

# Sentiment Analysis of Students Tweets on Unilorin CBT Examinations

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## ABSTRACT

Feedback is essential for any system or service to continue serving the purpose for which it was put in place. Students' opinions about a service rendered by their institution can contribute to the improvement of such service. Most studies carried out on students opinions about different issues have been quantitative-based while those based on qualitative feedback have been processed manually, however, this study focused on performing sentiment analysis on students' opinion expressed in tweets on their various Twitter account using a hashtag relating to the university of Ilorin CBT examinations such as Unilorin CBT, CBT Unilorin. A lexicon-based sentiment analysis approach was used to derive the polarity of students' tweets by classifying the tweets into positive, negative or neutral. The following polarity level was found from analyzed data: 40.54% negative, 34.17% positive and 25.29% others. The results revealed that many students hold a negative opinion about the CBT examination due to challenges faced when writing the examination. To curtail this trend, the study suggested that more CBT halls should be constructed to cater to the high increase in student intake and examination time should be scheduled according to faculty to prevent a situation where the entire students for a particular exam are queuing at the same time.

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## I. Introduction

There is no doubt that social media data has helped in generating a large volume of sentiment rich data from users, which appears in different forms such as tweets, Instagram posts, discussion, images, status updates, Facebook posts, comments, blog posts and videos [1]. These communications offered by social media platforms give data analysts the opportunities to access the perspectives of users on topics of interest as well as understand them, in different fields of work such as forecasting social and business phenomena like product sales [2], stocks return [3], political outcome during election [4], [5]. One key area in data analysis is the evaluation of opinion referred to as sentiment present in the way users express themselves on social media platforms while communicating through text. Sentiment analysis is a key area in research used for the improvement of automation recognition of sentiment portrayed in the text.

It has been explained by [6] that the main concept of sentiment analysis is to examine a group of text in order to understand the opinion expressed by it. This is normally done by quantifying the sentiment with a value that is positive or negative, known as polarity. From the sign of the polarity, the overall sentiment is often deduced as positive, neutral or negative. The impact of sentiment analysis is more shown on a text that is subjective in context rather than text that is the only objective in context. Where objective text is usually used to describe normal statements or facts devoid of any feeling, mood or emotion, the subjective text is a statement that has an element of feelings, emotions, and moods. Of all the numerous social media platforms available, twitter has been widely adopted and has experienced a speedy growth in communication volume serving as a better source of knowing people's opinions

about a subject of discussion. Twitter is a micro-blogging platform where users engage one another by either broadcasting to their followers or sending “tweets” to another user. The statistics of Twitter users as of 2019 are over 326 million all over the world active within a given month and a total of 1.3 billion accounts. It was ranked 12th among commonly used social networking platforms globally [7]. Social networks, such as Twitter comprise the use of small texts, and users may use diverse words and abbreviations which makes extracting their sentiment difficult by present Natural language processing systems. This has led many researchers to use techniques like deep learning and machine learning to extract and mine the polarity of the text [8]. Use of abbreviations such as LOL for Laugh out Loudly, OMG for Oh my God and so on makes sentiment analysis of tweets on Twitter more challenging [9].

The University of Ilorin Computer Based Test (CBT) examinations are taken at the Unilorin CBT Center which is located in the University permanent site behind the University e-library. The center was established to cater for the tremendous challenges faced with the paper-based examination during the Post Unified Tertiary Matriculation Examination (Post-UTME) in 2008, such as risks of accident during travel by both staff of the university and potential students; subjective scoring and plausible manipulation of results; cost of conduct of the examination on the part of the university including honoraria for invigilators, markers, coordinators, collators and other allied staff; late release of results and missing grades etc. [10]. Over time, the university has adopted CBT in the conduct of other internal examinations including university-wide courses that have a large population of students from 500 and above. Such exams include General Studies and medical courses.

The automated form of examination known as CBT is aimed at bringing comfort in taking examination by the student in the university but the situation faced by students who are to take an exam is not appealing or conducive for proper exam-taking exercise which has led to various unfavorable consequences, hence, this study was undertaken to look deeply into what is wrong or right about the Unilorin CBT process in order to provide insight into the problem and recommend solutions to stakeholders so that informed decisions can be taken.

## II.II. Literature Review

Sentiment Analysis also referred to as opinion mining, subjectivity analysis and appraisal extraction is “a process that automates mining of opinions, views, attitudes and emotions from the text, tweets, speech and database sources through Natural Language Processing (NLP)”[1]. It involves classifying opinions in a body of text into categories like “positive”, “negative” or “neutral”. Sentiment analysis includes many tasks, first is sentiment extraction, next is sentiment classification, then subjectivity classification, followed by summarization of opinions or opinion spam detection, among others. It is targeted at analyzing people’s sentiments, emotions, opinions, attitudes etc. with respect to elements such as, products, topics, individuals, organizations or services.

The four major elements in sentiment analysis are:

1. Object: this is an entity that can be a person, organization, event, topic or product on which sentiment score is to be determined.
2. Features: these are the characteristics describing the object on which sentiment analysis could be done.
3. Opinion orientation/polarity: the orientation of an opinion on a feature f, depicts whether the opinion should be classified as positive, negative or neutral.
4. Opinion holder: this is a person or an organization expressing the opinion.

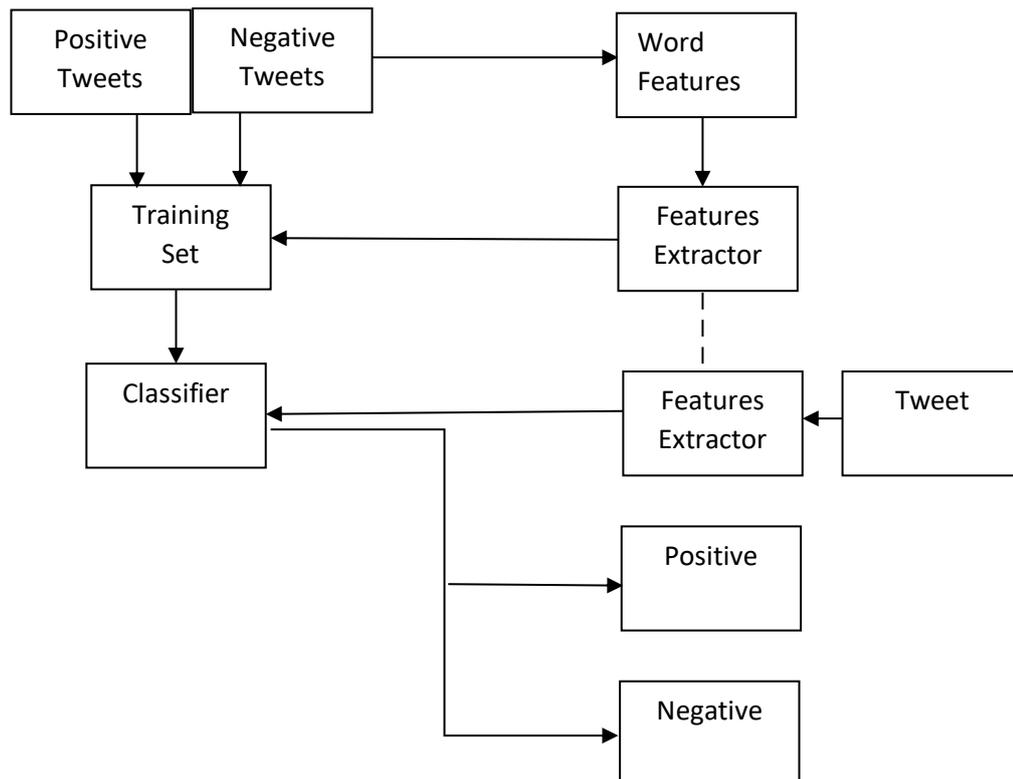


Fig 1: Sentiment Analysis Architecture [1]

In the study of [11] carried out to address challenges affecting the proper assimilation of discussed topic and engagement of students, several studies that could be used for learning sentiment from students' feedback were looked into. Using real students' feedback, Naive Bayes, Maximum Entropy, Complement Naive Bayes (CNB) and Support Vector Machine (SVM) were trained. The two classifiers that were prominently better at learning sentiment were SVM with the highest accuracy at 94% and CNB at 84%. The neutral class was also evaluated and the results showed that, generally when the neutral class was excluded, classifiers perform better. In another study by [12] which focused on "analyzing the social media sentiment as a complementary source for evaluating universities in Germany", published participants' opinion on twitter was analyzed by classifying their sentiment into "positive" and "negative" tweets. Findings showed that the extracted results can support aspects of university rankings that experience criticism as far as measuring vital indicators is concerned.

In addition, [13], worked on "developing a teacher's performance evaluation tool using opinion mining with sentiment analysis". The study provided insight in identifying the strong points and weak points of the faculty members based on the positive and negative feedback given by the students. The system provided the sentiment score from the qualitative data as well as numerical response ratings collected from the quantitative data of teachers' evaluation. Reference [14] explored data mining tools to evaluate peoples' sentiments (positive or negative) towards the administration of the Federal government of Nigeria (FGN) under President Muhammadu Buhari (PMB). Naïve Bayes (NB) classifier was adopted to classify various tweets into positive and negative sentiments. The results showed that the proportion of positive and negative sentiment, as obtained from the data, was 45.2% and 54.8% respectively, indicating a more negative opinion. The study of [15] worked on "using a natural language processing and machine learning approach to classify students' feedback in order to address problem areas in teaching and learning". The proposed system analyzed student comments from course surveys and online sources to discover sentiment polarity, the type of emotions expressed as well as satisfaction versus dissatisfaction. A comparison of the results with that of direct-assessment demonstrated the system's reliability. In the study of [16] on "assessing students' sentiments towards the use of a Building Information Modelling (BIM) learning platform in a construction project management course", the research was aimed at addressing limited study on student's perception towards the implementation of BIM courses, about BIM learning platforms and about the BIM tools

themselves. The findings suggested that online BIM learning platforms are highly regarded by students as a positive learning experience, showing a need for more incorporation of such tools and approaches in AEC courses.

### III. Methodology

The study used a text mining technique for tweet collection. The method was considered appropriate as it is not limited by space that is, a student who is widely distributed across various faculties and departments in the university can tweet to express their opinion from wherever they are and at their convenience. The tweeted opinions were collected automatically using an online tweet mining software known as Twitter Archiving Google Sheet (TAGS) based on the search queries. The software is a free Google Sheet template that allows the setup and automated collection of searched tweets based on different search queries such as search/tweet, favorites/list, and statuses/user-timeline. The data collection process involved getting access key from twitter through the creation of a twitter application and then the actual mining of data from twitter. Out of a pool of six hundred and forty-one tweets, five hundred and eighteen tweets were considered appropriate for the study as others were not oriented towards the topic of interest.

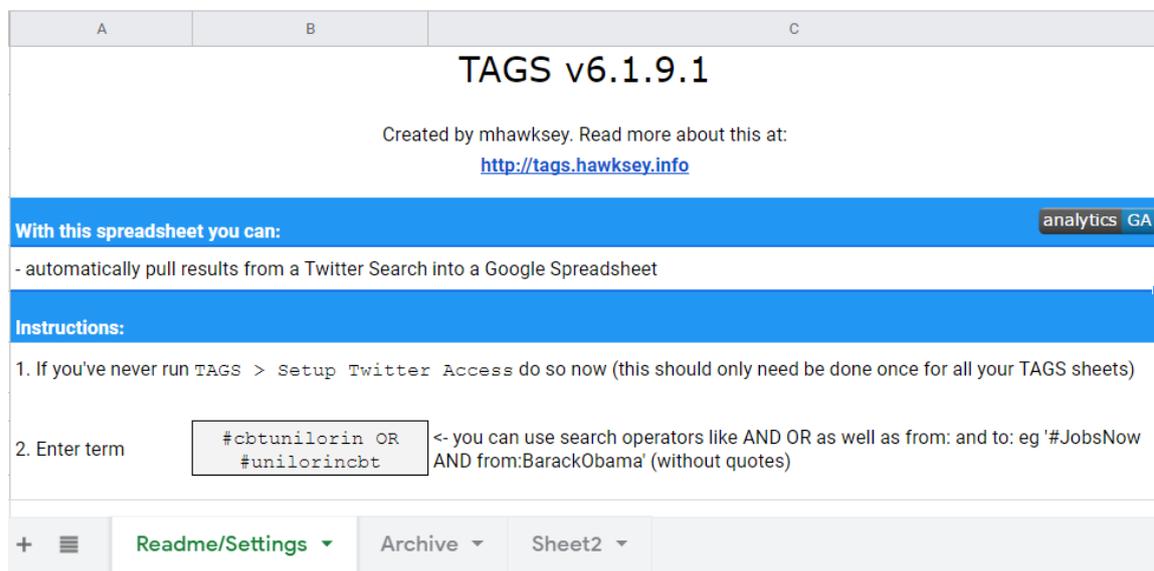


Fig 2: Tweet Mining

A Sentiment analysis software known as Meaning Cloud was used in analyzing the collected data. It provides two levels of analysis to the user. The first is a global, more general analysis of the whole text and the second is a feature level analysis, where aggregated polarity in the text is obtained after extracting entities and concepts. The software makes use of semantic approaches grounded on advanced natural language in all aspects of syntax, morphology, pragmatics and semantics. The engine generates a syntactic-semantic tree of the text over which terms of the lexicon are applied so as to spread their polarity values along the tree, the values are properly combined depending on the morphological category of the word as well as the syntactic relations that affect them. Besides the overall polarity of the text, the engine also returns the polarity for word-groups or segments of the text in 6 likely levels which are positive (P), negative (N), very positive (P+), very negative (N+), neutral (NEU) and none (NONE) when no polarity is involved.

### IV. Results and Discussion

Figure 3 depicts student opinion in the original tweet form, while figure 4 shows a graphical representation of students tweet with word cloud software which combines keywords and present it in graphical form.



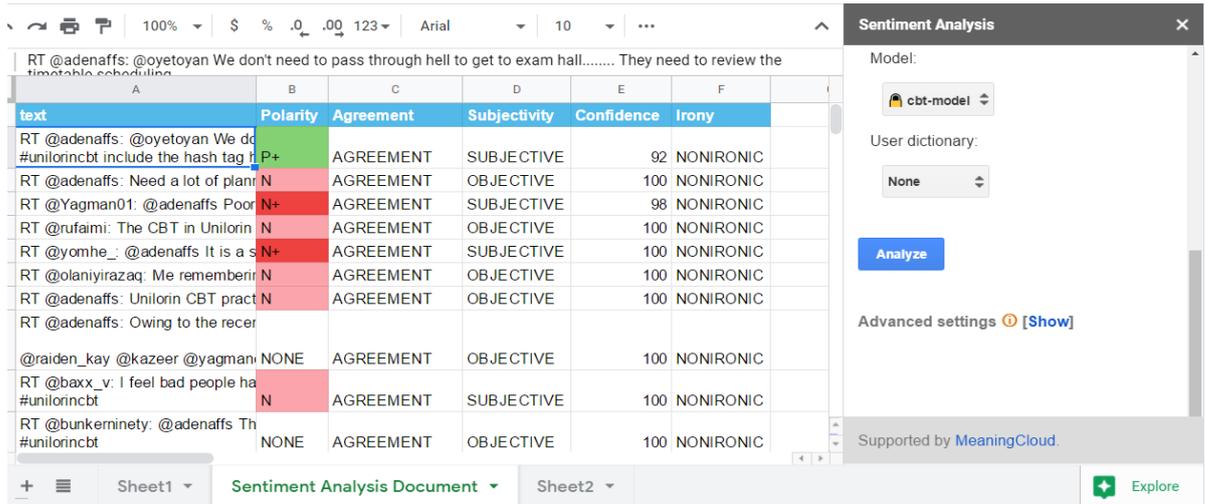


Fig 5: Sentiment Analysis Result of Students’ Tweets

In order to derive the necessary meaning from the study, the sentiment analysis approach of textual data was carried out. This helped to categorized subjectivity of tweet into subjective and objective and also its polarity level into positive and negative. With these, students’ opinions could be clearly understood and can lead to a need for amendment and improvement in practices. This is in agreement with the assertion of [13] that opinion polarity shows a level of appraisal and critics. Fig 6 shows the sentiment score by the polarity of each tweet and figure 7 shows the polarity distribution by percentage. The result reveals that many of the students’ tweets carried negative polarity, with 30.5% negative, 10.04% strong negative, 4.44% neutral, 20.85% none, 27.22% positive and just 6.95% strong positive. This gives a total of 40.54% negative, 34.17% positive, and 25.29% others.

Row Labels	Count of Polarity
N	158
N+	52
NEU	23
NONE	108
P	141
P+	36
<b>Grand Total</b>	<b>518</b>

Fig 6: Distribution of Sentiment Score by Polarity

Row Labels	Count of Polarity
N	30.50%
N+	10.04%
NEU	4.44%
NONE	20.85%
P	27.22%
P+	6.95%
<b>Grand Total</b>	<b>100.00%</b>

Fig 7: Distribution by Percentage of Grand Total

Figures 8a, b and c present the representation of tweets by its subjectivity. It shows the level of subjectivity and objectivity of students’ tweets. It is evident from the figures that the tweets were more

objective than subjective. The data collected here shows its appropriateness for the study as the analysis demonstrates that student opinions are more objective i.e. showing facts, rather than being subjective or showing personal feelings.

Row Labels	Count of SUBJECTIVE
OBJECTIVE	323
SUBJECTIVE	194
<b>Grand Total</b>	<b>517</b>

Fig 8a: Opinion by Subjectivity Count

Row Labels	Count of SUBJECTIVE
OBJECTIVE	62.48%
SUBJECTIVE	37.52%
<b>Grand Total</b>	<b>100.00%</b>

Fig 8b: Opinion by Percentage Subjectivity

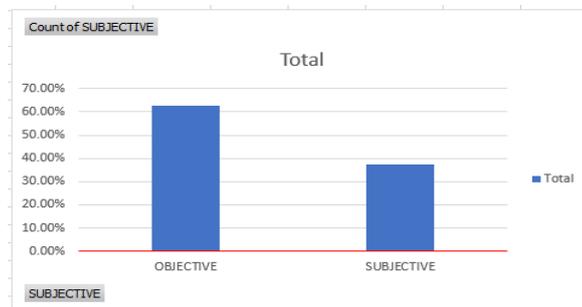


Fig 8c: Graphical Representation of Opinion by Subjectivity

Figure 9 presents positive opinion tweets by the student. Some of the positive opinions shown in students’ tweets include: preference of objective-based examination overwritten, timely upload of the result but these are found to be few from students’ posts.

University of Ilorin #UNILORIN is the most sought after University in Nigeria.2014 - 1st2015 - 1st2016 - 1st2017 - 1st2018 P  
 RT @Gidi\_Traffic: "eniola\_opeyemi: FLASH: University of Ilorin #UNILORIN is the most sought after University in Nigeria P  
 You think of safari friendly with animal #visit unilorin zoological garden for the experience and talk to us @omotoshotours P  
 RT @adenaffs: @oyetoyan We don't need to pass through hell to get to exam hall..... They need to review the timetable P+  
 RT @Raiden\_kay @kazeer @darapson @CNwadiogbu @olanirirazaq @falomo @ishaqDM @Larnford @Tolu P+  
 RT @adenaffs: @caboni @belloxii @ibnsalam123 @phatimmm @GENIUSakaOCJ @dami\_lare @kareemtobiazeez @as P+  
 RT @MusefiuA: @adenaffs @oyetoyan We don't need to pass through hell to get to exam hall..... They need to review P+  
 RT @adenaffs: @oyetoyan We don't need to pass through hell to get to exam hall..... They need to review the timetable P+  
 RT @MusefiuA: @adenaffs @oyetoyan We don't need to pass through hell to get to exam hall..... They need to review P+  
 RT @adenaffs: @Raiden\_kay @kazeer @darapson @CNwadiogbu @olanirirazaq @falomo @ishaqDM @Larnford @Tolu P+  
 RT @adenaffs: @caboni @belloxii @ibnsalam123 @phatimmm @GENIUSakaOCJ @dami\_lare @kareemtobiazeez @as P+  
 @caboni @belloxii @ibnsalam123 @phatimmm @GENIUSakaOCJ @dami\_lare @kareemtobiazeez @asquarez @unilo P+  
 @Raiden\_kay @kazeer @darapson @CNwadiogbu @olanirirazaq @falomo @ishaqDM @Larnford @Tolulope saw a lady P+  
 @adenaffs @oyetoyan We don't need to pass through hell to get to exam hall..... They need to review the timetable sct P+  
 @oyetoyan We don't need to pass through hell to get to exam hall..... They need to review the timetable scheduling #u P+  
 RT @thalksbossx: That splendid moment when the answers to multiple-choice questions appear bold. #UnilorinCBT P+  
 RT @thalksbossx: That splendid moment when the answers to multiple-choice questions appear bold. #UnilorinCBT P+  
 RT @YHUNG\_KHALIFAH: No one passed away at the #unilorinCBT centre o all was just a rumour Buh @unilorin need to P+  
 RT @thalksbossx: That splendid moment when the answers to multiple-choice questions appear bold. #UnilorinCBT P+  
 RT @thalksbossx: That splendid moment when the answers to multiple-choice questions appear bold. #UnilorinCBT P+  
 RT @YHUNG\_KHALIFAH: No one passed away at the #unilorinCBT centre o all was just a rumour Buh @unilorin need to P+  
 RT @thalksbossx: That splendid moment when the answers to multiple-choice questions appear bold. #UnilorinCBT P+  
 RT @Smart\_adeyemi: Signed out 📧📧📧📧 4 years of abundant grace🙏#unilorin #microbiology https://t.co/mvIH1fS P+  
 RT @Smart\_adeyemi: Signed out 📧📧📧📧 4 years of abundant grace🙏#unilorin #microbiology https://t.co/mvIH1fS P+  
 RT @Smart\_adeyemi: Signed out 📧📧📧📧 4 years of abundant grace🙏#unilorin #microbiology https://t.co/mvIH1fS P+

Fig. 9: Presentation of Positive Opinion



## V. Conclusion

Owing to the numerous negative opinions of students on the challenges faced in writing CBT examinations which often occur as a result of so many factors like inappropriate time-table scheduling, insufficient facilities, bad student-staff relationship etc, the University of Ilorin Management must effectively re-strategize the objectives of the CBT center in order to derive the desired outcome. Nevertheless, some positive tweets on the CBT examinations such as timely results, preference of CBT examination to written due to the multiple-choice nature of the exam should be maintained and improved on.

## VI. Recommendations

Based on the outcome of the study, the following recommendations are made:

1. There should be more CBT halls to cater to the exponential increase in student intake at the University of Ilorin.
2. Examination time should be scheduled by faculty to alleviate the massive queue always experienced before students take their exams.
3. Time taken for the exam after students' login should be consistent; if an exam is scheduled for 5 minutes then the exam should actually last for 5 minutes after login.
4. There should be an improvement in the student-staff relationship at the CBT center as such a harmonious relationship can increase the chances of a student doing well in the exam.
5. The students should be made to obey rules and regulations guiding CBT examinations to avoid unnecessary embarrassment and allow for smooth examination exercise before and during an examination.
6. High capacity UPS should be put in place to cater to an unexpected interruption in power supply.

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