Investigating the characteristics and research impact of sentiments in tweets with links to computer science research papers

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Investigating the Characteristics and Research Impact of Sentiments in Tweets with Links to Computer Science Research Papers

Abstract. Research papers are often shared in Twitter to facilitate better readership. Tweet counts are embedded in journal websites and academic databases, to emphasize the impact of papers in social media. However, more number of tweets per paper is doubted as an indicator of research quality. Hence, there is a need to look at the intrinsic factors in tweets. Sentiment is one of such factors. Earlier studies have shown that neutral sentiment is predominantly found in tweets with links to research papers. In this study, the main intention was to have a closer look at the non-neutral sentiments in tweets to understand whether there is some scope for using such tweets in measuring the interim quality of the associated research papers. Tweets of 53,831 computer science papers from the Microsoft Academic Graph (MAG) dataset were extracted for sentiment classification. The non-neutral sentiment keywords and the attributed aspects of the papers were manually identified. Findings indicate that although neutral sentiments are majorly found in tweets, the research impact of papers which had all three sentiments was better than papers which had only neutral sentiment, in terms of both bibliometrics and altmetrics. Implications for future studies are also discussed.

Keywords: Twitter, Tweet Sentiments, Research Impact, Computer Science, Research Metrics.

1 Background

Social media has become a widely accessible information source since it enables users to post their opinions and multimedia content without much external verification [1]. Social media has transformed the communication between scholars and the public by facilitating access to research articles at a comparatively lesser cost and faster pace [2]. Accordingly, readers tend to recommend research articles which are relevant and useful to other users in their social media networks [3]. As a popular example, the microblogging platform Twitter is used by researchers and academicians to network with people of similar interests and to share information with wider audience.

It is well know that the impact of research outputs is measured using traditional indicators known as Bibliometrics [4]. On the other hand, the rise of social media platforms and increasing online activity of users, have led to the development of a new set of indicators called Altmetrics, a term proposed in 2010 [5]. Popular examples of these social media metrics include tweets count, Mendeley readers count, bookmarks count for the corresponding research papers. Subsequently in recent years, research has been conducted on themes such as investigating researchers' intent behind social media sharing and outreach [6, 7]. Studies have shown that these metrics are weak indicators of research impact due to the lack of meaningful context while sharing research papers in social media platforms [8].

The Matthew effect in citations leads to highly cited papers to be cited even more [9]. This effect is facilitated by academic search engines and databases which rank papers based on higher number of citations. Unless the user changes the sort options to rank papers by recency, the highly cited papers keep attracting user's attention. Social media impact indicators can be perceived as an alternative to rank papers in academic systems. However, these sources are not used by everyone in the research community. For instance, Twitter is banned in some countries where they have their own microblogging platforms (e.g., Weibo). Mendeley is not widely used as Endnote. Most importantly, these metrics do not assure quality. A high altmetric score for a research paper indicates that the paper is popular in different social media platforms. Among the different altmetric indicators, only Mendeley readers count has been found to be correlated with citations count [10]. Other social media metrics mostly have weak positive correlations [11, 12]. Hence, the impetus is to mine deeper into the social media data to get better insights on the quality of the papers.

In this study, the focus is on Twitter since it is one of the popular social media platforms for researchers. It is often observed that a research paper with more number of tweets has a high aggregated altmetric score. Tweet count is the main Twitter metric. Some of the associated disadvantages of relying solely on tweet counts have already been underlined in earlier studies [8]. Apart from the tweet count, retweets count and favorites count are other Twitter metrics whose use is restricted due to high data sparsity. Apart from these metrics, the tweet content can be used for gleaning insights about the opinions of Twitter users about the research papers that are shared through the tweets. Twitter content analysis has been an area of research conducted to study different type of events such as pandemics [13] and politics [14], to name a few. One of the methods of content analysis, sentiment analysis is a way of determining the sentiment or opinion about a product or subject in a discussion or conversation [15]. An opinion is "simply a positive or negative sentiment, view, attitude, emotion, or appraisal about an entity or an aspect of the entity" [16]. This method has been used with the content from social media platforms as well [17, 18].

Although Twitter content analysis studies are frequently conducted, studies on sentiment analysis of tweets containing links to research papers are very few. Three studies have been conducted on this topic. In the earliest study [19], a manual content analysis was conducted on 270 tweets from papers published in 2012. 96% of the tweet had neutral sentiments while the remaining 4% tweets had positive sentiments. There were no negative sentiment tweets found. In this study, other facets such as main content of tweet, authorship attribution and expression of interest were also identified.

In the next study [20], sentiment analysis was done on an extract of 1,000 tweets using the SentiStrength[1] tool. In this study, 94.8% of the tweets had neutral sentiment while positive and negative sentiments were found in 4.3% and 0.9% of the tweets respectively. The authors conclude that sentiment analysis tools do not perform an adequate identification of negative tweets. In another study conducted by the same authors

[1] SentiStrength http://sentistrength.wlv.ac.uk/

[21], a larger extract of 487, 610 tweets were classified. The percentage of positive tweets is the highest in this study with 11% and even negative tweets were identified for 7.3% of the tweets while neutral sentiment tweets were at 81.7%. Since this study was conducted on papers from different disciplines, authors identify that the highest percentage of negative tweets were found in social sciences and humanities disciplines. However, this study lacks in-depth analysis of the tweets containing non-neutral sentiments.

2 Research Objectives

In this study, we have attempted to understand the role and nature of sentiments in tweets by starting with a qualitative analysis of tweets with non-neutral sentiments. In addition, we have also compared the performance of papers with all sentiments against papers with just neutral sentiment in tweets. These two objectives were conceptualized due to the need for identifying new metrics or data items from Twitter, which could be used as proxy measures for ascertaining quality of research papers. For this study, we wanted to focus on Computer Science (CS) research papers since CS papers are popular in Twitter. The research reported in this paper addresses the following questions.

RQ1: How are the sentiments represented in the tweets, in terms of composition, keywords and attributed aspects?

RQ2: How do papers with all three sentiments compare against papers with only neutral sentiments in terms of impact indicators?

3 Methodology

3.1 Data Collection and Pre-processing

The Microsoft Academic Graph (MAG) dataset provided by Microsoft Research [22] was used for this study. The dataset version used in this paper was released on February 2016. Computer science (CS) related papers were extracted from the MAG dataset using the CS venue entries indexed in DBLP, a bibliographic database which covers publications from major CS journals and conference proceedings. The citation counts of the extracted papers were calculated with the MAG dataset internally. From this initial extract of CS papers, the papers published since 2012 were shortlisted (n=53,831) as most papers published before that period, tend to have very minimal social media data. The altmetric impact indicators of these papers were extracted using the APIs provided by Altmetric.com and PlumX. From these 53,831 papers, it was found that only 13,809 papers (25.65%) had tweets. Bot and spam accounts are a well-known phenomenon in Twitter [23]. To remove such accounts, the twitter user's description field was used. Keywords such as bot and robot were employed for this filtering purpose. In the next stage, the paper titles were removed from the tweets. At this stage, there were 77, 914 tweets. In the next step, retweets were also removed and the final extract of tweets to be classified and analyzed stood at 49,849 tweets for 12, 967 associated papers.

3.2 Determining Sentiment Polarity and Score

The TextBlob[2] package in Python was used for determining the sentiment polarity of tweets. The TextBlob module has a scoring scale range from -1 to +1. This range was initially divided into five equal parts and classified as shown in Table 1. To verify the current classification scheme used, manual annotation process was carried out on entries which fell under the positive and negative sentiment category. When comparing the manually annotated sentiment category tweets, it was found that some of the neutral tweets were classified as either positive or negative. Through further analysis, it was found that actual neutral tweets had a sentiment score between -0.3 and 0.3. The score scheme was adjusted accordingly. The modified scoring scheme has been included in Table 1.
The existing sentiment classification tools and libraries used in general domains, are not directly applicable for classifying tweets that contains links to research papers. The main reason being the presence of paper titles in the tweets [19], which could be resolved to some extent by data cleaning. The secondary reason being the training model built with data from other domains. In the current study's classification phase, it was decided that the tweets which are initially classified as neutral could be left unchanged. The positive and negative tweets were manually checked to reclassify certain tweets to the neutral category. Thus, the modified sentiment score range could be adopted in future studies where the TextBlob library is used to classify sentiments.

Table 1. Initial and modified sentiment score ranges

Initial sentiment score range	Modified sentiment score range	Sentiment category
> 0.5 and <= 1.0	> 0.5 and <= 1.0	Extremely Positive
> 0.0 and <= 0.5	> 0.3 and <= 0.5	Positive
= = 0.0	>= -0.3 and <= 0.3	Neutral
< 0.0 and >= -0.5	< -0.3 and >= -0.5	Negative
< -0.5 and >= -1.0	< -0.5 and >= -1.0	Extremely Negative

3.3 Extraction of Sentiment Keywords and Identification of Aspects

After the sentiment classification exercise was completed, the next step was to extract the keywords representing positive and negative sentiments in the tweets. Along with these keywords, the aspect of the papers for which the sentiment was expressed, was also identified for each non-neutral tweet. The identification of aspects was first performed by a single coder and later validated and corrected by two other coders. For this coding exercise, coding book was not employed, instead the coders decided the aspect codes through a grounded theory approach [24].

[2] TextBlob: Simplified Text Processing https://textblob.readthedocs.io/en/dev/

4 Results

4.1 Representation of Sentiments in Tweets

In Table 2, the statistics related to the distribution of the sentiment categories in tweets are listed along with the associated papers count and averages of likes count and retweets count of the tweets. A vast majority of the tweets had neutral sentiment (97.16%) which is even more than the previous studies [19, 20]. Positive sentiments accounted for about 2.8% of the tweets while negative sentiments were found in a meagre 0.05% of the tweets. Among the tweets classified for the total 12,973 papers, non-neutral sentiments were found in 991 papers (7.8%). Interestingly, non-neutral tweets had more likes and retweets than neutral tweets at an average level. It is re-iterated that the retweets were removed from the extract before the data was analyzed.

Table 2. Sentiment classification stats

Sentiment	Tweet Count	Associated Paper Count	Likes Count (μ)	Retweets Count (μ)
Positive	866 (1.74%)	579	1.15	1.03
E. Positive	527 (1.06%)	393	1.65	1.58
Negative	15 (0.03%)	12	1.73	0.93
E. Negative	9 (0.02%)	7	0.78	3.33
Neutral	48432 (97.16%)	12791	0.94	0.83

The extracted keywords from the positive and negative sentiment tweets are illustrated as tag clouds in Figures 1 and 2 respectively. 92 positive and 18 negative unique keywords were extracted from the 2,709 non-neutral tweets. The existence of common positive keywords such as *interesting, nice, good* and *great* was apparent since these keywords are used as a general form of appreciation in conversations. Comparatively, negative keywords such as *stupid, bad* and *terrible* were found to be used with more intent. In Tables 3 and 4, the top 5 aspects and corresponding keywords along with examples are listed for positive and negative tweets respectively.

Fig. 1. Positive keywords in tweets

Table 3. Aspects and keywords in positive tweets

Aspect	Keywords Used	Example Tweets*
Overall paper	awesome, great, interesting, fascinating, nice, new	*a paper published on cloud biolinux. awesome. [URL]*
		this is really good. simple rules for better figures [URL] great tips with examples
Readership	good, great, interesting, nice, worth	*[TH] [TH] the value of draft picks. nerdy but a great read [URL]*
		looks worth a read #ploscompbio: [Paper] [URL] #oxcompbio
Review	awesome, good, great, interesting, nice	*adjusting confounders in ranking #biomarkers: a model-based roc approach - #awesome review [TH] [URL]*
		a nice review paper about image segmentation on gpus [TH] [TH] #gpgpu [URL]
Work	amazing, excellent, impressive, interesting, nice	*[TH] just read article on usability testing serious games [URL] excellent work. will be sharing with my students.*
		brainbrowser: distributed, web-based neurological #dataviz. impressive work via [TH] w/ [TH] and more. [URL]
Study	beautiful, best, cool, interesting, nice	*beautiful study on how the canary sings! relevant to sequence organization in animal behavior in general. [URL]*
		cool study by browning harmer suggesting anxiety disrupts the expectancy learning process (for threat info) - [URL]

Note: [TH] stands for Twitter handle

In the case of positive sentiments, the most commonly attributed aspect was the *overall paper*. There are two main reasons for the prominence of this aspect. Due to the character limit imposed in Twitter, end-users tend to tweet in a terse manner. Secondly, the readers might be just indicating the initial impression of these papers [solid ending needed]. The other prominent aspects were *readership, review, work* and *study*. The *readership* aspect can be considered a derivative of the *overall paper* aspect, but it adds more credibility since the users indicate they have read the papers. The *review* aspect is applicable for literature review/survey papers which tend to quite popular among readers. The next two aspects are more intrinsic in nature. In the *work* aspect tweets, the workmanship was appreciated while the *study* aspect tweets indicate the superior quality of the research study described in the associated papers. Among these five aspects, *work, study* and *readership* are aspects that highlight the sound quality of research conducted in the tweeted research studies.

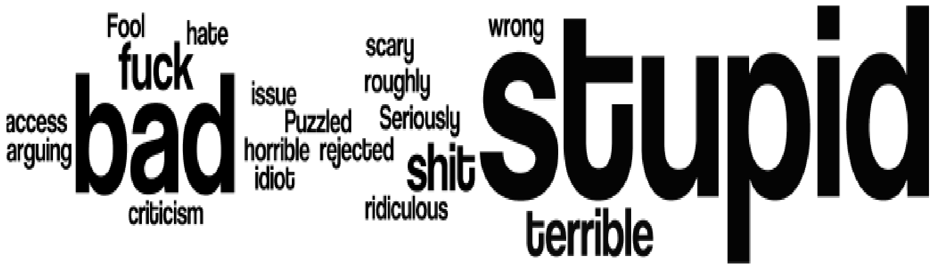

Fig. 2. Negative keywords in tweets

Table 4. Aspects and keywords in negative tweets

Aspect	Keywords Used	Example Tweets*
Overall paper	fool, seriously, shit, terrible, fuck	*this is terrible science ignore it: [URL] the article ([URL] even cites wakefield (2002).*
		#roundup has gone and fucked up. - has anybody else seen this published 4/18/13, linking roundup weed killer to... [URL]
Study	bad, stupid	*another bad study on narcissism social media [URL] 19 yr use twitter, 35 yr facebook. lots p surveys not comparable*
		this study should be called, facebook making us stupid [URL]
Opinion on authors	idiot	*[TH] here is one. so you are totally [URL] why am i arguing with an idiot who thinks he speaks for science*
Paper length	stupid	*keep it long and complicated, stupid. [URL]*
Paper title	horrible	*[Paper]. [URL] pevzner group. cool. (but what a horribly overloaded name!)*

Note: [TH] stands for Twitter handle

The number of aspects identified for negative sentiment tweets was low due to the overall lesser number of negative tweets. Similar to the positive sentiment tweets, the presence of aspects *overall papers* and *study* was apparent. The other three aspects were *opinion on authors, paper length* and *paper title*. Unlike positive sentiment aspects, the aspects *overall paper* and *study* could be considered as indicators of inferior research quality. The other three aspects appear to be lot more biased and personal in nature. However, such comments could end up being a precursor to undermine the impact of the corresponding research papers in the future.

4.2 Comparison of Paper Groups with Impact Indicators

The papers were classified into two groups. The first group included the papers (*n*=901) which had tweets with all three sentiments while the second group included papers (*n*=12066) which had tweets with only neutral sentiment. The two groups' impact performance was compared with six indicators. Citations was the singular bibliometric indicator while the other five were social media metrics (altmetrics). They were usage total (paper views and downloads count), likes count and retweets count from Twitter, Mendeley readers count and the Altmetric score (an aggregated score calculated by Altmetric.com[3]). The usage total data was extracted using PlumX API, likes and retweets count were extracted using web scraping with tweet URLs while all the other social media metrics data were extracted using Altmetric.com API.

The mean values and median values of the two groups are listed in Tables 5 and 6 respectively. The two groups were compared using arithmetic mean (average) and median values. The mean differences were found to be statistically significant using a t-test at $p<0.05$ level. Results indicate that the citations count of group 1 (μ=13.52) was higher than group 2 (μ=9.09). For the five other social media indicators, the values for group 1 were considerably higher than group 2. Papers in group 1 were viewed (usage total [μ=1765.78]) and read (Mendeley [μ=91.62]) more than group 2 (usage total [μ=557.51]); Mendeley [μ=48.77]). Hence, the altmetric score was also considerably higher for group 1 (μ=28.85) in comparison to group 2 (μ=3.97). The median values comparison results were also similar. However, the citation count of group 1 ($\tilde{x}$=5) was closer to group 2 ($\tilde{x}$=4). All the other indicator median values of group 1 was considerably higher than group 2, except for likes count and retweets count since zero values seem to be prevalent for most papers in both the groups.

Table 5. Mean values of the two groups

Paper Group	Citations	Usage Total	Likes Count	Retweets Count	Mendeley Readers	Altmetric Score
All sentiments (group 1)	13.52	1765.78	1.83	1.73	91.62	28.85
Only neutral (group 2)	9.09	557.51	0.66	0.56	48.77	3.97

[3] How is the Altmetric Attention Score calculated https://help.altmetric.com/support/solutions/articles/6000060969-how-is-the-altmetric-attention-score-calculated-

Table 6. Median values of the two groups

Paper Group	Citations	Usage Total	Likes Count	Retweets Count	Mendeley Readers	Altmetric Score
All sentiments	5	92	0	0	53	6
Only neutral	4	65.5	0	0	30	1.25

5 Discussion

The existing sentiment classification tools and libraries used in general domains, are not directly applicable for classifying tweets that contains links to research papers. The main reason being the presence of paper titles in the tweets [19], which could be resolved to some extent by data cleaning. The secondary reason being the training model built with data from other domains. In the current study's classification phase, it was decided that the tweets which are initially classified as neutral would be left unchanged. The positive and negative tweets were manually checked to reclassify certain tweets to the neutral category. Thus, the modified sentiment score range could be adopted in future studies where the TextBlob library is used to classify sentiments in tweets.

It was a tad surprising to find more neutral tweets (97.16%) in the current study. In previous studies, neutral tweets accounted for 81.7% [21] and 96% [19] of the total tweets. The general practice for Twitter users is to share informative web links to their network with very little commentary [8]. Hence, neutral sentiment is expected to be prevalent. Positive sentiment tweets were more visible than the negative sentiments. Yet, the percentage in the study (2.8%) was lower than both the earlier studies. The presence of negative sentiments continues to be meagre. Public criticism of research in social media does not seem to be a customary practice. Therefore, the likelihood for witnessing negative opinions on research papers will be low.

Sentiments are attributed to certain aspects of research papers. These aspects were identified for the positive and negative tweets by the coders. The aspects *overall paper* and *study* were common for both non-neutral sentiments. Providing opinion on the research paper is probably the most convenient method for a Twitter user as he/she might can post the initial thoughts on the paper. In [19], it is reported that 82% of the tweets did not attribute authorship. The same observation was made in this study where tweets had very little author-related information. If the Twitter users were colleagues or friends of the authors, they would have tagged such users. Yet, this type of tagging was not witnessed. Hence, it could be assumed that such positive/negative tweets were posted by researchers from the public domain. The *review* aspect among positive tweets is very similar to the *overall paper* aspect and the main difference being that this aspect is specifically for literature review/survey papers. The *readership* aspect among positive tweets, indicates that the Twitter users have read the papers and accordingly, such tweets carry more weightage than the aforementioned two positive aspects. Among the positive tweets, the remaining two aspects *work* and *study* are probably the most detailed aspects since such tweets contain specific opinion on the quality of the conducted research. The *study* aspect is also found among negative tweets.

For ascertaining the research impact performance, the papers were split into two groups – the first group with papers which had all three sentiment tweets and the second group which had only neutral sentiment tweets. The naïve hypothesis was that group 1 papers would have better values than group 2. Even though, the sample size of second group was comparably lesser than group 1, the difference in the means was statistically significant. For all the six indicators, group 1 had higher mean values than group 2. The difference was small only for the citation count while for the other social media metrics, the difference was substantial. The reason for this difference could be due to the higher number of tweets per paper for group 1 which had all three sentiments. More chatter in social media leads to more views and downloads, more readership in Mendeley and subsequently, higher aggregated altmetric score. However, the bibliometric indicator citations count also supports the better performance for group 1. Hence, for the papers in group 1, altmetric impact leads to a better bibliometric impact (i.e. more citations). This observation is new for research metric studies where earlier works haven't managed to show that higher altmetric scores correlate with higher citations count [11, 12]. From the analyses that were conducted, we posit that the non-neutral sentiment and aspect pair from tweets can be used to boost the weightage of papers when they are retrieved or recommended in academic search engines, databases and digital libraries.

There are a few limitations in this study. By the end of 2017, Twitter increased the character count in tweets to 280 from the earlier 140 characters. Hence, users can post more descriptive content and tag more users in their tweets. Therefore, this user-interface (UI) level change could possibly alter the usage dynamics of Twitter users. Secondly, the sentiment classification was performed only for computer science research papers in this study. This exercise needs to be extended to other disciplines for validating the findings.

6 Conclusion

Research performance has been traditionally measured using bibliometric indicators. These indicators take time to be measured as they are predominantly based on scientific citations. On the other hand, social media-based altmetric research indicators are often readily available but these indicators accurately represent mainly the popularity of the research papers and not necessarily the quality. Hence, there is a need to look at detailed level of social media data for ascertaining the quality of papers. In this study, tweet sentiments of 53,831 computer science papers from the Microsoft Academic Graph (MAG), were analyzed for this purpose. On expected lines, neutral sentiment accounted for about 97% of tweets. The keywords from the non-neutral tweets were extracted along with the attributed aspects of the papers. It was found that sentiments were mostly attributed to the overall paper followed by opinions on the study and research work. To test whether papers with all sentiments performed better than papers with only neutral tweets, six bibliometric and altmetric indicators were compared. Results indicated that papers with all sentiments performed better both in terms of citations and altmetric footprint. Through this study, we make a case for using non-neutral sentiment-aspect pairs as a proxy measure of quality. This filtered information could be used to appropriately rank recent papers in academic search engines, digital libraries and databases. In our future studies, we will be working on methods and techniques for incorporating non-neutral sentiment-aspect pairs in scientific paper retrieval and recommender systems.

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