Using Social Media to Measure Student Wellbeing: A Large-Scale Study of Emotional Response in Academic Discourse

Svitlana Volkova[1], Kyungsik Han[2], and Courtney Corley[1]

[1]Data Sciences and Analytics Group, [2]Visual Analytics Group
Pacific Northwest National Laboratory
902 Battelle Blvd, Richland, WA 99354
{svitlana.volkova,kyungsik.han,court}@pnnl.gov

Abstract. Student resilience and emotional wellbeing are essential for both academic and social development. Earlier studies on tracking students' happiness in academia showed that many of them struggle with mental health issues. For example, a 2015 study at the University of California Berkeley found that 47% of graduate students suffer from depression, following a 2005 study that showed 10% had considered suicide. This is the first large-scale study that uses signals from social media to evaluate students' emotional wellbeing in academia. This work presents fine-grained emotion and opinion analysis of 79,329 tweets produced by students from 44 universities. The goal of this study is to qualitatively evaluate and compare emotions and sentiments emanating from students' communications across different academic discourse types and across universities in the U.S. We first build novel predictive models to categorize academic discourse types generated by students into personal, social, and general categories. We then apply emotion and sentiment classification models to annotate each tweet with six Ekman's emotions – joy, fear, sadness, disgust, anger, and surprise and three opinion types – positive, negative, and neutral. We found that emotions and opinions expressed by students vary across discourse types and universities, and correlate with survey-based data on student satisfaction, happiness and stress. Moreover, our results provide novel insights on how students use social media to share academic information, emotions, and opinions that would pertain to students academic performance and emotional well-being.

Keywords: social media analytics, opinion and emotion prediction, student wellbeing, academic discourse

1 Introduction

Social media has been widely used by people as a way of sharing what they do, how they live, where they visit, whom they interact with, what they are interested in, etc. The use of social media goes beyond simply sharing one's personal life or interests and has been extensively used in various contexts [25]. Especially in the context of education and academia, a great body of research has demonstrated its positive influences. For example, class instructors use Twitter to notify students of any class updates or additional class-related information, and students use Facebook to discuss course materials or issues and have peer-to-peer, social interactions outside the class [8, 10]. Research has indicated that instructors' and students' online discussions or activities in a classroom environment show a positive relationship with course engagement and grades [11]. In addition, leveraging social media in Massive Open Online Courses (MOOCs) has been found to increase students retention in class [36]. Scholars (i.e., professors, researchers) use Twitter for professional purposes to access research-related information, share their thoughts or updates related to their research interests, and build professional networks [32]. With social media platforms, people are not only information consumers but also active co-producers of academic content.

Given that heavy use of social media by young generations, including students [25], it is important to understand the emerging practices of social media use and engagement for academic purposes, because those insights can be related to students overall academic engagement, satisfaction, goals, well-being, and career expectation within or after their degree. Although prior research has extensively presented social media influence on education and academia, we realized there are missing components in the effort to better understand student communications in social media as follows.

First, there is a lack of studies that have paid close attention to academic discourse by students by looking into the actual content shared by them. Much prior research has primarily relied on survey responses [1, 8, 10–12], and it appears that very few studies have looked into and qualitatively analyzed emotions and opinions emanating from the actual content that students share online.

Second, there is little understanding of academic discourse by students by means of a large-scale data analysis. Prior research has mostly relied on small sample sizes (e.g., 100-200 students) and small-scale contexts (e.g., single classroom) which would fail to deliver a comprehensive picture of students' academic engagement through social media platforms.

With these motivations, we study how students use social media broadly, and Twitter specifically, for academic purposes through a mixture of qualitative and quantitative approaches. To do that we collected 26,710 academic-related tweets posted by 133 students and annotated their content as having three main categories (general, personal, and social) and six sub-categories of academic discourse. We then used these data to build classification models to predict academic-discourse types, and applied emotion and sentiment prediction models to predict affects. We applied these models to label 79,329 tweets produced by students from 44 universities with academic-discourse types, sentiments, and emotions. This gives us an opportunity to measure not only a level of academic engagement, but also affects in academic discourse that would pertain to students' academic performance and wellbeing. Our study is original in the following ways:

- Building models to classify academic-discourse types as social, personal, and general in social media.

– Analyzing emotions and sentiments (affects) emanating from social, personal, and general academic discourse.
– Measuring variations in emotions and sentiments expressed by students in different academic discourse across universities.
– Correlating affects expressed in social media with public survey data on student satisfaction rates, the level of happiness, or stress across universities.

Our novel findings demonstrate how emotions and opinions vary across discourse types e.g., sadness is expressed more in personal discourse (students share achievements, activities, thoughts), disgust in general discourse (students report academic information), positive and neutral opinions in social communications (students are involved in academic dialogs), and across universities e.g., students from Ohio University (OU) produce the most joy and positive opinions, and the least sadness, anger, and negative opinions compared to other colleges.

Moreover, by correlating our affect signals in social media with public survey data on student satisfaction rates and university tuition, we found that lower tuition correlates with positive affects, and higher tuition with negative emotions and sentiments. The more students report to be satisfied with their schools the more positive emotions and sentiments are being observed in social media. Thus, similar to recent studies on large-scale public opinion polling [19, 30], the results of this work imply that signals from public social media could be a faster and less expensive way to understand public opinions [3].

2 Related Work

2.1 Social Media Use for Academic Purposes

A great body of research has presented how scholars and students use social media for accessing and sharing academic-related information. We have identified two primary research efforts – describing positive effects of social media in this context and articulating how people use social media for academic purposes.

First, understanding the effects of leveraging social media usually refers to its positive outcomes for students and scholars. Researchers studied the role of Twitter used for educational purposes how it would impact students' engagement and grades [11]. From a total of 125 students, they conducted a comparative analysis between control and experimental groups. They found a greater level of engagement and higher grades from the students in the experimental group. Similarly, another work presented the use of Facebook by comparing two groups – higher education faculty ($n = 62$) and students ($n = 120$) through the survey [29]. The results indicate that students are much more likely than faculty to use Facebook and are significantly more open to the possibility of using Facebook and similar technologies to support classroom work. A recent study found that social media use is positively associated with their academic engagement and satisfaction [9]. Other works found that using Facebook for collecting and sharing information was positively predictive of overall GPA, while using Facebook for socializing was negatively predictive [11]. Another study found scholars' positive attitudes

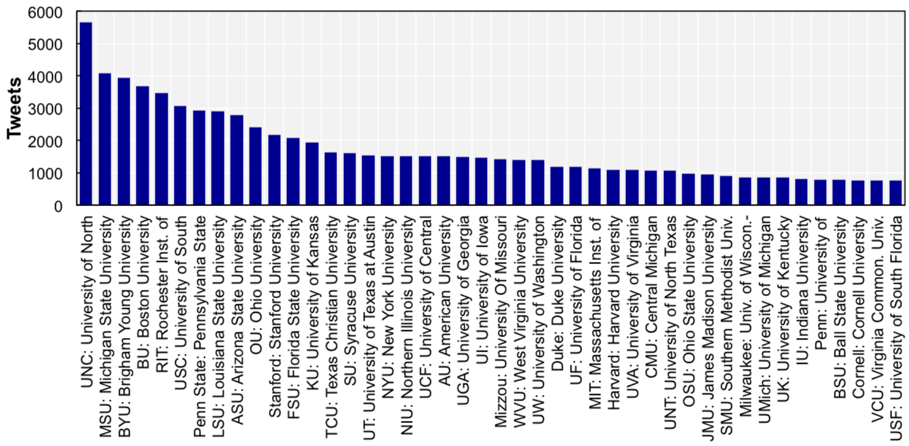


Fig. 1: The list of 44 U.S. universities and the number of tweets per university.

and practices toward finding and citing articles through Twitter because of faster speed of citation and showing scholarly impact [26]. Overall, using social media for academic purposes appears to positively influence students' and scholars' academic engagement and achievement.

Second, the practice of using social media for academic purposes incorporates individual and collaborative standpoints. Researchers detailed scholars' practices on Twitter including information, and media sharing, expanding learning opportunities, requesting assistance, connecting and networking [32]. Results in [9] indicated that students mainly use social media for broadcasting and keeping up with up-to-date academic information. However, making connections and developing networks is also one of the primary reasons for social media use.

Although such prior research has presented many aspects of utilizing social media for academic purposes from various populations (e.g., students, instructors) with respect to its effects, practices, and user motivations, there exists a lack of detailing academic activities and discourse through the analysis of content posted by students and presenting large-scale data-driven and comprehensive results. Thus, in this paper, we aim to address these limitations by conducting content analysis and applying the results of the analysis to a large set of tweets. Especially for the large-scale analysis, we developed classification models and obtained the outcomes of academic discourse, emotions, and opinions emanating from 79,329 tweets posted by students in social media across 44 universities.

2.2 Sentiment and Emotion Analysis

Emotion analysis[1] has been successfully applied to many kinds of informal and short texts including emails, blogs [13], and news headlines [31]. Although *sen-*

[1] EmoTag Project: http://nil.fdi.ucm.es/index.php?q=node/186

timent classification in social media has been extensively studied [22, 21, 20, 18, 37], *emotions* in social media, including Twitter and Facebook, have only been investigated recently [34].

Researchers have used supervised models trained on word ngram features, synsets, emoticons, topics, and lexicons to determine which emotions are being expressed on Twitter [35, 28, 27, 17]. Most of this line of work focused on capturing six high-level emotions proposed by Ekman – joy, anger, sadness, fear, disgust, and surprise [7]. Other papers studied moods, including tension, depression, fatigue, and issues such as politeness, rudeness, embarrassment, and formality. To the best of our knowledge, this is the first large-scale study of emotions and opinions expressed in different types of academic discourse produced by students from 44 universities in social media.

3 Data and Methods

3.1 Tweets Annotated with Universities

We base our analysis on a large corpus of tweets tagged with education attributes e.g., universities collected by [15].[2] Education labels were obtained by crawling user profiles on Google Plus[3] to find seed users who reported their education and had a link to their Twitter profiles. Then, for these seed users a set of tweets that mention education entities e.g., #USC (University of South Carolina) were collected via the Twitter search API.[4] Finally, the Freebase API[5] was used to resolve ambiguous university names e.g., Harvard University, Harvard. The original dataset included 124,801 education-related tweets from 7,208 users.

We used a subsample of the original data of 79,329 tweets associated with the most frequently mentioned 44 universities. We excluded universities with less than 750 tweets from our analysis. The distribution of the number of tweets per university is shown in Figure 1.

3.2 Tweets Anotated with Academic-discourse Type

To collect academic-relevant discourse, we considered several research fields, including bioinformatics, computer science, social science, psychology, economics, and political science, in order to maintain sample diversity. Such search keywords for using Twitter API include *#biology, #bioinformatics, #bioengineering #computerscience, #hci, #socialscience, #sociology, #psychology, #economics*, and *#politicalscience*. Through the official Twitter API, we then collected the profiles of the users who posted the tweets with the corresponding hashtags. We chose users who indicated that they are currently a student in their profile. We also only considered current, active Twitter users who posted more than 500

[2] http://web.stanford.edu/~jiweil/ACL_profile_data.zip
[3] Google+ API – https://developers.google.com/+/web/api/
[4] Twitter API – https://dev.twitter.com/rest/public
[5] Freebase – https://www.freebase.com/

Table 1: The example tweets annotated with three types of academic discourse – social, personal, and general. The total number of annotated tweets is 1,569.

Main category	Sub-category (Tweet Example)
General (850)	(1) General academic information [46] *New 2 year postgraduate positions [name] in social studies of algorithms and data! 1st deadline Sept 26th.*
	(2) Other research studies, reports, or activities (804) *Insightful comparison of the two statistical cultures (data & algorithmic) by [name]. [URL]*
Personal (495)	(3) Personal academic achievements (32) *I'm excited to intern at @Microsoft this summer!*
	(4) Personal academic activity updates (210) *Submission complete... First conference submission as a first author. Woo!*
	(5) Personal academic thoughts or questions (253) *Is it weird that while I'm so tired w/ work, completing tasks somehow makes me feel good? #school*
Social (224)	(6) Academic interest dialogues (224) *@[name1] @[name2] Seems there is a theoretical limit on the number of citations you can fit into 10 pages...*

tweets. As a result, we had 133 unique samples. We next collected their tweets posted in 2015, yielding 46,648 tweets in total. We excluded retweets, because we were mostly interested in the content posted by the users, although retweets imply ones similar opinion. We finally used 26,710 tweets for the analysis.

We used a qualitative method to analyze the data. We manually read over tweets and checked if each tweet contained any academic-related content. First, from a small number of users' Twitter activities, we took an initial data analysis session to identify core themes. We then employed axial coding to further generate categories. Next, categories were refined by an iterative coding process that involved two coders. The preliminary results offered a coding guideline for the next round of coding for new datasets. We continued this coding process until the following round of analysis was not able to discover any more new themes or categories. As a result, we identified a total of 2,074 tweets related to users' academic interests or activities. Our analysis revealed three main and six secondary categories relating to academic activities in social media as shown in Table 1.

3.3 Discourse Type Classification Models

We trained discourse type classification models from the manually annotated data described above to automatically label tweets with three types of academic discourse – general, personal, and social. We used logistic regression implemented in scikit-learn [23] to train models that can predict personal, social, and general academic discourse. We relied on a variety of features including, words ngrams (unigrams, bigrams, and trigrams), tf-idf (term frequency-inverse document frequency), and text embeddings (described below) to learn the mapping between each tweet t and the most likely academic-discourse type value assignment $A(t) = a$ as shown below:

$$\Phi_A(t) = \text{argmax}_a \text{P}(A(t) = a \mid t) \tag{1}$$

We relied on pretrained text embeddings such as GLoVe[6] [24], Normalized Pointwise Mutual Information (NPMI) [14] and Word2Vec[7] [16]. We varied the number of embedded clusters $c = [30, 50, 100, \ldots, 2000]$ to estimate the best classification accuracy.

3.4 Sentiment and Emotion Classification Models

Emotions and sentiments directly or indirectly imply the way we feel and think, and what we say or do in online social networks. Though both are affective states, there are important differences between them. Emotions are the states of consciousness in which various internal sensations are experienced. They can be triggered by events in the external environment. Sentiments are our likes and dislikes, and they involve a person-object relationship e.g., people express sentiments towards people, products, or services. Emotions are relatively short in duration, while sentiments display themselves over longer periods of time [6].

We used publicly available emotion and sentiment classification models developed by [33][8] that rely on lexical (word ngrams), syntactic, and stylistic (e.g., elongations, positive and negative emoticons, hashtags, punctuation, and negation) features. The sentiment classifier was trained on 19,555 tweets annotated with three sentiment classes – positive, negative, and neutral. The emotion classifier model was trained from 52,925 tweets annotated with six Ekman's emotions – joy, fear, sadness, surprise, anger, and disgust. Sentiment prediction quality was estimated on 3,223 tweets released as an official SemEval-2013 test set [18]. Emotion prediction quality was evaluated using 10-fold cross validation on their emotion dataset of 52,925 tweets. Prediction performance was reported in terms of weighted F-score – F1=0.6 for sentiment (3 categories) and F1=0.78 for emotion (6 categories).

3.5 Analysis

We report our findings using two types of analyses – university-based and discourse-based as described below. Each tweet $t \in T$, $|T| = 79,329$ is annotated with an emotion $e \in E$, sentiment $s \in S$ and academic discourse $a \in A$:

$$\begin{aligned} E &\rightarrow \{\text{joy, sad, fear, disgust, anger, surprise}\}, \\ S &\rightarrow \{\text{positive, negative, neutral}\}, \\ A &\rightarrow \{\text{social, personal, general}\}. \end{aligned}$$

[6] http://nlp.stanford.edu/projects/glove/

[7] https://radimrehurek.com/gensim/models/word2vec.html

[8] Pretrained models were released during NAACL Tutorial on Social Media Predictive analytics: http://naacl.org/naacl-hlt-2015/tutorial-social-media.html

For the *discourse-based analysis* we calculate proportions of emotions and sentiments aggregated over three discourse types as shown for the example emotion below:

$$p^{e=\text{joy}}_{a=\text{personal}} = \frac{\sum_t t^e_a}{\sum_t t_a}. \tag{2}$$

For the *university-based analysis* we aggregate tweets by university $u \in U$, $|U| = 44$ and measure proportions of affects as shown for the example opinion below:

$$p^{s=\text{positive}}_{u=\text{Harvard}} = \frac{\sum_t t^s_u}{\sum_t t_u}. \tag{3}$$

For the *correlation analysis* of student emotions and sentiments expressed in social media and public survey data we relied on several public university rankings: (1) student satisfaction rate reported at myPlan.org,[9] (2) Forbes college ranking as of 2014,[10] (3) the list of top 10 most happy[11] and stressed[12] colleges.

4 Results

This section presents the results of academic-discourse type classification and reports novel findings on emotions and sentiments expressed in different academic discourse across universities in social media.

4.1 Discourse Type Classification

We applied binary vs. frequency-based word ngrams (unigrams and bigrams), tf-idf, and word embedding features to learn and evaluate models for academic-discourse type prediction (Table 2). We found that (a) binary ngrams outperform frequency-based ngrams, and (b) bigrams yield higher performance compared to unigrams – F1 = 0.60. Table 2 reports classification results obtained using word embeddings – GLoVe, Word2Vec and NPMI. We found that all embedding types yield comparable performance (F1 is between 0.56 and 0.58), which is significantly lower than tf-idf features. We observed that tf-idf features boost classification performance to F1 = 0.64. We realize that the best model performance in not ideal (F1 = 0.64), but it can be potentially improved by annotating more tweets with academic discourse types e.g., via crowdsourcing.

We thus used the best models learned using tf-idf features to label 79,329 academic-related tweets with three classes – general, social and personal and report the discourse type distribution per university in Figure 2. We observed

[9] http://www.myplan.com/education/colleges/college_rankings_1.php
[10] http://www.forbes.com/top-colleges/list/#tab:rank
[11] http://www.huffingtonpost.com/2013/12/31/happiest-colleges-daily-beast-2013_n_4521921.html
[12] http://www.universityprimetime.com/top-50-colleges-with-the-most-stressed-out-student-bodies-1/

Table 2: Discourse type classification results obtained using 10-fold cross validation. We used tf-idf features to train models.

Features	Precision	Recall	F1
Tweet ngrams	0.65	0.66	0.60
Tweet TDIDF	**0.71**	**0.69**	**0.64**
GLoVe	0.54	0.59	0.56
Word2Vec	0.56	0.61	0.58
NPMI	0.55	0.60	0.57

that the most representative classes were general (62%) and personal (34%), and only 4% of all tweets were labeled as social.

We observed that students from several universities produced significantly more general than personal tweets, for example, University of Iowa (UI), University of Wisconsin-Milwaukee (Milwaukee), Louisiana State University (LSU), and Harvard. On the other hand, students from some other universities generated an equal amount of general and personal communications, for example, University of Kentucky (UK), American University (AU), and Ohio University (OU). Overall, the result indicates that students from different university utilize social media as a way of describing their academic discourse in different ways.

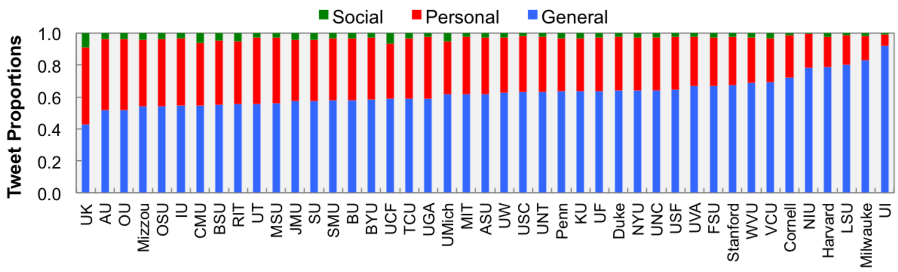
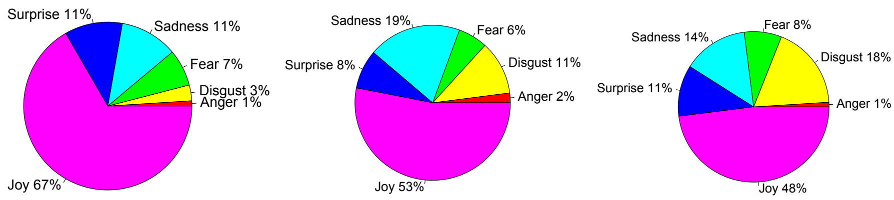


Fig. 2: Proportion of tweets per university classified as general, personal, and social. Proportions are sorted by general type in an ascending order.

4.2 Discourse-Based Analysis

Figure 3 reports the proportion of six basic emotions emanating from three communication types. We found that: *joy* was the most prevalent emotion across all discourse types; *sadness* was expressed more frequently and *surprise* was expressed less frequently in personal compared to other discourse types; *disgust* was expressed more frequently in social discourse than other tweets; *anger* and *fear* were expressed equally across all three communication types.

We report our results on sentiment proportions across three discourse types in Table 3 and outline our key findings below. *Positive* and *neutral* sentiments were expressed more frequently in social tweets. *Negative* opinions were gener-



(a) General: 53,190 tweets (b) Personal: 28,461 tweets (c) Social: 2,498 tweets

Fig. 3: Discourse-based analysis results: emotion proportions extracted from 79,329 tweets aggregated over 44 universities.

Table 3: Discourse-based analysis results: sentiment proportions extracted from 79,329 tweets over 44 universities.

Discourse Type	General	Personal	Social
Neutral	29%	**38%**	**44%**
Negative	**51%**	36%	24%
Positive	20%	25%	32%
Subjective	**71%**	62%	56%

ated more in general tweets. *Subjective opinions (positive and negative)* were expressed more in general discourse compared to social and personal tweets.

Joy was the prevalent emotion across all three discourse types, but when it comes to sentiment, positive was generally lower than others types of opinions. This finding further confirms that emotions and sentiment are both affective states but there are important differences between them.

4.3 University-Based Analysis

For the university-based analysis we aggregated emotions and sentiments expressed in all discourse types by university. Figure 4 demonstrates that affect proportions not only vary across discourse types e.g., personal (achievements, activities, thoughts) vs. general (academic informations, studies) as discussed in a previous section, but also differ by university. We outline our key findings on affect differences across 44 universities and report schools with the most↑ and the least↓ expressed affect proportions below.

- *Anger:* U. of Central Florida (UCF)↑, Ohio University (OU)↓.
- *Disgust:* American University (AU)↑, Northern Illinois University (NIU)↓.
- *Fear:* University of Kansas (KU)↑, Ohio University (OU)↓.
- *Sadness:* University of Kentucky (UK)↑, Ohio University (OU)↓.
- *Surprise:* Louisiana State University (LSU)↑, Milwaukee↓.
- *Joy:* Ohio University (OU)↑, University of Kentucky (UK)↓.
- *Neutral:* University Of Missouri (Mizzou)↑, University of Iowa (UI)↓.
- *Negative:* Virginia Commonwealth Univ. (VCU)↑, Ohio State University (OSU)↓, Duke Univ. (Duke)↓, Syracuse University (SU)↓.

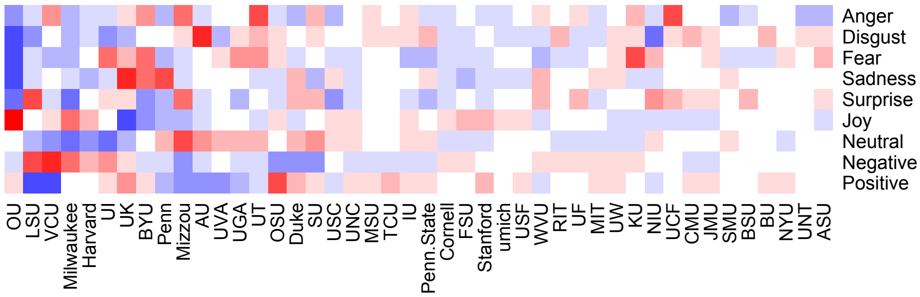


Fig. 4: University-based analysis results: sentiment and emotion proportions expressed across universities extracted from all discourse types. Red↑ represents high, blue↓ represents low sentiment and emotion proportion values.

– *Positive:* Ohio State University (OSU)↑, Louisiana State University (LSU)↓, and Virginia Commonwealth Univ. (VCU)↓.

In addition, we found that there are some differences in the degree of expressing emotions and sentiments across universities. For example, BU, NYU, UNT, and ASU only showed few emotions or sentiments compared to others. With these results, we further investigated how the emotions are related to other university-based, publicly available results.

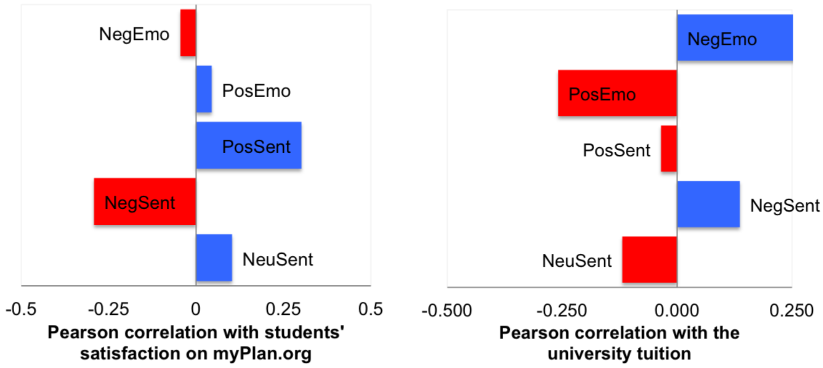
4.4 Correlation Analysis with Public Survey Data

Figure 5 presents Pearson correlation of affects expressed by students in social media and (a) students' satisfaction and (b) university tuition.[13] Our results demonstrate that: (a) the more satisfied students are with their school, the significantly higher positive sentiment and emotions they showed in their academic-related tweets; the less satisfied they are with their school, the higher negative sentiments and emotions they expressed in their academic discourse (Figure 5, left), (b) the higher tuition schools have, more negative tweets posted by students; the lower tuition schools have, more positive tweets posted by students (Figure 5, right). Our findings show that students' tweets about their academic life could be potentially used to understand their attitudes toward their school e.g., student satisfaction.

4.5 Top Positive and Negative University Ranking

Table 4 presents top 10 colleges that are most opinionated (express positive and negative sentiments) vs neutral, and most positive vs negative in terms of sentiments and emotions. We found that several schools (highlighted in bold in Table 4) – OSU, Stanford, BYU, FSU and Harvard are among top 10 universities with the most positive sentiments and emotions expressed according to our

[13] We found that correlations with Forbes university ranking are not significant.



(a) Student satisfaction (p<0.05) (b) University tuition (p<0.1)

Fig. 5: Comparing university-specific emotion and opinion distributions with public survey data: student satisfaction rate reported on myPlan.org (left) and university tuition (right).

Table 4: Top 10 colleges that are the most subjective vs. neutral, produce most positive vs. negative opinions, and produce most positive vs. negative emotions. Colleges in bold show the overlap with the top happiest schools[11], and schools in italic show the overlap with the top stressed schools[12] obtained using survey data, demonstrating that affects depicted in students tweets could be used to understand their happiness (or stress) in their school life.

Opinionatedness		**Sentiments**		**Emotions**	
NEUTRAL	SUBJECTIVE	POSITIVE	NEGATIVE	POSITIVE	NEGATIVE
Mizzou	UI	UST	VCU	OU	BYU
USC	Milwaukee	**OSU**	LSU	Milwaukee	UK
AU	VCU	UK	Milwaukee	**FSU**	*Penn*
SU	Harvard	Duke	UI	**Harvard**	*UNC*
UGA	UK	**Stanford**	Harvard	USC	*AU*
UVA	Carolina	TCU	RIT	LSU	UT
Penn	LSU	**BYU**	*UNC*	Cornell	KU
UT	UW	USF	*UF*	**Stanford**	UGA
Duke	Stanford	SU	WVU	UNC	UW
Penn State	UF	JMU	Cornell	UMich	*JMU*

analysis and are among the top happiest schools in the U.S. according to public survey data.[11] Similarly, we found that several universities (highlighted in italic in Table 4) – UNC, UF, Penn, AU and JMU among top 10 universities with the most negative sentiments and emotions expressed according to our analysis and are among the top stressed schools in the U.S. according to public survey data.[12] This result indicates that affects depicted in students' tweets could be used to understand their happiness (or stress) in their school life.

Lastly, we looked into affects at a state level. Figure 6 aggregates affects across universities for 25 U.S. states (the rest of the states with no affect proportion observations are shown in grey). We observe that students from the universities

(a) Positive emotion proportions (b) Negative emotion proportions

(c) Subjective opinion proportions (d) Neutral opinion proportions

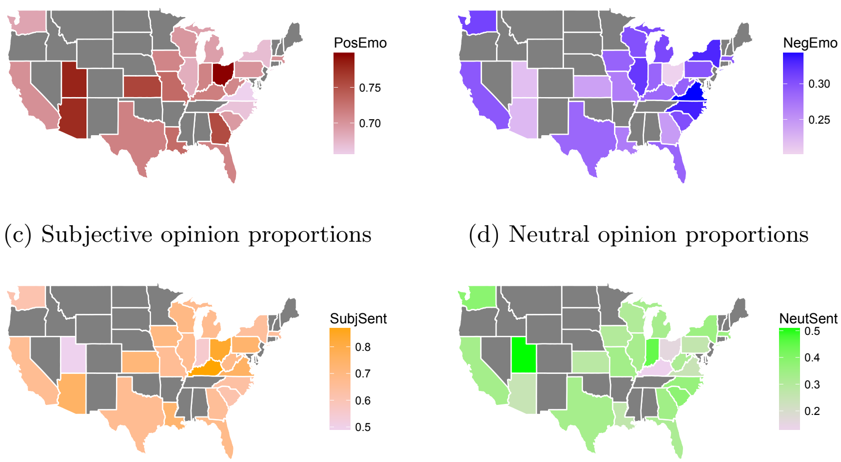


Fig. 6: Geo-located positive and negative emotion proportions, neutral and subjective sentiment proportions aggregated across universities and U.S. states (grey color shows states with no emotion and sentiment data available).

located in Ohio, Arizona, and Utah express the most positive emotions, and students from the universities located in Virginia, New York, and North Carolina express the most negative emotions. Similarly, students from the universities located in Kentucky, Ohio, and DC are the most opinionated, and students from the universities located in Indiana and Utah are the most neutral.

5 Discussion and Limitations

Our findings on variations of social, personal, and general academic discourse across universities call for a follow-up study of understanding the relationship between social media use for academic purposes and some other academic perspectives. Prior research has shown how personality affects social media use and engagement [5] and the positive association between social media engagement and final grades for undergraduates [11]. With the categories identified, we can specifically investigate how students academic activities in social media are associated with their personality, motivations of pursuing degrees, academic achievements, or satisfaction, etc. In addition, we can compare academic activities in social media between scholars (e.g., faculty, instructors) and students, and see how each group utilizes social media for academic purposes in different fashions. This could be further used to build models that reflect additional yet important academic aspects.

According to the American College Health Association, 32 percent of students say they have felt highly depressed "that it was difficult to function."

Even so, the rate of suicide among college students is lower than that of the general population e.g., between 6 and 8 percent of students report having suicidal thoughts, but only between 1 and 2 percent will actually attempt suicide each year.[12] A recent 2015 study at the UC Berkeley found that 47% of graduate students suffer from depression, following a 2005 study that showed 10% had considered suicide.[14] Models designed in this study not only allow understanding students' wellbeing at scale. We found that emotion and opinion signals expressed on Twitter correlate with university tuition, and student satisfaction.

Moreover, our findings on emotions and sentiments expressed in academic discourse across universities not only correlate with public survey data on the most happy and stressed colleges in the U.S., but go beyond that. We report novel findings on how universities are different in terms of their students expressing anger, disgust, fear, and surprise, in addition to joy and sadness emotions. Moreover, in addition to measuring students' emotional responses, we estimate subjective (e.g., positive and negative) vs. neutral opinions expressed in academic discourse. These results further reflect on how students from difference colleges use social media to express their opinions vs. share information.

We acknowledge some limitations of our study. First, for the data collection in the content analysis, our sample may not represent a larger group of students on Twitter. Second, although we had a rigorous data manipulation process, there may still exist human-biases from a manual categorization. We could mitigate these concerns by collecting a large number of students in different domains and inviting more annotators to label the tweets and only use samples which achieved agreement from all coders for the analysis. Next, we note that our classification models are capable of predicting affects and discourse types in tweets with a certain level of accuracy, which might bring mislabeled annotations to our analysis. Despite that, due to the size of the analyzed dataset, we believe our conclusions regarding emotion and sentiment differences across academic-discourse types and universities are correct.

6 Conclusion

Our study contributes to a better understanding of students engagement in academic activities in social media as well as student wellbeing estimated by measuring emotions and sentiments expressed in students' academic discourse across many universities in the U.S.

We believe our findings are the initial steps to unpack the roles and design elements of social media for students academic engagement, wellbeing, and success. In the future we will explore the role of other variables that can potentially influence students' mood e.g., geo-location and weather. We will also improve our models to measure emotions and opinions over time, and capture differences in affects expressed by users of different demographics e.g., male vs. female and departments e.g., computer science vs. mathematics across multiple social media platforms e.g., Facebook and Twitter.

[14] UC Berkeley report: http://ga.berkeley.edu/wellbeingreport/

References

1. Vladlena Benson, Stephanie Morgan, and Fragkiskos Filippaios. Social career management: Social media and employability skills gap. *Computers in Human Behavior*, 30:519–525, 2014.
2. Danah Boyd, Scott Golder, and Gilad Lotan. Tweet, tweet, retweet: Conversational aspects of retweeting on twitter. In *System Sciences (HICSS), 2010 43rd Hawaii International Conference on*, pages 1–10. IEEE, 2010.
3. Linchiat Chang and Jon A Krosnick. National surveys via rdd telephone interviewing versus the internet comparing sample representativeness and response quality. *Public Opinion Quarterly*, 73(4):641–678, 2009.
4. Christine C Cheston, Tabor E Flickinger, and Margaret S Chisolm. Social media use in medical education: a systematic review. *Academic Medicine*, 88(6):893–901, 2013.
5. T. Correa, A. W. Hinsley, and H. G. De Zuniga. Who interacts on the web?: The intersection of users personality and social media use. *Computers in Human Behavior*, 26(2):247–253, 2010.
6. Pieter MA Desmet. *Designing emotion.* 2002.
7. Paul Ekman. An argument for basic emotions. *Cognition & Emotion*, 6(3-4):169–200, May 1992.
8. Gabriela Grosseck, Ramona Bran, and Laurentiu Tiru. Dear teacher, what should i write on my wall? a case study on academic uses of facebook. *Procedia-Social and Behavioral Sciences*, 15:1425–1430, 2011.
9. Kyungsik Han, Svitlana Volkova, and Courtney D. Corley. Understanding roles of social media in academic engagement and satisfaction for graduate students. In *Proceedings of the ACM CHI Conference on Human Factors in Computing Systems*, pages 1215–1221. ACM, 2016.
10. Wade C Jacobsen and Renata Forste. The wired generation: Academic and social outcomes of electronic media use among university students. *Cyberpsychology, Behavior, and Social Networking*, 14(5):275–280, 2011.
11. Reynol Junco, Greg Heiberger, and Eric Loken. The effect of twitter on college student engagement and grades. *Journal of computer assisted learning*, 27(2):119–132, 2011.
12. Charles G Knight and Linda K Kaye. to tweet or not to tweet?a comparison of academics and students usage of twitter in academic contexts. *Innovations in Education and Teaching International*, pages 1–11, 2014.
13. Michal Kosinski, David Stillwell, and Thore Graepel. Private traits and attributes are predictable from digital records of human behavior. *Proceedings of the National Academy of Sciences*, 2013.
14. Vasileios Lampos, Nikolaos Aletras, Daniel Preoţiuc-Pietro, and Trevor Cohn. Predicting and characterizing user impact on twitter. In *Proceedings of the 14th Conference of the European Chapter of the Association for Computational Linguistics (EACL)*, pages 405–413, 2014.
15. Jiwei Li, Alan Ritter, and Eduard Hovy. Weakly supervised user profile extraction from Twitter. *Proceedings of ACL*, 2014.
16. Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*, 2013.
17. Saif M. Mohammad and Svetlana Kiritchenko. Using hashtags to capture fine emotion categories from tweets. *Computational Intelligence*, 2014.

18. Preslav Nakov, Sara Rosenthal, Zornitsa Kozareva, Veselin Stoyanov, Alan Ritter, and Theresa Wilson. Semeval-2013 task 2: Sentiment analysis in Twitter. In *Proceedings of SemEval*, pages 312–320, 2013.
19. Brendan O'Connor, Ramnath Balasubramanyan, Bryan R. Routledge, and Noah A. Smith. From tweets to polls: Linking text sentiment to public opinion time series. In *Proceedings of ICWSM*, pages 122–129, 2010.
20. Alexander Pak and Patrick Paroubek. Twitter as a corpus for sentiment analysis and opinion mining. In *Proceedings of LREC*, 2010.
21. Bo Pang and Lillian Lee. Opinion mining and sentiment analysis. *Foundations of Trends in IR*, 2(1-2):1–135, January 2008.
22. Bo Pang, Lillian Lee, and Shivakumar Vaithyanathan. Thumbs up?: sentiment classification using machine learning techniques. In *Proceedings of EMNLP*, pages 79–86, 2002.
23. Fabian Pedregosa, Gal Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, Peter Prettenhofer, Ron Weiss, Vincent Dubourg, Jake Vanderplas, Alexandre Passos, David Cournapeau, Matthieu Brucher, Matthieu Perrot, and Edouard Duchesnay. Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.
24. Jeffrey Pennington, Richard Socher, and Christopher D Manning. Glove: Global vectors for word representation. In *Proceedings of EMNLP*, volume 14, pages 1532–1543, 2014.
25. Andrew Perrin. Social media usage: 2005-2015, 2015.
26. Jason Priem and Kaitlin Light Costello. How and why scholars cite on twitter. *Proceedings of the American Society for Information Science and Technology*, 47(1):1–4, 2010.
27. Ashequl Qadir and Ellen Riloff. Bootstrapped learning of emotion hashtags# hashtags4you. *Proceedings of WASSA*, 2013.
28. Kirk Roberts, Michael A Roach, Joseph Johnson, Josh Guthrie, and Sanda M Harabagiu. Empatweet: Annotating and detecting emotions on Twitter. In *Proceedings of LREC*, 2012.
29. M. D. Roblyer, M. McDaniel, M. Webb, J. Herman, and J. V. Witty. Findings on facebook in higher education: A comparison of college faculty and student uses and perceptions of social networking sites. *The Internet and higher education*, 13(3):134–140, 2010.
30. Marcel Salathé and Shashank Khandelwal. Assessing vaccination sentiments with online social media: implications for infectious disease dynamics and control. *PLoS Comput Biol*, 7(10):e1002199, 2011.
31. Carlo Strapparava and Rada Mihalcea. Semeval-2007 task 14: Affective text. In *Proceedings of SemEval*, pages 70–74, 2007.
32. George Veletsianos. Higher education scholars' participation and practices on twitter. *Journal of Computer Assisted Learning*, 28(4):336–349, 2012.
33. Svitlana Volkova and Yoram Bachrach. On predicting sociodemographic traits and emotions from communications in social networks and their implications to online self-disclosure. *Cyberpsychology, Behavior, and Social Networking*, 18(12):726–736, 2015.
34. Svitlana Volkova, Yoram Bachrach, Michael Armstrong, and Vijay Sharma. Inferring latent user properties from texts published in social media (demo). In *Proceedings of AAAI*, 2015.
35. Wenbo Wang, Lu Chen, Krishnaprasad Thirunarayan, and Amit P Sheth. Harnessing Twitter "big data" for automatic emotion identification. In *Proceedings of SocialCom*, pages 587–592, 2012.

36. Saijing Zheng, Kyungsik Han, Mary Beth Rosson, and John Carroll. The role of social media in moocs: How to use social media to enhance student retention. In *Proceedings of the ACM Conference on Learning@ Scale*, pages 419–428. ACM, 2016.
37. Xiaodan Zhu, Svetlana Kiritchenko, and Saif M Mohammad. NRC-Canada-2014: Recent improvements in the sentiment analysis of tweets. *Proceedings of SemEval*, 2014.