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Who says what about the most-discussed articles of Altmetric?[1]

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Abstract
In Altmetrics, tweets are considered as important potential indicators of immediate social impact of scholarly articles. However, it is still unclear to what extent Twitter captures the actual scholarly impact. Therefore, it is necessary to investigate the people who cite the articles and the content of the tweets with attitude towards the articles comprehensively. In this paper, we combine different indicators to identify opinion leaders in the spread of the articles, and use sentimental analysis to quantify the sentimental polarity of tweets. Altmetrics should highlight the positive role of scientific research results to the public, which is more valuable than simple numbers.

Introduction

The altmetrics indicators (news stories, blog posts, tweets, facebook posts, etc.) have a very rapid response and feedback to the latest hotspots, which precisely complement the time lag issue of traditional citation-based indicators. The multiple indicators and data sources can improve the fairness of academic impact evaluation and reflect the quality and influence of academic literature in multiple dimensions.

Altmetrics are one of the most popular research topics in scientometric research recently. Lutz Bornmann (2014) investigated the usefulness of altmetrics for measuring the broader impact of research, and the results indicated that Facebook and Twitter might provide an indication of which papers are of interest to a broader circle of readers. Wouters and Costas (2012) discussed the features, advantages and disadvantages, and applicability of altmetrics. The current research on altmetrics focuses more on the application in assessing impact, the significance of altmertrics research, and the relationship between altmetrics indicators and traditional citation indicators. Since correlation analyses with traditional citations do not really reveal the meaning of altmetrics, people are rethinking about the role of altmetrics. What do altmetrics replace? What is the essential meaning of altmetrics? Bornmann (2016) has called for altmetrics content analysis mainly for tweets and blogs containing content information. At present, the content analysis is still in the initial stage.

Twitter is one of the most important sources of altmetric data (Bornmann 2014; Bornmann and Haunschild 2016) and the number of tweets is taken into account when computing the score. There are still some issues about the use of tweets for measuring the social impact of articles. For example, it is still unclear to what extent Twitter captures actual research impact (Friedrich et al. 2015). Some articles are highly discussed, but their qualities are not

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necessarily high. The diversity of motivations for tweeting a paper made the value of tweeting papers inconclusive (Robinson-Garcia et al. 2017). The users behind twitter attention (Ke et al. 2017) and the purposes of tweeting need further exploration.

In the spread of information on twitter, different users play different roles. The recommendations of some communicators make the information quickly perceived by a large number of ordinary users, and with a large probability, their attitudes will affect the attitudes of these people. The classical "two-step flow" theory of communication (Katz and Lazarsfeld 1955) argued that the mass media influenced the public via an intermediate layer of opinion leaders. This theory is re-examined as the rising mass media (Wu 2011). Based on this theory, in the context of scholarly communication on Twitter, we would like to investigate the following questions: a. How to effectively quantify the opinion leaders? b. What are their opinions and attitudes towards the articles, and if their attitudes affect the ordinary users?

In this paper, we propose a method to combine two factors to identify the opinion leaders, who play an important role in the spread of scholarly information, and the contents of the tweets are analyzed using sentiment analysis tool. The results could shed light on the understanding of the meaning of tweets as altmetric measure, and the improvement of the design of reasonable altmetric indicator.

Data and Methods

Data

Altmetric[2] has been tracking mentions of different research outputs and summarizes top 100 most-discussed articles every year. We download the top 100 articles every year from 2013 to 2017, and the corresponding twitter information including when and who says what about the articles (Altmetric shows at most 10000 tweets per article).

A tweet consists of text, hashtags, user names, and/or links to websites. User names, URLs, and the title of articles are removed, as they do not reflect any extra information and the attitude and emotion of the users towards the articles.

Methods

Opinion leader identification

In the context of twitter, we propose a new method to identify the opinion leaders based on "two-step flow" theory of communication. We choose the users who directly tweet articles and belong to the intermediate layer on Twitter as candidates of opinion leaders. The number of followers and the number of retweets they receive are both considered as important indicators for identifying leaders (Kwak, 2010). The F_1 score in statistical analysis, which is the harmonic average of the precision and recall, is applied to combine the above two factors. F_1 score of a user u reaches its best value at 1 and worst at 0.

$$F_1(u) = 2 \cdot \frac{\#followers(u)' \cdot \#retweets(u)'}{\#followers(u)' + \#retweets(u)'} \tag{1}$$

For an article, when the F_1 score of a user u is computed, $\#followers(u)$ and $\#retweets(u)$ are rescaled to the range in [0,1] as follows, where U is the user set that tweets the article on Twitter.

$$\#followers(u)' = \frac{\#followers(u) - \min_{v \in U}(\#followers(v))}{\max_{v \in U}(\#followers(v)) - \min_{v \in U}(\#followers(v))} \tag{2}$$

[2] https://www.altmetric.com/

$$\#retweets(u)' = \frac{\#retweets(u) - \min_{v \in U}(\#retweets(v))}{\max_{v \in U}(\#retweets(v)) - \min_{v \in U}(\#retweets(v))} \quad (3)$$

All the users are ranked by the F_1 score, and the top users are identified as opinion leaders, while the others act as ordinary users.

Sentimental analysis

After identifying the opinion leaders, we are interested in the contents and the opinions of the tweets about the article. In order to analyze the opinions of the tweeting users towards the article, SentiStrength (Thelwall, 2012) is applied to convert the qualitative emotional factors into quantitative emotional values. SentiStrength assigns values from -5 to +5 to certain terms in a lexicon. Each processed tweet receives a negative and a positive value. To assign each tweet to exactly one category (positive, negative, neutral), the stronger value determines the sentiment.

Results and Discussion

In this paper, we would like to demonstrate the analysis on the level of a single article. We select the top most-discussed article "Associations of fats and carbohydrate intake with cardiovascular disease and mortality in 18 countries from five continents (PURE): a prospective cohort study" that published in The Lancet, August 2017 as an example to show the preliminary results of the proposed method. In the future work, the method will be applied to larger data for a more comprehensive study.

Opinion leaders

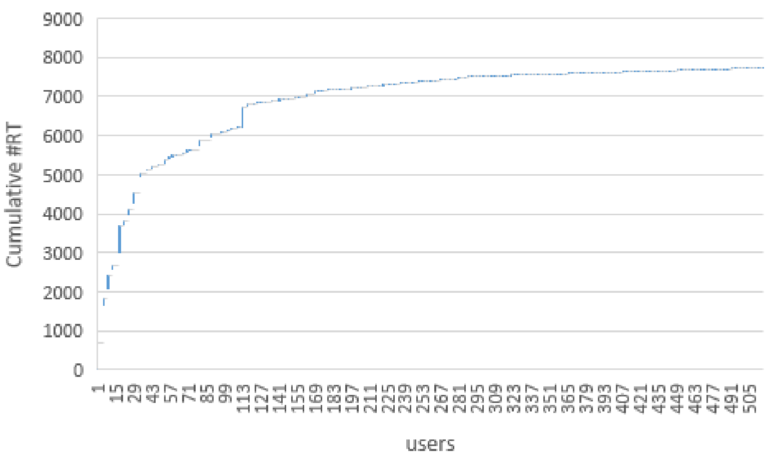
Table 1 shows the top 10 users ranked by F_1 score and the user information on Twitter. Not surprisingly, *@TheLancet* ranks top one in the list, as it is the official twitter of the lancet, and released the tweet of the article at a very early time. *@EricTopol* sent the tweet even earlier than *@TheLancet*, who ranked second. They do not have the largest number of followers, however, they have both large number of followers and large number of retweets, obtaining a higher F_1 score.

Table 1. Top 10 users ranked by F_1 score.

user	***#followers***	***#retweets***	***#followers'***	***#retweets'***	***F_1 score***
@TheLancet	308705	687	0.553	1.000	0.712
@EricTopol	126884	619	0.227	0.901	0.363
@Mutib_Altamimi	171021	113	0.306	0.163	0.213
@ProfTimNoakes	103326	158	0.185	0.229	0.205
@jordanbpeterson	558513	79	1.000	0.114	0.204
@garytaubes	56542	183	0.101	0.265	0.147
*@_atanas_*	89662	74	0.161	0.106	0.128
@drjasonfung	44929	164	0.080	0.238	0.120
@DrAseemMalhotra	38020	325	0.068	0.472	0.119
@RobertLustigMD	42649	130	0.076	0.188	0.109

In order to investigate how much influence the top opinion leaders have, we plot the cumulative distribution of number of retweets in Fig. 1. The number of retweets received by the top 20% users accounts for over 80% of the total number of retweets, which is consist with the Matthew effect "the rich get richer ".

Figure 1. The cumulative distribution of number of retweets.



Sentimental analysis

The opinion leaders play an important role in spreading the information. Their attitudes also could affect the other users. The public opinions should be considered for constructing the social impact of articles. For example, the article "Variation in Melanism and Female Preference in Proximate but Ecologically Distinct Environments" that published in Ethology, ranked top two most-discussed articles in 2014. Altmetric data did not reflect the scholarly quality, as almost all the tweets of this article were criticism. Most users expressed a critical attitude towards the article, tweeting "*Not sure how this made it through proofreading, peer review, and copyediting*." Therefore, it is very necessary to consider the opinions when measuring the social impact of articles.

We use SentiStrength to assess every tweet received by the exemplary article. The tool assigns values from -5 to +5 to certain terms and each tweet receives a negative and a positive value as shown in Fig.2. To assign each tweet to exactly one category (positive, negative, neutral), the stronger value determines the sentiment. Fig.3(a) is the distribution of the sentiments of all the tweets, from which we could see a roughly normal-distribution with most of the users have a neutral sentiment towards the article. The sentiments of the tweets sent by opinion leaders also follow the similar distribution (Fig.3(b)), which implies there are correlations between the public opinions and the leaders opinions and confirms our previous conjecture.

Figure 2. Positive and negative values of the tweets received by the exemplary article.

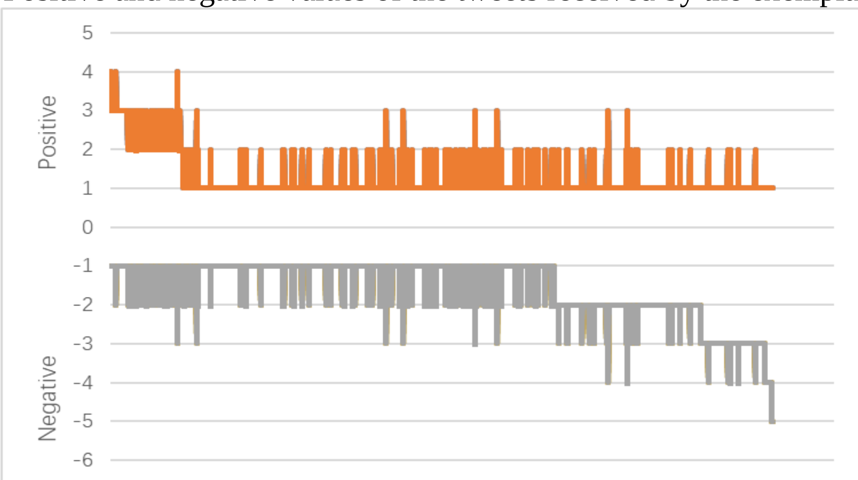


Figure 3. (a) The sentiments of all the tweets; (b) The sentiments of the tweets sent by opinion leaders.

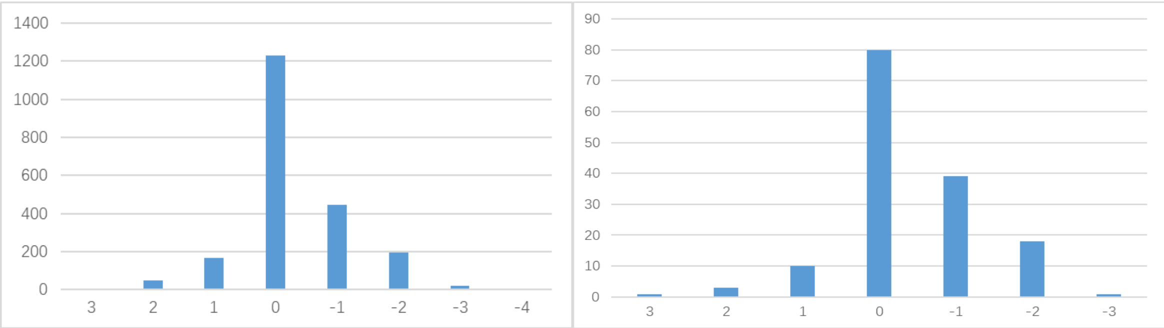
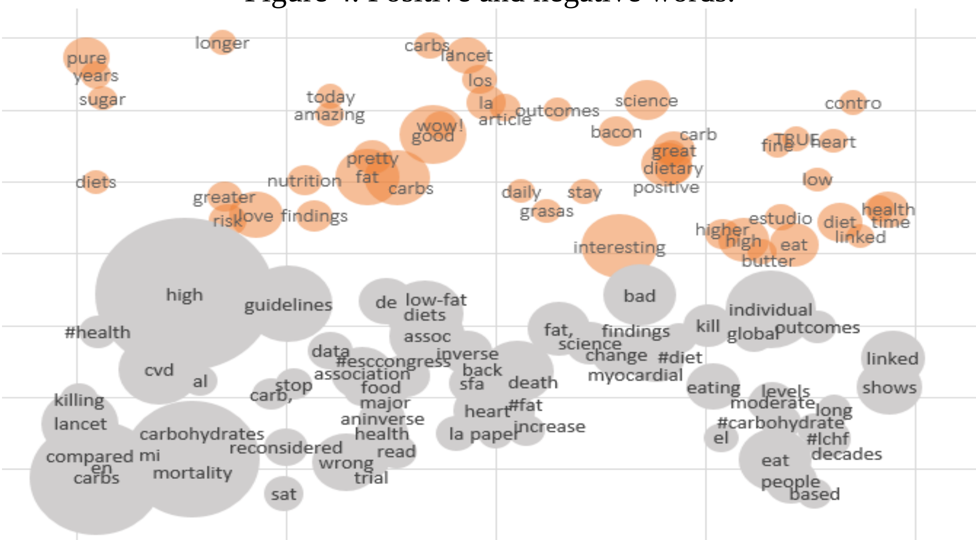


Figure 4. Positive and negative words.



We also visualize the words in positive tweets and negative tweets in Fig.4. The size of the bubble indicates the number of times the word occurred in the tweets. The bubbles on the upper part indicates the words in positive tweets, while the lower part contains the words in negative tweets.

Although the results are promising, current sentimental analysis tools cannot accurately determine the sentimental polarity of some tweets. In the future work, we would like to work on improving the ability to recognize emotions to scientific papers.

Conclusion

In the assessment of social impact of articles, we should consider in what context the articles are cited and discussed, which is more valuable than simple numbers. In this paper, we firstly propose a method to identify the opinion leaders that play an important role in the spread of information. Then, a sentiment analysis tool is used to assess the sentimental polarity of the tweets. We find that the number of retweets received by the top 20% users accounts for over 80% of the total number of retweets. The contents of tweets have clearly attitudes towards articles and there are correlations between the public opinions and the leaders' opinions. This indicates that when assessing the social impact of articles, we should investigate the opinion leaders' sentimental polarity into account.

This study could help us understand the meaning of tweets as altmetric measure, and the improvement of the design of reasonable altmetric indicator. In the future work, we want to combine the sentimental polarity with other altmetrics indicators, and apply to more data to test the reliability of the method.

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