Introduction

Indicators of emotion within communication have led to questions exposing the relationships between cognition and emotion, especially within academic settings. Emotions are important factors that can greatly influence learning experiences (D’Mello, 2013) because of their connection to cognitive processes. This link demonstrates that emotion and cognition do not merely influence one another, but also depend on one another (Barrett et al., 2007), giving this link the potential to provide insight into the performance of students in modern education, specifically those of a computer-mediated nature. One result from an influx of technology is Massive Open Online Courses (MOOCs), which are classes offered online by academic institutions and experts in differing fields. This research project is conducted by a team of two linguists, in which we utilize linguistic data provided by MOOC discussion forums through examination and analysis to decipher the affects of the most impactful states to a learner’s educational development. To extract these states, we coded the naturally produced student language so as to interpret the emotional quality of an environment with hopes of also predicting means for further learning opportunities and optimizing educational technologies (Graesser & D’Mello, 2014). This research takes into account the cognitive, affective, and social interactivity of MOOC participants by means of linguistic analysis with the purpose of real life application.

Literary Review

Emotions are fundamental human processes (Barrett et al., 2007) interwoven with cognitive activity and health. Affective states and cognition influence each other respectively, with varying outcomes and respect to situations in which they are elicited (Barrett et al., 2007). For example, cognitive processes, such as learning, are imbued with emotional reactions (D’Mello & Graesser, 2012). Thus, positive or negative affective learning states accompany and influence learners throughout their learning processes and outcomes (D'mello & Graesser, 2011), giving merit for emotional environments to be explored and informed. Consequently, links between learning and emotion need to be established by means of examination of the emotional quality of learning environments, especially educational settings, so as to improve learners' experiences and outcomes. One approach in the field of linguistics is sentiment analysis, which is a Natural Language Processing (NLP) application that focuses on language sentiment produced within settings such as academia (Altrabsheh, Cocea, & Fallahkhair, 2014).

A recent surge in technological advances has expanded educational contexts beyond the classroom and globalized learning opportunities (Anderson, 2004). Along with the digitization of academia, also comes a massive influx of data regarding many aspects of instruction. Pedagogical settings are supplemented by computer-mediation such as massive open online courses (MOOCs) (Wulf et al., 2014). The web access of these courses provide advantages such as learning opportunities to individuals across the world, interactive communication between learners and experts, little to no restrictions on conditions of participation, and digitized content accessible in a didactical concept in which "the teaching process and the development of knowledge follows pre-defines learning objectives" (Wulf et al., 2014). These MOOCs contain instructional videos, slides, and readings, quizzes, assignments, and discussion forums (Bali, 2014). A key characteristic of these online classes is peer support, during which participants can obtain help on content problems and troubleshooting of technological issues, as well as collaboration on assignments and projects (Glance, Forsey, & Riley, 2013). These interactions are enabled by online forum platforms, accessible by all the participants and educators of the course (Glance, Forsey, & Riley, 2013). These forums help establish a large learning community of international individuals from a multitude of educational backgrounds, which fosters reflection and application of knowledge and student motivation in initiating activities (Glance, Forsey, & Riley, 2013). With their open availability, forum platforms generate a large amount of posts (Mak, Williams, & Mackness, 2009) with a multitude of information readily accessible for scientific research.

Manual linguistic analysis of large corpus of data is described as painful by many researchers because of the massive amount of information to sift through. Most researchers have created automated methods to examine online data; but automation is not foolproof and often requires post-human analysis of said data. Most of the schemes examined in natural language are subjective when expressed through writing. Sentiment is not easily identifiable through written speech and creating coding schemes to extract emotions in language becomes a strenuous task. A coding scheme is made up of pre-defined categories and is used to classify text. Researchers collaborate to create these categories using theories and revise each category to obtain reliability (Stelmer, 2001).

While variables, especially that of affective nature, can be difficult to measure, Likert scales provide visual means of measurement on a numbered scale. Numbers represent the direction and strength of opinion on the subject being examined (Garland 1991). Scales can vary in ranks both in breadth and in evenness, such as a five-point or a four-point scale, depending on what is being measured and the discretion of the researcher. Because of the widespread use of Likert scales, arguments pertaining to the optimal number of scale points have generated substantial debate (Garland 1991). Within these arguments are the questions of not just how many options should be present, but also if a neutral option, or mid-point, should be present as well. Neutral options on scales have not been encouraged in the past; however, recent findings have indicated that if a mid-point is not present in the scale, data is at a higher risk of providing distorted results (Wakita, Ueshima, & Noguchi 2012). Psychological tests on respondents have also indicated that the number of options on a scale, if five points or higher, does not have a prominent influence on the respondents' measurements (Wakita, Ueshima, & Noguchi 2012).

Methodology

Our particular coding scheme was produced to standardize categories of emotions demonstrated by the linguistic features of 714 log files taken from a Massive Open Online Course's discussion forum. The MOOC examined enrolled 43,000 students and was sponsored by the Teacher's College of Columbia University. Our scheme includes 12 categories of emotions that, according to research (Phye, Schutz, & Pekrun 2007), have the most relevant effects on a learner's cognitive performance: delight, curiosity, surprise, contempt, success, responsibility, cooperation, dejection, anxiety, frustration, confusion and engagement. Data from discussion posts were coded and adjudicated on a 5-point Likert scale according to the coding scheme measuring emotional and cognitive states. Table 1 below represents the scheme used to code the files and a more detailed definition of the states being examined.

Results

In the current stage of research, results have so far indicated that correlations between linguistic features of the log files and the coded affective states are present. Certain states were found more frequently than others, which in turn can tell us which states are more influential in the learners' cognitive patterns. We both reached inter-rater reliability on 10 of the 12 affective states on our coding scheme, achieving above a 0.7 in correlation and above 0.6 in kappa values. These standard values are the threshold for acceptable reliability of ratings, in which our results exceeded these values. Having exceeded the standard values for reliability, our team can confidently move forward with the integrity of the data maintained.

Discussion and Future Development

Affect classification is challenging because of the subjective nature of emotions, and a “gold standard” is not easily created since they must agree on all criteria. The two categories in which inter-rater reliability were not reached were the states of anxiety and surprise. We did not reach the numerical threshold for reliability because the log files simply did not contain those affective states often enough for those said states to remain relevant to the study. We included a neutral option in our scale for this purpose, if in the event the linguistic features provided within the files did not adequately or directly depict an affective state, so as to maintain the integrity of the data. With the current results, we will now be able to enlist Antconc, a corpus analysis tool used for textual concordancing, in our search for key words within the data and discovering their corresponding affective states. Our search and analysis will consist of n-grams, bigrams, and trigrams, which are different word combinations. Those combinations will then be used to produce textual samples containing high or low affect in hopes of predicting future states with similar linguistic features. We want this research to be used for bettering educational settings and the emotional quality within those settings. Language and its connection to affective states in such environments can provide means of influence for learners’ success or failure.

Conclusion

The study of emotions has led to the understanding that affect is inextricably connected to cognitive processes, and affective learning states are correlated with learning outcomes in complex learning settings. The computerization of academic environments allows for the digitization of data expressed in MOOC forum posts accompanied by affective learning states (Graesser & D'Mello, 2012). This framework assigns affective states as deciding factors in learning outcomes (D'Mello, Lehman, & Person, 2010). It also constitutes the basis for research on affect sensitive technologies implemented in advanced learning environments (Picard et al., 2004). Student affect is examined in relation to course completion with a focus on student engagement (Wen, Yang, & Rose, 2014). Attrition has been reported by previous studies as a major problem of MOOC students, which gears research towards analyzing student affect and its relation to course completion with aims of improving MOOC teaching techniques and technologies (Wen, Yang, & Rose, 2014). The aim of this research of sentiment analysis in educational settings is to assess student affect in naturally produced text within academic contexts with hopes of predicting performance outcomes and improving advanced teaching technologies.

Table 1

Affective coding scheme

Delight				
Language shows state of satisfaction attained when goal is reached.				
1	2	3	4	5
Strongly delighted	Delighted	Neutral	Not delighted	Strongly not delighted

Surprise
Language demonstrated reaction that results in state of wonder stemming from an unexpected outcome.
1 2 3 4 5 Strongly surprised Surprised Neutral Not surprised Strongly not surprised

Curiosity
Language shows active desire to learn material and acquire deeper knowledge when encountering information.
1 2 3 4 5 Strongly curious Curious Neutral Not curious Strongly not curious

Dejection
Language indicates state related to failure of task and loss of motivation.
1 2 3 4 5 Strongly dejected Dejected Neutral Not dejected Strongly not dejected

Responsibility
Language demonstrates state of self-direction, self-monitoring, and control over cognitive processes.
1 2 3 4 5 Strongly responsible Responsible Neutral Irresponsible Strongly irresponsible

Success
Language indicates a positive performance outcome.
1 2 3 4 5 Strongly successful Successful Neutral Unsuccessful Strongly unsuccessful

Engagement
Language demonstrates a state in which the student is attentive to the task at hand.
1 2 3 4 5 Strongly engaged Engaged Neutral Disengaged Strongly disengaged

Confusion
Language shows a state of uncertainty about the information being

presented.
1 2 3 4 5 Strongly confused Confused Neutral Not confused Strongly not confused

Frustration
Language shows dissatisfaction as a result of cognitive struggles with the learning material.
1 2 3 4 5 Strongly frustrated Frustrated Neutral Not frustrated Strongly not frustrated

Anxiety
Language indicates a state of nervousness.
1 2 3 4 5 Strongly anxious Anxious Neutral Not anxious Strongly not anxious

Contempt
Language demonstrates a state of annoyance and irritation with something or someone.
1 2 3 4

5 Strongly contempt Contempt Neutral Not contempt Strongly not contempt

Cooperation
Language shows goal-oriented and constructive interactions.
1 2 3 4 5 Strongly cooperating Cooperating Neutral Uncooperating Strongly uncooperating

Delight – High level of satisfaction attained when challenge of task is conquered and goal at hand is attained. Level of intensity supersedes the basic positive emotion of happiness, but correlations remain, as well with positive learner outcomes and increased motivation for future tasks (Ocumpaugh, J., Baker, R. S, Rodrigo, M. M. T., 2015). Usually characterized by joy and positive behaviors once success (or a positive outcome) is achieved.

Surprise – Reaction resulting in state of wonder or amazement; Relatively infrequent, epistemic emotion in which one experiences through unexpected outcomes, feedback, and presentation of new information (D'Mello, S. K., 2013). Prefaced by misjudgment of authenticity of learning context and content (D'Mello, S. K., Lehman, B., Pekrun, R., & Graesser, A., C. 2014).

Curiosity – Active desire to learn material and acquire deeper knowledge when encountering topic, task or novelty of interest to learner (D'Mello, S. K., Lehman, B., Pekrun, R., & Graesser, A., C., 2014). Helps instigate higher level of engagement and interest.

Dejection – State that learner experiences followed by failure of task and results in loss of motivation to continue. Learner usually experiences embarrassment or shame and demonstrates evidence of being overwhelmed or distressed by the challenge at hand and sometimes attempts to hide this emotion (Ocumpaugh, J., Baker, R. S, Rodrigo, M. M. T., 2015). Often accompanied by sadness, may be deepened with slander (values appraisals) and can bring negative outcomes such as lack of self-belief, engagement, and motivation to learn (known as an "achievement emotion" (Phye, G. D., Schutz, P., & Pekrun, R., 2007)).

Responsibility – Student is self-directed and manages their learning through monitoring of their contextual and cognitive progress. Control is applied and maintained to learner tasks and activities while sustaining effort and initiating interest throughout. "Self-regulated learners are both active and reflective participants and assume appropriate control in the learning process" (Garrison, 2003). When demonstrating irresponsibility, student does not demonstrate ability to control cognition or its processes. Lacks attention to task and lacks regulation of construction of knowledge. Does not exercise self-control internally or externally.

Success – Performance outcome which instigates pride, joy, and relief if success is expected. Success of one's self is felt and environments (or appraisals) are influential. Positive emotional intensity increases with level of controllability (Phye, G. D., Schutz, P., & Pekrun, R., 2007). Failure is the performance outcome that instigates sadness and frustration; notion of failure of one's self; shame ensues and environments (or appraisals) are blamed; negative emotional intensity increases with level of uncontrollability.

Engagement – State in which student demonstrates focused attention on task. The learner is fully involved in the task at hand (devotes an adequate amount of time and energy to the task), and remains vigilant (maintains attention) through the learning experience (Heaslip, Donovan, & Cullen, 2013). Engagement is characterized by cognitive investment, active participation, and emotional commitment to learning (Zepke and Leach, 2010). High levels of engagement in educational environments are necessary and contribute to academic success (Greenwood, Horton, & Utley, 2002). Disengagement is characterized by a state of boredom in which the student is disengaged from activity and looking for stimulation (Ocumpaugh, Baker, & Rodrigo, 2015).

Confusion – State that occurs when incoming information does not align with acquired knowledge on a subject. This new information cannot be processed using existing mental schemes and inconsistencies in the information flow prevent new information from being processed. The learner is at an impasse and is uncertain about how to progress in the learning activity.(Lehman et. Al, 2013) Confusion is positively correlated with learning outcomes because it provides a learning opportunity (D'Mello, Lehman, Pekrun, & Graesser, 2014).

Frustration – Affective state experienced when students repeatedly make mistakes, get stuck, or when important goals are blocked (D'Mello, 2013) and is characterized by dissatisfaction, annoyance, and anger (Graesser et al., 2006). The state occurs when a student is struggling with difficult material, has not yet achieved understanding. Frustration had a negative impact on learning outcomes and is harmful to learning (D'Mello, 2013).

Anxiety – State of apprehension and nervousness characterized by a vague fear (Scovel, 1978), negative feelings of self-efficacy, and embarrassment (Lehman et al., 2013). Anxiety occurs when the possibility of failure has high consequences and efforts to progress in the learning task seem ineffectual (D'Mello, 2013). Has potential to become overwhelming and negatively impact learning outcomes because the learner becomes demotivated and disengaged with the material (Lehman et al., 2013).

Contempt – Extremely negative affective state defined as the act of despising or disrespecting something or someone (Craig, D'Mello, Witherspoon, & Graesser, 2008). Sarcasm, mockery, insults, and hostile humor are indicators of contempt (Coan & Gottman, 2007). Viewed as an increased degree of frustration, contempt can inhibit learning (Craig, D'Mello, Witherspoon, & Graesser, 2008) even though it is relatively infrequent learning state (D'Mello, 2013).

Cooperation – Mutual understanding and communication between learner and facilitator, task, or material. Interactions are constructive and goal-oriented (Levin 2015). Respectful, active engagement takes place (Coan, A. J. & Gottman, M. J., 2007).

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