEEE Access: Practical Innovations, Open Solutions*, 8, 106799–106810. doi:10.1109/ACCESS.2020.3000739
- Kechaou, Z., Ammar, M. B., & Alimi, A. M. (2011). *Improving e-learning with sentiment analysis of users' opinions*. In *2011 IEEE global engineering education conference (EDUCON)*. IEEE.
- Khan, A. I., Kaliteevskii, V., Shnai, I., & Chechurin, L. (2019). Analysis of students' performance in an online discussion forum: A social network approach. In *International Conference Cyber-Physical Systems and Control*. Springer.
- Kim, E., & Klinger, R. (2018). *A survey on sentiment and emotion analysis for computational literary studies*. arXiv preprint arXiv:1808.03137.
- Kralj Novak, P., Smailović, J., Sluban, B., & Mozetič, I. (2015). Sentiment of emojis. *PLoS One*, 10(12), e0144296. doi:10.1371/journal.pone.0144296 PMID:26641093
- Kumar, A., Ekbal, A., Kawahra, D., & Kurohashi, S. (2019). Emotion helps sentiment: A multi-task model for sentiment and emotion analysis. In *2019 International Joint Conference on Neural Networks (IJCNN)*. IEEE. doi:10.1109/IJCNN.2019.8852352
- Lewis, D. D. (1998). Naive (bayes) at forty: The independence assumption in information retrieval. In *European conference on machine learning*. Springer.
- Liu, S., Peng, X., Cheng, H. N., Liu, Z., Sun, J., & Yang, C. (2019). Unfolding sentimental and behavioral tendencies of learners' concerned topics from course reviews in a mooc. *Journal of Educational Computing Research*, 57(3), 670–696. doi:10.1177/0735633118757181
- Liu, Z., Luo, P., Wang, X., & Tang, X. (2015). Deep learning face attributes in the wild. *Proceedings of the IEEE International Conference on Computer Vision*, 3730–3738. doi:10.1109/ICCV.2015.425
- Martínez, A. M., & Kak, A. C. (2001). Pca versus lda. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 23(2), 228–233. doi:10.1109/34.908974

- McHugh, M. L. (2012). Interrater reliability: The kappa statistic. *Biochemia Medica*, 22(3), 276–282. doi:10.11613/BM.2012.031 PMID:23092060
- Medhat, W., Hassan, A., & Korashy, H. (2014). Sentiment analysis algorithms and applications: A survey. *Ain Shams Engineering Journal*, 5(4), 1093–1113. doi:10.1016/j.asej.2014.04.011
- Mishra, L., & Rinsangi, L. V. (2020). Job satisfaction of degree college teachers of mizoram. *International Journal of Management*, 11(7).
- Mite-Baidal, K., Delgado-Vera, C., Solís-Avilés, E., Espinoza, A. H., Ortiz-Zambrano, J., & Varela-Tapia, E. (2018). Sentiment analysis in education domain: A systematic literature review. In *International Conference on Technologies and Innovation*. Springer. doi:10.1007/978-3-030-00940-3_21
- Molinari, G., Chanel, G., Betrancourt, M., Pun, T., & Bozelle Giroud, C. (2013). Emotion feedback during computer-mediated collaboration: Effects on self-reported emotions and perceived interaction. *To see the world and a grain of sand: Learning across levels of space, time, and scale: CSCL 2013 conference proceedings*.
- Moreno-Marcos, P. M., Alario-Hoyos, C., Muñoz-Merino, P. J., Estevez-Ayres, I., & Kloos, C. D. (2018a). A learning analytics methodology for understanding social interactions in moocs. *IEEE Transactions on Learning Technologies*, 12(4), 442–455. doi:10.1109/TLT.2018.2883419
- Moreno-Marcos, P. M., Alario-Hoyos, C., Muñoz-Merino, P. J., Estévez-Ayres, I., & Kloos, C. D. (2018b). Sentiment analysis in moocs: A case study. In *2018 IEEE Global Engineering Education Conference (EDUCON)*. IEEE. doi:10.1109/EDUCON.2018.8363409
- Nimala, K., & Jebakumar, R. (2021). Sentiment topic emotion model on students feedback for educational benefits and practices. *Behaviour & Information Technology*, 40(3), 311–319. doi:10.1080/0144929X.2019.1687756
- Ögüt, H., & Onur Taş, B. K. (2012). The influence of internet customer reviews on the online sales and prices in hotel industry. *Service Industries Journal*, 32(2), 197–214. doi:10.1080/02642069.2010.529436
- Onan, A. (2020). Sentiment analysis on massive open online course evaluations: A text mining and deep learning approach. *Computer Applications in Engineering Education*.
- Ortigosa, A., Martín, J. M., & Carro, R. M. (2014). Sentiment analysis in facebook and its application to e-learning. *Computers in Human Behavior*, 31, 527–541. doi:10.1016/j.chb.2013.05.024
- Pang, B., & Lee, L. (2008). Opinion mining and sentiment analysis. *Foundations and Trends in Information Retrieval*, 2(1-2), 1–135. doi:10.1561/15000000011
- Pappano, L. (2012). The year of the mooc. *The New York Times*, 2(12).
- Parr, C. (2013). Mooc completion rates below 7%. *Times Higher Education*, 9.
- Patel, T., Undavia, J., & Patela, A. (2015). Sentiment analysis of parents feedback for educational institutes. *International Journal of Innovative and Emerging Research in Engineering*, 2(3), 75–78.
- Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., & Dubourg, V. (2011). Scikit-learn: Machine learning in python. *The Journal of Machine Learning Research*, 12, 2825–2830.
- Pennington, J., Socher, R., & Manning, C. D. (2014). Glove: Global vectors for word representation. *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*, 1532–1543. doi:10.3115/v1/D14-1162
- Phan, H. T., Tran, V. C., Nguyen, N. T., & Hwang, D. (2019). Decision-making support method based on sentiment analysis of objects and binary decision tree mining. In *International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems*. Springer. doi:10.1007/978-3-030-22999-3_64
- Pong-Inwong, C., & Songpan, W. (2019). Sentiment analysis in teaching evaluations using sentiment phrase pattern matching (sppm) based on association mining. *International Journal of Machine Learning and Cybernetics*, 10(8), 2177–2186. doi:10.1007/s13042-018-0800-2

- Pursel, B. K., Zhang, L., Jablokow, K. W., Choi, G. W., & Velegol, D. (2016). Understanding mooc students: Motivations and behaviours indicative of mooc completion. *Journal of Computer Assisted Learning*, 32(3), 202–217. doi:10.1111/jcal.12131
- Rani, S., & Kumar, P. (2017). A sentiment analysis system to improve teaching and learning. *Computer*, 50(5), 36–43. doi:10.1109/MC.2017.133
- Reeves, T. C., & Hedberg, J. G. (2007). Evaluation strategies for open and distributed learning environments. In *Flexible Learning in an Information Society* (pp. 226–235). IGI Global. doi:10.4018/978-1-59904-325-8.ch022
- Reich, J., & Ruipérez-Valiente, J. A. (2019). The mooc pivot. *Science*, 363(6423), 130–131. doi:10.1126/science.aav7958 PMID:30630920
- Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology*, 39(6), 1161–1178. doi:10.1037/h0077714
- Sailunaz, K., & Alhaji, R. (2019). Emotion and sentiment analysis from twitter text. *Journal of Computational Science*, 36, 101003. doi:10.1016/j.jocs.2019.05.009
- Samuel, A. L. (1959). Some studies in machine learning using the game of checkers. *IBM Journal of Research and Development*, 3(3), 210–229. doi:10.1147/rd.33.0210
- Schachter, S., & Singer, J. (1962). Cognitive, social, and physiological determinants of emotional state. *Psychological Review*, 69(5), 379–399. doi:10.1037/h0046234 PMID:14497895
- Scherer, K. R. (2005). What are emotions? and how can they be measured? *Social Sciences Information. Information Sur les Sciences Sociales*, 44(4), 695–729. doi:10.1177/0539018405058216
- Sim, J., & Wright, C. C. (2005). The kappa statistic in reliability studies: Use, interpretation, and sample size requirements. *Physical Therapy*, 85(3), 257–268. doi:10.1093/ptj/85.3.257 PMID:15733050
- Spearman, C. (1907). Demonstration of formulae for true measurement of correlation. *The American Journal of Psychology*, 18(2), 161–169. doi:10.2307/1412408
- Tseng, C.-W., Chou, J.-J., & Tsai, Y.-C. (2018). Text mining analysis of teaching evaluation questionnaires for the selection of outstanding teaching faculty members. *IEEE Access: Practical Innovations, Open Solutions*, 6, 72870–72879. doi:10.1109/ACCESS.2018.2878478
- Tucker, C., Pursel, B. K., & Divinsky, A. (2014). Mining student-generated textual data in moocs and quantifying their effects on student performance and learning outcomes. *Computers in Education Journal*, 5(4), 84–95. doi:10.18260/1-2--22840
- Wang, L., Hu, G., & Zhou, T. (2018). ‘Semantic analysis of learners’ emotional tendencies on online mooc education’. *Sustainability*, 10(6), 1921. doi:10.3390/su10061921
- Xing, W., & Du, D. (2019). Dropout prediction in moocs: Using deep learning for personalized intervention. *Journal of Educational Computing Research*, 57(3), 547–570. doi:10.1177/0735633118757015
- Yu, X., & Wu, S. (2015). Typical applications of big data in education. In *2015 International Conference of Educational Innovation through Technology (EITT)*. IEEE. doi:10.1109/EITT.2015.29
- Zheng, L., & Huang, R. (2016). The effects of sentiments and co-regulation on group performance in computer supported collaborative learning. *The Internet and Higher Education*, 28, 59–67. doi:10.1016/j.iheduc.2015.10.001
- Zhou, J., & Ye, J. (2020). Sentiment analysis in education research: A review of journal publications. *Interactive Learning Environments*, 1–13. doi:10.1080/10494820.2020.1826985