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Measuring User influence based on multiple metrics on YouTube

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***Abstract*—User influence in online social networks has been measured by different metrics and algorithms, and these methods roughly fall into two main genres: attribute-based approaches and graph-based approaches. However, most attribute-based approaches only consider single metric, such as total view counts or retweet counts. And graph-based approaches cannot apply to the platforms where it is difficult to obtain graphs of some metrics. In this paper, we propose a triangular fuzzy number-based method to measure user influence, which covers multiple metrics and is graph free. By taking YouTube as an example, based on triangular fuzzy number, we synthesize view, comment and like counts to measure user influence. We first compute the triangular fuzzy number of each metric to represent user influence, and then use the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) method to synthesize multiple triangular fuzzy numbers and rank users. The experiments based on YouTube data show that, when only considering view counts, our results are in good agreement with other popular measures such as h-index. However, beyond view counts, our method provides a comprehensive measure which can cover multiple metrics.**

Keywords- User influence; Triangular fuzzy number; YouTube; Social media

I. Introduction

User influence in online social networks has always attracted much attention from the researchers for a long time. Learning and measuring influence of users can be useful for many applications, such as viral marketing, expertise recommendation, information propagation, social customer relationship management[1, 2]. Therefore, there is a vast literature about measuring user influence and identifying the most important users on social networks.

Since there are plenty of metrics and algorithms that can be used to measure user influence, the methods of measuring influence are highly diversity [2, 3]. These methods roughly fall into two main genres: attribute-based approaches and graph-based approaches. Attribute-based approaches [4-8] measure user influence relying on different attributes or metrics, such as number of retweets, followers and views. Some work simply uses the original values of these metrics, and others extend the values by introducing methods in other domains. For example, the numbers of followers or retweets are directly used to measure user influence [4-6], while mention counts in Twitter and view counts are extended to measure user influence by introducing Newton's second law in physics and h-index in bibliometrics respectively [7, 8]. Most graph-based approaches [9-13] are based on Page-Rank, HITS, or their variants. These algorithms consider the hub users as important nodes within the interaction network.

In spite of these advanced approaches, measuring user influence continues to pose a challenge to existing algorithms in various ways. In fact, the existing approaches suffer from the following shortcomings. On one hand, existing attribute-based approaches only consider one kind of metric. For example, measurements based on the original values of metrics [4-6] mainly aim to compare the user rankings under different metrics and do not consider the problem of how to synthesize multiple metrics. The method based on Newton's second law [7] only consider the number of mentions on Twitter, and the method based on h-index [8] only consider the count of views on YouTube. On the other hand, although existing graph-based approaches can consider multiple metrics, they cannot cover certain metrics because of the lack of corresponding graphs. For example, it is difficult for users to obtain graphs of view relation in online content-share social networks such as YouTube and Flickr. Even for the metrics whose graphs can be obtained by users, it is still difficult to obtain their complete networks[7, 14]. In fact, currently there are no measures which use all the different metrics, and defining a more comprehensive measure covering all types of metrics is an open problem on Twitter [2].

In this paper, we aim to present a more comprehensive measure that covers multiple metrics and graph free. Specifically, we propose a fuzzy mathematics-based method that measures user influence by covering multiple metrics including the total view counts, comment counts, like counts and so on.

To cover multiple metrics for measuring influence, there are two problems that should be solved: how to quantify each metric and how to synthesize multiple metrics. So we introduce fuzzy triangular number to overcome the two problems. Firstly, in term of one metric, such as view counts of YouTube videos, there is no exact threshold which can be used to identify whether a user is highly influential. In fact, user influence is fuzzy. Therefore, we introduce the triangular fuzzy number to represent the influence of users. The triangular fuzzy number [15] is a widely used mathematic theory to deal with the fuzzy problem. A triangular fuzzy number α can be defined by a

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triplet $\left(\alpha_L, \alpha_M, \alpha_U\right)$, where α_L, α_M and α_U is the lower bound, the most possible value and upper bound respectively.

On online content-share social networks, such as YouTube, users generally upload many videos, and they get different numbers of views. The upper bound of influence of a user, in terms of view counts, should be less than the maximum of the view numbers among his videos, while the lower bound of his influence should be the minimum of the view numbers. And the most possible value of his influence should be the average of the view numbers of his videos. These three numbers correspond exactly to the upper bound, lower bound and most possible value of the triangular fuzzy number. Therefore, in terms of one metric, user influence can be represented by the triangular fuzzy number.

For synthesizing multiple metrics, we use the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) [16] to merge the triangular fuzzy numbers of multiple metrics. The TOPSIS is a widely used method for synthesizing and ranking triangular fuzzy numbers. After computing the triangular fuzzy number of each metric, the TOPSIS take multiple triangular fuzzy numbers into account and rank users from high influence to low one.

Based on the YouTube data, we evaluate the triangular fuzzy number-based method when using view counts and using multiple metrics. The experiments show that, when only using view counts, our method is in good agreement with other popular measures such as h-index. And when covering the counts of views, comments and likes, our method is related with others, but exhibits difference. Therefore, beyond the view counts, our method provides a comprehensive measure about user influence.

II. RELATED WORK

With the upsurge of online social networks, the problem of measuring user influence becomes increasingly important and has been widely investigated in recent years. The approaches for this problem can be broadly divided into two categories: attribute-based approaches and graph-based approaches.

A. Attribute-based approaches

Generally, the original numbers related to users and their contents, such as the number of user followers and the count of retweets, can reflect, to some extent, the influence of users. Therefore, attribute-based approaches use these original values or extend them to measure user influence.

For using original values to measure influence, Cha et al. [4] investigated three measures of influence: indegree (number of people who follow a user), retweets (number of times others forward a user's tweet), and mentions (number of times others mention a user's name) in order to rank users in Twitter. To identify influential on Twitter, Kwak et al. [5] rank users by the number of followers and PageRank, and find two rankings are similar. And ranking by retweets differs from the above two rankings. Li et al. [6] explore the correlation between the academic influence and social influence of scholars. And the social influence is investigated based on network centrality metrics: Degree, Closeness and Betweenness.

Two methods in other domains are introduced to extended original values to measure user influence [7, 8]. Specifically, Gayo-Avello et al. [7] Measure user influence based on laws of dynamic friction and uniformly accelerated linear motion. They translate the concepts from dynamics such as velocity, acceleration, mass and force to an online social network scenario. Concretely, the velocity represent user influence, acceleration can be used to detect trending users in real time, the mass of a user is the number of followers, and the force applied to put a user in motion is the number of mentions. And then based on Newton's second law, user influence can be computed. Hovden [8] demonstrates that, besides academic publications, h-index also can be adapted to social media, such as YouTube. And in YouTube, the h-index is defined as the number of videos with more than 10^5 views. When compared with total view counts, the h-index and g-index can better capture both productivity and impact. In addition, the attribute-based approaches can also be used to identify topical influencers. For example, Ghosh et al. [17] propose a new method for discovering topic experts relying on Twitter Lists.

These above attribute-based approaches achieve good performance in reflecting user influence in terms of single metric. However, since they generally use one of the metrics to measure user influence, these methods cannot reflect comprehensive influence of users. Instead, we will synthesize multiple metrics to measure user influence.

B. Graph-based approaches

Graph-based approaches are common in the literature. The key idea is to represent the environment as a graph in which nodes correspond to users and arcs correspond to the interactions between users. The influence of nodes is generally measured by means of graph-based ranking algorithms such as Page-Rank or HITS or their variants.

For instance, Romero et al. [9] designed an algorithm similar to HITS named the Influence Passivity algorithm to quantify the influence of users in a Twitter network. This algorithm utilizes both the structural properties of the network and the diffusion behavior among users. Agarwal et al. [10] studied the problem of identifying a ranked list of influential users in online community blogs. The influence of a blog post is estimated by combining four metrics: inlinks to the blog post, outlinks to other posts, number of comments and blog post length. To balance the effect of these four metrics, four user-defined weighting parameters are used in the combination formula. While the accuracy of the results depends heavily on proper tuning of the values of these parameters. Tang et al. [11] incorporates users' reply relationships, conversation content, and response immediacy to build a weighted social network, and two PageRank-based approaches are proposed to quantify influence using the weighted network. Li et al. [12] take the interactions, like retweeting, commenting and mentioning into consideration, and propose a PageRank-based method to evaluate user influence.

Besides the general measures, there is a body of work which aims to identify influential users in some specific topic. For these cases, besides the graphs, the contents users published are commonly involved to specify the topic. For example, Silva al. [13] propose a new information diffusion model based on random walks over a user-content graph to identify influential users and relevant content. Weng et al. [18] propose a Page-Rank-like algorithm named TwitterRank that uses both the Twitter graph and processed information from tweets to identify experts. To detect topic-based influencers in social media, Herzig et al. [19] build a content-based citation graph, where nodes represent authors and readers, and edges represent reader-to-author citations, and propose three algorithms based on an extension of the Topic-Sensitive PageRank algorithm. Katsimpras et al. [20] introduce a supervised algorithm, called Topic-Specific Supervised Random Walks, which assimilates valuable structural and textual information into one unified model to measure the topic-sensitive influence of a user.

The graph-based approaches are widely used algorithms to measure user influence and have certain advantages in certain online social networks. However, it cannot apply to all the platforms, because in some platforms it is difficult to obtain the graphs of some metrics. For example, on YouTube users can hardly obtain the graphs of view and like relations, which are one of the most important metrics in reflecting user influence.

III. USER INFLUENCE ASSESSMENT

A. Triangular Fuzzy Number

Before assessing user influence by triangular fuzzy number, we first introduce the definition of triangular fuzzy number. We consider the following well-known description of the triangular fuzzy number.

Definition 1[15]. A triangular fuzzy number α can be defined by a triplet $(\alpha_L, \alpha_M, \alpha_U)$, where $0 \le \alpha_L \le \alpha_M \le \alpha_U$, and its membership function defined as follows:

$$\mu_\alpha(x) = \begin{cases} 0, & x < a_L, \\ \dfrac{x - a_L}{a_M - a_L}, & a_L \le x \le a_M, \\ \dfrac{x - a_U}{a_M - a_U}, & a_M \le x \le a_U, \\ 0, & a_U < x, \end{cases} \tag{1}$$

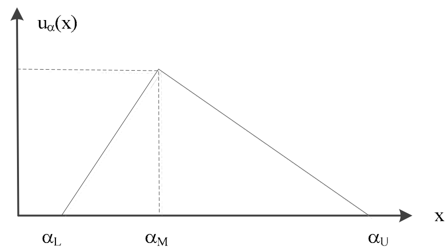

Figure 1. A triangular fuzzy number.

Where α_M is the most possible (modal) value of the fuzzy number, and α_L and α_U are the lower and upper bounds respectively. The number is often used to reflect the fuzziness of the subjective evaluation. The function graph of the triangular fuzzy number α can be described as Fig. 1.

B. User Influence Assessment

Here, we present how to use triangular fuzzy numbers to represent user influence. We firstly consider one metric, such as view counts, i.e., in term of view counts how is a triangular fuzzy number used to indicate user influence.

In YouTube, different videos of one user receive different number of views. For the user, the lower bound of his influence should be greater than the minimum of the view counts among his videos, and the upper bound of his influence should be lower than the maximum of the view counts among his videos. Also the most possible value of his influence should be the average number of views of his videos. These three numbers correspond exactly to the lower bound, most possible value and upper bound of the triangular fuzzy number.

As a result, the influence of a user for one metric can be computed by a triangular fuzzy number α, which can be defined by a triplet $(\alpha_L, \alpha_M, \alpha_U)$, where α_L, α_M and α_U is the minimum, average and maximum view counts of his videos respectively.

The triangular fuzzy numbers of other metrics, such as comment and like counts in YouTube, can be computed by the similar way.

IV. THE FUZZY RANKING ALGORITHM

After computing the triangular fuzzy number of each metric, we further present how to rank users by synthesizing multiple numbers. To this end, a widely used technique TOPSIS [16] is adopted to rank users. The detailed steps are given below.

Step 1: Compute the triangular fuzzy number for each metric from each user.

Suppose there are *n* users denoted by $u_i\ (i = 1, 2, \cdots, n)$, and there are *m* metrics (such as views, comments and likes) denoted by $s_j\ (j = 1, 2, \cdots, m)$.

Therefore, in term of the *j*-th metric, the triangular fuzzy number that represents user influence is described by:

$$\alpha_{ij} = \left(\alpha_{Lij}, \alpha_{Mij}, \alpha_{Uij}\right) \tag{2}$$

Where $\alpha_{Lij}, \alpha_{Mij}$ and α_{Uij} is the minimum, average and maximum value of the *j*-th metric among all the videos of user u_i respectively.

Step2: Establish a fuzzy decision matrix. The structure of the matrix can be expressed as follows:

$$A = \begin{pmatrix} a_{11} & \cdots & a_{1m} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nm} \end{pmatrix} \tag{3}$$

Where α_{ij} is the triangular fuzzy number $\left(\alpha_{Lij}, \alpha_{Mij}, \alpha_{Uij}\right)$, which is the value indicating the influence of each user with respect to each metric (view, comment or like counts) .

Step 3: Normalize the fuzzy decision matrix. Suppose that the normalized matrix is B, and it is can be computed as below:

$$B = \left(b_{ij}\right)_{n\times m} \tag{4}$$

$$b_{ij} = \left(b_{Lij}, b_{Mij}, b_{Uij}\right) = \left(a_{Lij} \Big/ \sqrt{\sum_{i=1}^{n} a_{Uij}^2}, a_{Mij} \Big/ \sqrt{\sum_{i=1}^{n} a_{Uij}^2}, a_{Uij} \Big/ \sqrt{\sum_{i=1}^{n} a_{Uij}^2}\right) \tag{5}$$

Step 4: For each metric s_j, suppose that it has associated weight W_j^c. And then we can get the normalized weighted decision matrix as:

$$R = \left(r_{ij}\right)_{n\times m} \tag{6}$$

$$r_{ij} = \left(r_{Lij}, r_{Mij}, r_{Uij}\right) = W_u^c b_{ij} \tag{7}$$

Step 5: Identify the positive ideal solutions:

$$X^+ = \left(r_1^+, \cdots, r_j^+, \cdots, r_m^+\right) \tag{8}$$

$$r_j^+ = \left(r_{Lj}^+, r_{Mj}^+, r_{Uj}^+\right) = \left(\max_{i=1,2,\cdots,n} r_{Lij}, \max_{i=1,2,\cdots,n} r_{Mij}, \max_{i=1,2,\cdots,n} r_{Uij}\right) \tag{9}$$

Step 6: Calculate the distance of each alternative from X^+ using the following equations:

$$S_i^+ = \sum_{j=1}^{m} d\left(r_{ij}, r_j^+\right) \tag{10}$$

$$d\left(r_{ij}, r_j^+\right) = \sqrt{\frac{1}{3}\left[\left(r_{Lij} - r_{Lj}^+\right)^2 + \left(r_{Mij} - r_{Mj}^+\right)^2 + \left(r_{Uij} - r_{Uj}^+\right)^2\right]} \tag{11}$$

Step 7: Rank alternatives according to $d\left(r_{ij}, r_j^+\right)$ in descending order.

Following the above steps, users can be ranked from high influence to low one. And the steps can present a comprehensive ranking of user influence by taking multiple metrics.

V. EMPIRICAL EVALUATION

In this section, we evaluate the performance of our triangular fuzzy number-based method based on YouTube data. Because current attribute-based methods about measuring user influence, such as h-index, only consider single metric (total view counts), we firstly compare the results of our method when only using the view counts with the h-index[8]. And then we present the results of our method when covering three metrics (view, comment and like counts). We call the triangular fuzzy number-based method using view counts and three metrics *fuzzy-view* and *fuzzy-synthesis* for convenience.

A. Data description

In this paper, we use the data from YouTube, which is currently the largest host to streaming video content on the Internet. To collect popular YouTube users, we download YouTube user list from three popular websites (socialblade.com, statsheep.com and vidstatsx.com), which provide the list of the most subscribed users. After removing the repeated users, there are 12,194 unique users. We continue to download more than 17 million videos they uploaded. Also the profiles of these users and videos are obtained by YouTube APIs. The statistic information is shown in Table 1.

TABLE I. DATA DESCRIPTION

The number of users	12,194
The number of videos	17,224,030
The average number of views per user	170,018,767
The average number of subscribers per user	515,077
The average number of comments per user	255,079
The average number of likes per user	1,449,175

B. Influence using the single metric

Since h-index only considers single metric, i.e., the total view counts, here we only consider the view counts to compute user influence using the triangular fuzzy number-based method (fuzzy-view), and conduct the comparison with results of h-index and view counts.

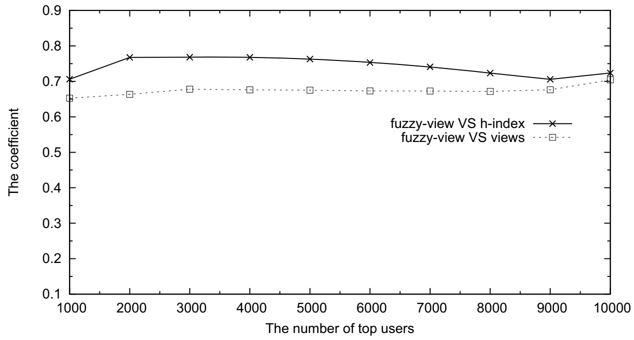

Figure 2. The Pearson correlation coefficients of fuzzy-view to h-index and views.

To evaluate the correlation between them, we compute the Pearson correlation coefficients for the different number of most-subscribed users, as shown in Fig. 2. The x-axis is the number of the top users based on their subscribed number. And the y-axis is the correlation coefficient of fuzzy-view to h-index and views.

From the Fig. 2, the apparent phenomenon is that the ranking of fuzzy-view is highly correlated with that of h-index and view counts. The lowest coefficient of correlation between rankings of fuzzy-view and view counts for top 1000 users is 0.65, and the highest coefficient reaches 0.70. The coefficient of correlation between rankings of the fuzzy-view and h-index is always higher than that of fuzzy-view and view counts. These indicate that the fuzz-view has a strong correlation with the h-index and view counts.

Therefore, based on these analyses, we can conclude that our triangular fuzzy number-based method when only considering view counts is highly consistent with the results of h-index and total views.

C. Comprehensive influence using multiple metrics

Now we show the results of synthesizing three metrics (the counts of views, comments and likes) using the triangular fuzzy number-based method (fuzzy-synthesis). We suppose each metric has the same weight, i.e., 1/3, in Step 4 of Section IV. Here we compare the fuzzy-synthesis with the h-index and total numbers of views, comments and likes.

Table 2 shows the rankings of YouTube users based on fuzzy-synthesis, total views and comments. Depending on the metric of choice—fuzzy-synthesis, total views and comments—different users will outperform others. For example, the top two YouTube users based on fuzzy-synthesis, officialpsy and justinbiebervevo, drop to 13-th and 6-th based on the total view counts, while officialpsy do not fall in the top 25 and justinbiebervevo drop to 14-th for comments. The results of h-index and likes, not shown here for space constraints, show similar trends. Hence, the table shows that the ranking of fuzzy-synthesis is partly overlapped with the total views and comments. At the same time, it is different from them.

In addition, the Pearson correlation coefficients of the fuzzy-synthesis to h-index and the total view, like and comment counts, based on the different number of most-subscribed users, are shown in Fig. 3. And from the figure the coefficient of correlation between them vary along with the change of number of top users based on the most-subscribed users, i.e., the bigger the number of top users is, the higher the coefficient is. For the lowest user number(x=1,000), there are weak correlations between the fuzzy-synthesis and h-index, the total view, like and comment counts with coefficients of 0.51, 0.47, 0.37, and 0.29 respectively. And for the highest user number(x=10,000), the coefficients of them reach 0.73, 0.78, 0.73, and 0.65. These indicate that the fuzzy-synthesis is related with the h-index, total view, like and comment count, but is different from them. Therefore the fuzzy-synthesis is an integrated and comprehensive measurement for user influence.

TABLE II. RANKINGS OF YOUTUBE USERS USING DIFFERENT METHODS.

No.	Fuzzy-synthesis	Views	Comments
1	officialpsy	pewdiepie	pewdiepie
2	justinbiebervevo	emimusic	thejoves
3	thejoves	disneycollectorbr	machinima
4	taylorgangent	rihannavevo	theyoungturks
5	taylorswiftvevo	katyperryvevo	raywilliamjohnson
6	katyperryvevo	justinbiebervevo	ignentertainment
7	mileycyrusvevo	taylorswiftvevo	thesyndicateproject
8	eminemvevo	spinninrec	sxephil
9	meghantrainorvevo	machinima	rezendeevil
10	tvnorge	getmovies	itowngameplay
11	markronsonvevo	eminemvevo	vegetta777
12	lmfaovevo	shakiravevo	macbarbie07
13	onedirectionvevo	officialpsy	roosterteeth
14	ryanlewisproductions	theellenshow	justinbiebervevo
15	shakiravevo	smosh	bluexephos
16	siavevo	gmmgrammyofficial	holasoygerman
17	onerepublicvevo	tseries	markipliergame
18	enriqueiglesiasvevo	onedirectionvevo	shaytards
19	carlyraejepsenvevo	wwefannation	watchmojo
20	gotyemusic	pitbullvevo	bfvsgf
21	iamother	atlanticvideos	skydoesminecraft
22	elektrarecords	movieclipstrailers	smosh
23	maroon5vevo	beyoncevevo	erb
24	edsheeran	blucollection	nigahiga
25	hdcyt	mashamedvedtv	whiteboy7thst

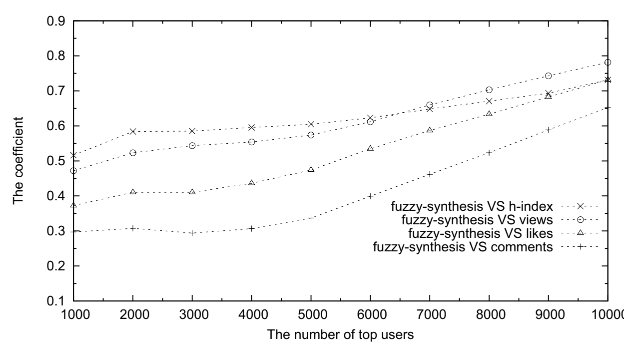

Figure 3. The Pearson correlation coefficients of fuzzy-synthesis to h-index, views, likes and comments.

VI. CONCLUSION

In this paper, we proposed a triangular fuzzy number-based method, which take multiple metrics into account to measure user influence. In our approach, for each metric we first compute its triangular fuzzy number, which can represent user influence in term of this metric, and then use TOPSIS method to synthesize multiple triangular fuzzy numbers and rank users. The experiments based on YouTube data show, when only considering view counts, our approach is in good agreement with other popular measures such as h-index. When covering multiple metrics, our approach exhibit differences from the h-index, view counts, like counts, and comment counts. Therefore, our method provides a comprehensive measure about user influence.

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