Twitter Sentiment Analysis: A Case Study of Ten University Libraries

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Abstract

Sentiment analysis is a computer rule based automatic process that has the ability to scrutinize the short text message, user comments, and other textual information and gives the sentiment score on a given subject. The current study is to examine the sentiment analysis of twitter comments of ten university libraries. The ten of universities list was compiled from World university rankings 2019 (Time Higher Education Website). A total of 15850 number of tweets collected between 1st Jan 2013 and 1st September 2019 via Twitter Application Programming Interface (API) for further analysis. The study found overall av. Pos. - av. Neg. was 0.4115. Out 15850 tweets majority of the tweets from The Bodleian Libraries, University of Oxford about 2760 tweets and highest friend followers 76180 found. Significantly, The Bodleian Libraries, University of Oxford was the highest Av. Nos. of positive sentiment (1.7728). However, the lowest Av. Neg. sentiment received by Yale Library about (1.1454). Moreover, the study found that the word "exhibition" (499) times and "archive" (401) times used in total tweets. Likewise, the word "Congratulations" found average positive sentiment (3.0152) mentioned in total tweets. The study recommended that the library can use social networking sites and examine the user comments, feedback, and reviews that, a user had given on different posts. By doing this, the library will be in better position to overcome the problem and make better decisions for future.

Keywords: Sentiment Analysis, Social Media, Twitter, University Library

Introduction

In the recent past years, there have been growing use of different social media platforms by peoples for doing professional activities (Sarlan, Nadam, & Basri, 2015). It is playing an significant role in the dissemination of information in large groups in a convenient way (Mohammadi, Thelwall, Kwasny, & Holmes, 2018). In addition, a large number of organizations, peoples have been using social media for sharing information (Thelwall & Cugelman, 2017).It is a popular medium for sharing personal information and mass communications (Gopalakrishna Pillai, Thelwall, & Orasan, 2018). Social media tools like Facebook, Twitter, Linkedin are very popular (Parabhoi & Pathy, 2017). Traditionally believe that it is used for entertainment purpose however, it has been widely used by different academics and institutions for sharing information. Twitter is a powerful microblogging website that attracts large number of audiences and frequently visited websites worldwide. It allows user to share short messages via the internet (Twitter, 2019). It provides a platform for sharing information and personal opinion, discusses and comments on the post (Rasool, Tao, Marjan, & Naveed, 2019). In

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addition, academics used this platform for sharing academic activities (Mohammadi et al., 2018). It is great source of information related to news items (Wilkinson & Thelwall, 2012). With the development of ICT and web-based social media platforms give opportunity to track emotion of event that has been visible via text and tweets (Thelwall & Buckley, 2013). In recent past year, sentiment analysis has been widely used (Thelwall et al., 2013) to evaluate product performance by trading company as well as it has been used in academic research for analyzing user comments, reviews and posted in online platform such as Facebook, Twitters and trading websites, etc. Sentiment analysis of twitter comments is a popular topic in recent past years. (Wegrzyn-Wolska, Bougueroua, Yu, & Zhong, 2016).However, it is a challenging job due to diversity and huge amount informant which has not been well-organize (Kanavos et al., 2017). Despite of, large number literature has been published on twitter comment analysis, however, no significant study of twitter account and their tweets on academic libraries. This study made an attempt of twitter sentiment analysis of ten university libraries.

Objectives

- To conduct a comparative sentiment analysis of the ten university library twitter account.
- Identify positive and negative sentiment of overall tweets.
- To find out, total friends and followers.
- To identify a strong social network on Twitter.
- To find out time series and average sentiment of total tweets, Green Library, and Archive word.

Related Research

In recent past year several studies have been conducted on sentiment analysis of user comments using social websites like Facebook, Twitters and YouTube videos comments etc (Gopalakrishna Pillai, Thelwall, & Orasan, 2018c; Gopalakrishna Pillai, Thelwall, & Orasan, 2018b;Thelwall et al., 2013;Thelwall & Buckley, 2013;Ji, Chun, Wei, & Geller, 2015;Shukri, Yaghi, Aljarah, &Alsawalqah, 2015). For instance (Shukri, Yaghi, Aljarah, & Alsawalqah, 2015) made an attempt on the automotive industry using two methods such as text mining and sentiment analysis. In this study, the author used twitter data posted by the user on Audi, BMW, and Mercedes Cars. The study noted that, 83% of positive reviews on Audi cars among BMW and Mercedes. Similarly, (Parabhoi & Saha, 2018)analysed YouTube comments related to Koha ILS. A total 404 YouTube comments were reviewed. (Parabhoi & Saha, 2018) noted 338 comments were subjective and 66 comments were objective. A notable study made by (Tafti, Zotti, & Jank, 2016) sentiment analysis of hot topic using web data mining techniques. Tafti et al., (2016) analyzed all posted tweets based on sentiment dictionary. Abbasi, Hassan, & Dhar, (2014) reviewed 20 sentiment analysis tools using five different testbeds.(Kale & Padmadas, 2018) analysed twitter tweets using lexical based approach to identify user sentiment. The data extracted from twitter using text mining technique. To analyzed user tweets sentiment on social event a notable study made by (Zhou, Tao, Yong, & Yang, 2013) and proposed a new method called the Tweets Sentiment Analysis Model (TSAM). In this study authors selected Australian federal election 2010. The study revealed the proposed method worked effectively. (Kumar & Nezhurina, 2020) analyzed the sentiment of traveller of long route superfast trains of Indian railways using machine learning techniques reviewed of 15777 tweets. The study noted that back propagation neural networks (BPNN) provided accoutred results as compared to support vector machines (SVM), Random forest (RF) techniques. To identify which mobile is better to purchase a study made by (Krishnan, Sudheep, & Santhanakrishnan, 2017) on mobile phones collected customers reviewed using lexical based approach. In this paper authors considered five mobile popular brands such as Samsung, Motorola, Nexus, iPhone, Lenovo. However, no literature found on tweet count and user sentiments of posted short messages on Twitter page of academic library. In this study, I analyzed the tweets of ten university libraries.

Method

The ten universities were selected from World University ranking 2019 and only selected top ten universities (Time Higher Education, 2019).The study used two free software's such as Webometric Analyst and Mozdeh (Statistical Cybermetrics Research Group, 2019). Webometric Analyst was used for collecting general profile information of the library such as friends and friend's followers and making networks. Whereas, sentiment analysis and time series, I used Mozdeh software. Initially, a total of 17197 number of tweets collected between 1st Jan 2013 and 1st September 2019 via Twitter Application Programming Interface (API) of most recent 3200 tweets for individual twitter account as per maximum rate fixed by Twitter (Thelwall, 2018). In the later stage, I removed some duplicate tweets for further analysis. Finally, 15850 numbers of tweets collected for further analysis.

Data Analysis

Table.1 shows friends and followers of university libraries. A total of 15850 number of tweets collected through Mozdeh software. Further, the data were sorted with the highest number of tweets. The highest number of tweets found from The Bodleian Libraries, University of Oxford 2760 tweets out of total sample of 15850 tweets and highest number of followers among top ten University library twitter accounts. Furthermore, data-informed that, highest number of friends 1408 by Yale Library, Yale University whereas, lowest friends found twitter account of Caltech Library, California Institute of Technology. Twitter follower is the indicators of popularity. It can be said that, among these top ten university library twitter account, The Bodleian Libraries was the most popular.

Table.1

Name	Screen Name	Followers	Friends	Total No of Tweets
The Bodleian Libraries, University of Oxford	bodleianlibs	76180	1155	2760
Harvard Library,Harvard University	Harvard Library	32377	1407	2131
Imperial Library, Imperial College London	imperial library	4010	247	2123
ChicagoLibrary,University of Chicago	UChicago Library	1347	340	2020

Stanford Libraries, Stanford University	StanfordLibs	3956	1174	1757
Cambridge University Library, Cambridge University	theUL	17418	346	1660
MIT Libraries, Massachusetts Institute of Technology	mitlibraries	17151	765	1479
Princeton University Library, Princeton University	PULibrary	1576	196	1250
Caltech Library, California Institute of Technology	CaltechLibrary	377	172	388
Yale Library, Yale University	yalelibrary	11887	1408	282

Sentiment Score:

The below Table.2 informs about the sentiment score of total tweets collected from the twitter account of ten university libraries. It was found that the average positive sentiment was 1.6355 while, the average negative sentiment was1.2240. Moreover, table informed that the average positive- negative score was 0.4115. It can be said that greeter av. Pos. sentiment as compare av. neg. sentiment.

Table: 2

Sentiment Analysis Results	
Average Sentiment Score	
Pos. 1.6355	
Neg. 1.2240	
Av. Pos. - Av. Neg.	0.4115

A friend and follower Network

The figure informs the friend and follower network and how they were well connected with others on Twitter. It can be seen that some libraries were directly connected with each other library whereas some libraries were not directly connected. For instance, Harvard university library was not directly connected with the Caltech library similarly Caltech library was not directly connected with MIT libraries. Some library directly connected with each other like MIT Library direct connected with Princeton University Library and Harvard library was connected with The Bodleian Libraries. Furthermore, Yale Library, Harvard Library, Stanford library, and Princeton Library had strong friends and followers.

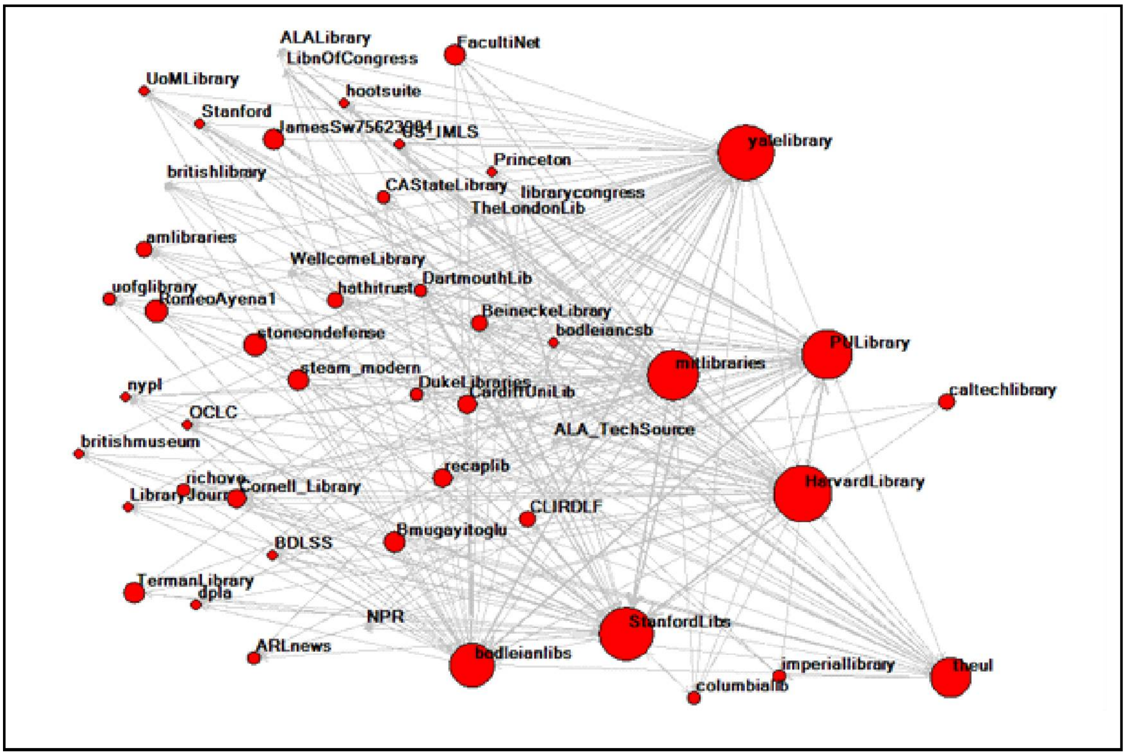

Figure.1

Average Sentiment Score

Table.3 informs the total number of tweets and sentiment scores of ten university libraries. The tweets of user can analyse whether positive or negative sentiment. The data was sorted highest number of tweets collected from twitters. It was found that highest number 2760 of tweets posted by the Bodleian Libraries, University of Oxford whereas, lowest number 282 tweets posted by Yale Library, Yale University. Similarity, highest Av.Pos-Av. Neg 0.5745 by Yale Library, Yale University whereas lowest Av. Pos-Av. Neg received by 0.2407 Imperial Library, Imperial College London. Furthermore, highest average Pos. 1.7728 response received The Bodleian Libraries, University of Oxford in total 2760 tweets however, lowest average positive1.4356 response received by Caltech Library, California Institute of Technology. Moreover, data-informed that highest average negatives sentiment received by Imperial Library, Imperial College London with 1.3005 average Neg. sentiment in their total post and whereas Yale Library, Yale University received lowest average neg. sentiment in their total posted tweets.

Average Sentiment Score Table.3

SNo	Name	Tweets	Av.Pos Av.Neg:	Average Pos.	Average Neg.
1	The Bodleian Libraries, University of Oxford	2760	0.4754	1.7728	1.2975
2	Harvard Library,Harvard University	2131	0.3656	1.5275	1.1619
3	Imperial Library, Imperial College London	2123	0.2407	1.5412	1.3005
4	Chicago Library, University of Chicago	2020	0.5688	1.7500	1.1812
5	Stanford Libraries, Stanford University	1757	0.3785	1.5657	1.1873
6	Cambridge University Library, Cambridge University	1660	0.3813	1.5988	1.2175
7	MIT Libraries, Massachusetts Institute of Technology	1479	0.5477	1.7539	1.2062
8	Princeton University Library, Princeton University	1250	0.3112	1.5408	1.2296
9	Caltech Library, California Institute of Technology	388	0.2887	1.4356	1.1469
10	Yale Library, Yale University	282	0.5745	1.7199	1.1454

Sentiment Score by Word

Table.4 gives information about the sentiment score of the mentioned words. Randomly selected 15 words for analyzing sentiment scores, however, this word was very popular in the library activities. The data was sorted by highest number of tweets found in total 15850 tweets. It was found that the word "Exhibition" (499) words significantly used in their post followed "Archive" (401) and "Congratulations" (132) times used. Furthermore, the data found that "Congratulations" word significantly average positive sentiment found with 3.0152. Similarly, the words "Plagiarism" 6 times found in total post and it was found highest 1.8333 average negative sentiment score.

Sentiment Score by Word Table.4

Sl No	Word	Total Tweets	Average Pos	Average Neg	Average Pos-Neg
1	Exhibition	499	1.7074	1.2345	0.4729
2	Archive	401	1.6559	1.1970	0.4589
3	Congratulations	132	3.0152	1.0833	1.9318
4	Green Library	106	1.5000	1.2925	0.2075
5	Open Access	97	1.2887	1.3196	-0.0309
6	Celebrating	86	2.3372	1.1395	1.1977

7	Rare book	60	1.6833	1.1333	0.5500
8	Repository	47	1.4043	1.1064	0.2979
9	Digital Library	29	1.6897	1.0345	0.6552
10	Copyright	27	1.5556	1.2963	0.2593
11	Web of Science	20	1.0000	1.5500	-0.5500
12	Research Data Management	14	1.2143	1.3571	-0.1429
13	Artificial Intelligence	10	1.9000	1.2000	0.7000
14	Scopus	8	1.2500	1.6250	-0.3750
15	Plagiarism	6	1.0000	1.8333	-0.8333

Time Series of all post

The time series Fig.2. informs the growth of total posted tweets from 1st Jan, 2013 to 1st September, 2019. The tweets rate was not stable and at the beginning of 2013, the tweets were very slow. However, significantly the posted tweets were growing end of the year 2018 and 2019. At the bottom of the graph average post sentiment can be seen. It shows that the average positive sentiment found in the year 2018 and 2019. Similarly, moderate negativity and positive sentiment found between 1st Jan, 2013 and 1st September, 2019.

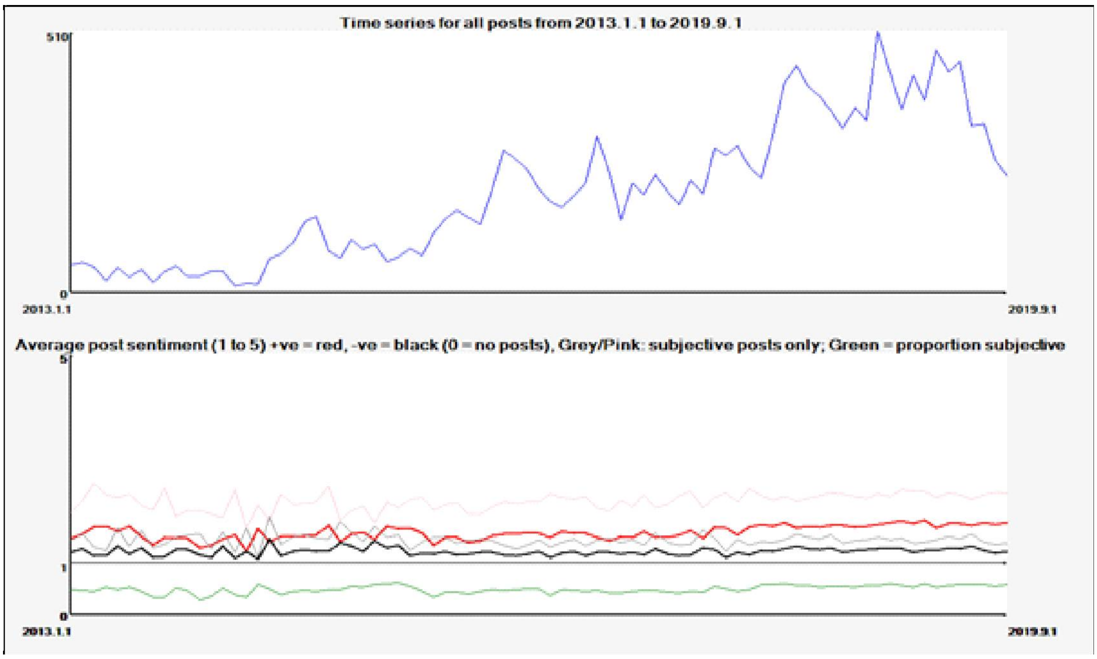

Figure.2

Time Series for all post mentioned Archive

Figure.3 shows the tweets mentioning word "archive" in the total tweets of corpus from 1st Jan 2013 to 1st September 2019. It can be said that several bursts of interest were found. At the beginning of 2013 the word "archive" was at the top of the interest however, decreased in interest over time and again increased in interest at end. At the bottom of the graph very low positivity and very low negativity average sentiment found. And very moderate subjectivity post found.

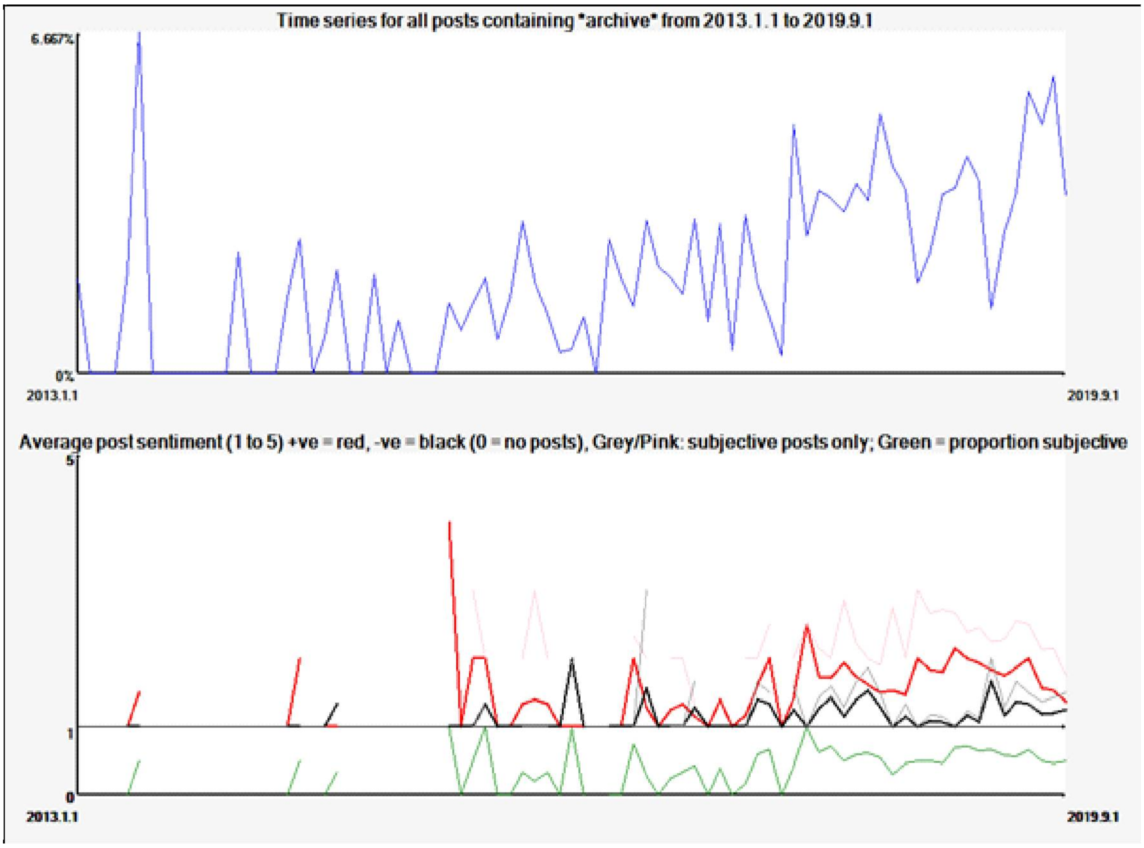

Figure.3: Time Series for All Posts Containing Archive Word

Time Series for all post mentioned Green Library:

Figure.4 gives information all tweets contained the word "Green Library" between 1st Jan, 2013 and 1st September, 2019. At the beginning of 2013, the tweets related to "Green Library" were very slow and there were two bursts of interest found and at the beginning one burst of interest found in the year 2013 and another big burst of interest was found in the year 2014. At the bottom of the graph very low positivity and very low negativity average sentiment found and moderate subjectivity post found.

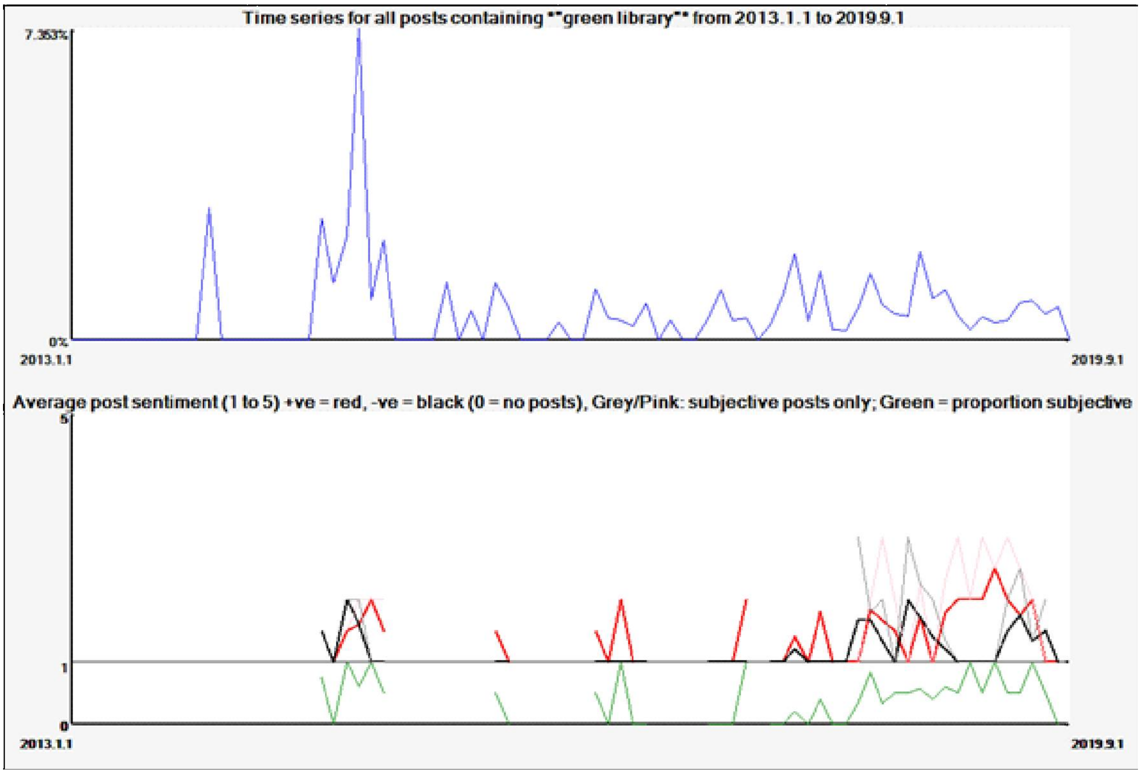

Figure.4: Time Series for All Posts Containing Green Library

Conclusion

Social networking sites have been increasingly used by diverse intuitions, organizations, trading websites to connect with the people. In addition, it allows the user to get feedback, comments, and reviews on the product and services. This research work has demonstrated that the sentiment analysis tweets posted by ten universities library worldwide. A total 15850 tweets were reviewed with av. Pos-av. Neg was 0.4115 found. Out 15850 tweets majority of the tweets from The Bodleian Libraries, University of Oxford about 2760 tweets and highest friend followers 76180 found. Significantly, The Bodleian Libraries, University of Oxford was the highest Av. Nos. of positive sentiment (1.7728) found, which the positive symbol of any institution was. However, lowest Av. Neg. sentiment received by Yale Library about (1.1454). Moreover, study found that the two words Exhibition (499) and Archive (401) mostly used out of total tweets. Likewise, "Congratulations" word significantly found average positive sentiment (3.0152) out of 15 words. Furthermore, the study found that the growth of tweets posted was very slow at the beginning 2013. However, significantly the posted tweets were growing end of the year 2018 and 2019. In conclusion; the library can use SNSs and analyse the user comments, feedback, and reviews that, user had given on users on different posts. By doing this, the library will be in better position to overcome the problem and make better decisions for future.

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