Identifying Influential Bloggers: Time Does Matter

Leonidas Akritidis, Dimitrios Katsaros, Panayiotis Bozanis
Department of Computer & Communication Engineering
University of Thessaly
Volos, Greece
{*leoakr, dkatsar, pbozanis*}*@inf.uth.gr*

***Abstract*—Blogs have recently become one of the most favored services on the Web. Many users maintain a blog and write posts to express their opinion, experience and knowledge about a product, an event and every subject of general or specific interest. More users visit blogs to read these posts and comment them. This "participatory journalism" of blogs has such an impact upon the masses that Keller and Berry argued that through blogging "one American in tens tells the other nine how to vote, where to eat and what to buy" [9]. Therefore, a significant issue is how to identify such influential bloggers. This problem is very new and the relevant literature lacks sophisticated solutions, but most importantly these solutions have not taken into account temporal aspects for identifying influential bloggers, even though the time is the most critical aspect of the Blogosphere. This article investigates the issue of identifying influential bloggers by proposing two easily computed blogger ranking methods, which incorporate temporal aspects of the blogging activity. Each method is based on a specific metric to score the blogger's posts. The first metric, termed MEIBI, takes into consideration the number of the blog post's inlinks and its comments, along with the publication date of the post. The second metric, MEIBIX, is used to score a blog post according to the number and age of the blog post's inlinks and its comments. These methods are evaluated against the state-of-the-art influential blogger identification method utilizing data collected from a real-world community blog site. The obtained results attest that the new methods are able to better identify significant temporal patterns in the blogging behaviour.**

***Keywords*-Blogosphere; influential bloggers; ranking**

I. Introduction

During the last years, we have witnessed a massive transition in the applications and services hosted on the Web. The obsolete static Web sites have been replaced by numerous novel, interactive services whose common feature is their dynamic content. The social and participatory characteristics that were included in these services, led to the generation of virtual communities, where users share their ideas, knowledge, experience, opinions and even media content. Examples include blogs, forums, wikis, media sharing, bookmarks sharing and many others, which are collectively known as the Web 2.0.

Blogs are locations on the Web where individuals (the bloggers) express opinions or experiences about a subject. Such entries are called blog posts and may contain text, images, embedded videos or sounds and hyperlinks to other blog posts and Web pages. On the other hand, the readers are provided with the ability to submit their own comments in order to express their agreement or disagreement to the ideas or opinions contained in the blog post. The comments are usually placed below the post, displayed in reverse chronological order. The virtual universe that contains all blogs is known as the *Blogosphere* and accommodates two types of blogs [1]: a) *individual blogs*, maintained and updated by one blogger (the blog owner), and b) *community blogs*, or multi-authored blogs, where several bloggers may start discussions about a product or event. Since in the former type of blogs, only the owner can start a new line of posts, the present article focuses only on community blogs.

In a physical community, people use to consult others about a variety of issues such as which restaurant to choose, which medication to buy, which place to visit or which movie to watch. Similarly, the Blogosphere is a virtual world where bloggers buy, travel and make decisions after they listen to the opinions, knowledge, suggestions and experience of other bloggers. Hence, they are *influenced* by others in their decision making and these others are defined in [9] as *the influentials*.

The identification of the influentials is of significant importance, because they are usually connected in large virtual communities and thus they can play a special role in many ways. For instance, commercial companies can turn their interest in gaining the respect of the influentials to become their "unofficial spokesmen", instead of spending huge amounts of money and time to advertise their products to thousands of other potential customers. It can also lead to the development of innovative business opportunities (related to commercial transactions and travelling), can assist in finding significant blog posts [3], [7], and can even be used to influence other peoples' voting behavior.

The issue of identifying influential bloggers is very recent and despite it seems similar to problems like the identification of influential blog sites [4] and the identification of authoritative Web pages [11], the techniques proposed for these problems can not be applied to the identification of influential bloggers. The problem of identifying the influential bloggers has been introduced in [2], and the literature lacks

other sophisticated solutions. That initial model, mentioned here as *the influence flow method*, explicitly discriminated the influential from the active (i.e., productive) bloggers, and considered features specific to the Blogosphere, like the blog post's size, the number of comments, and the incoming and outgoing links. Nevertheless, this model fails to incorporate temporal aspects which are crucial to the Blogosphere and does not take into account the productivity as another factor which affects the influence.

Motivated by these observations, this article proposes a new way of identifying influential bloggers in community blogs, by considering both the temporal and productivity aspects of the blogging behavior, along with the inter-linkage among the blogs posts. The proposed methods are evaluated against the aforementioned initial model (which is the only competitor so far) using data from a real-world blog site.

The rest of the paper is organized as follows: In Section II we briefly present the relevant work, describing in more details the only method which is closely relevant to the problem considered here. Section III introduces the proposed algorithms for the identification of influential bloggers; in Section IV we conduct experiments with a dataset obtained from a real-world blog community and finally, conclude the paper in Section V.

II. Relevant work

The recent explosion of Blogosphere has attracted a surge of research on issues related to Blogosphere modeling, mining, trust/reputation, spam blog recognition, and many others [1]; these issues though are not directly relevant to the present work. The specific problem of identifying the influential bloggers in a blog site draws analogies from the problems of identifying influential blog sites and identifying authoritative Web pages (Web ranking). The identification of influential blog sites [4] and the related study of the spread of influence among blog sites [5], [6], [8], [12] are orthogonal to the problem considered here, since we are interested in identifying influential bloggers in a single blog site, which might be or might not be an influential blog site. Similarly, the eigenvector-based methods for identifying authoritative Web pages [11], like PageRank and HITS, "*are not useful to our problem, since blog sites in Blogosphere are very sparsely linked*" [10]. Finally, it is obvious that the works which propose methodologies for discovering and analyzing blog communities [13], [15] can not be exploited/tailored to our problem.

The only work directly relevant to our problem is that reported in [2], which introduced the problem. To solve it, the authors proposed an intuitive model for evaluating the blog posts. This model is based on four parameters: Recognition (proportional to the incoming links), Activity Generation (proportional to the number of comments), Novelty (inversely proportional to the outgoing links) and Eloquence (inversely proportional to the post's length). These parameters are used to generate an influence graph in which the influence flows among the nodes. Each node of this graph represents a single blog post characterized by the four aforementioned properties. An influence score is calculated for each post; the post with maximum influence score is used as the blogger's representative post. The influence score $I(p)$ of a blog post p that is being referenced by ι posts and cites θ external posts, is determined by the following equation:

$$I(p) = w(\lambda)(w_{com}\gamma_p + w_{in}\sum_{m=1}^{|\iota|} I_p(m) - w_{out}\sum_{n=1}^{|\theta|} I_p(n)) \quad (1)$$

where $w(\lambda)$ is a weight function depending on the length λ of a post and w_{com} denotes a weight that can be used to regulate the contribution of the number of comments (γ_p). Finally, w_{in} and w_{out} are the weights that can be used to adjust the contribution of incoming and outgoing influence respectively. The calculation of this influence score is recursive (positive reinforcement from incoming links and negative reinforcement from outgoing links), similar to the PageRank definition. This score is the $\iota Index$ metric, which can be later used to identify the most influential bloggers. Isolating a single post to identify whether a blogger is influential or not, is an oversimplistic approach, and so it would be if they have used gross metrics, like average, median and so on. A blogger may have published only a handful of influential posts and numerous others of low quality, whereas other bloggers may have published several tens of influential blogs only, whose score though is lower than the score of the most influential blog of the former blogger. Therefore, the productivity of bloggers is a significant issue that has been overlooked by this preliminary model.

Another drawback of this preliminary model is that its output depends highly on user defined weights. The value change of the above properties can lead to different rankings. Hence, its outcome is not objective, as tuning the appropriate weights the model identifies influential bloggers with different characteristics. In other words this model cannot provide a satisfactory answer to the question *"who is the most influential blogger?"*; but it can give answers to questions of type *"who is the most influential blogger according to the number of comments that his/her posts received?"*.

But most importantly, this model (and also the naive models which are based on the k most active bloggers), ignore one of the most important factors in Blogosphere: Time. As already known [1], the Blogosphere expands at very high rates, as new bloggers enter the communities and some others leave it. Hence, an effective model that identifies influential bloggers, should take into consideration the date that a post was submitted and the dates that the referencing posts were published, in order to be able to identify the *now-influential bloggers*. Additionally, with such requirements it is mandatory to have fast methods (even on-line methods) for the discovery of the influentials, which precludes the use of

demanding and unstable recursive definitions, like that used by the influence-flow method proposed in [2].

III. New metrics for evaluating the impact of blog posts

In this section we present new methods to assign influence scores to the blog posts of a blogger. These scores that will be used later to identify the influentials. At first, we argue about what the desirable properties of these scores should be, and then we provide the formulae for their calculation.

A. Factors measuring a blogger's influence

Beyond any doubt, the number of incoming links to a blog post is a strong evidence of its influence. Similarly, the number of comments made to a post is another strong indication that this blog post has received significant attention by the community. The case of outlinks is more subtle. In Web ranking algorithms like PageRank and HITS, the links are used only as a recognition of (or to convey) authority. The influence-flow method of [2] assigns two semantics to a link: it is the means to convey authority, and also it the means to reduce the novelty. This mechanism results in two significant problems: a) it misinterprets the intention of the link creators, and b) it causes stability and convergence problems to the algorithm for the influence score calculation. It is characteristic that the authors admit ([2, page 215]) that the presence of outlinks in novel posts is quite common and it is used "to support the post's explanations". Therefore, we argue that the outlinks are not relevant to the post's novelty, and all links should have a single semantic, that of implying endorsement (influence).

The temporal dimension is of crucial importance for identifying the influentials. The time is related to the age of a blog post and also to the age of the incoming links to that post. An influential is recognized as such if s/he has written influential posts recently or if its posts have an impact recently. In the former case, the time involves the age of the post (e.g., in days since the current day) and in the latter case, the time involves the age (e.g., in days since the current day) of the incoming links to the post.

There is another observation evident by the analysis presented in [2]: a lot of the influential bloggers were also active (i.e., productive) bloggers (see Table 1 and Tables 3–5 of [2]). Although, productivity and influence do not coincide, there is a quite strong correlation among them. Therefore, productivity should somehow be taken into account when seeking for influential bloggers.

B. The novel influence scores

Based on the requirements described in the previous subsection, we develop formulae to estimate the influence of a blog post. We summarize some useful notation in Table I.

As already mentioned, the map in Blogosphere changes rapidly, in a manner that a blogger who would currently considered as an influential, is not guaranteed to remain influential in the future. New bloggers enter the community and thousands of posts are submitted every day. In Section IV it is demonstrated that a blogger may submit up to hundreds (or even thousands) of posts yearly. In this dynamic environment, the date that a blogger's post was submitted is crucial, since a blog post becomes "old" very quickly. An issue being discussed in a blog post at the present time and is now of major importance, may be totally outdated after two months. To account for this, we assign a score $S_j^m(i)$ to the i-th post of the j-th blogger as follows:

$$S_j^m(i) = \gamma(|C(i)| + 1)(\Delta TP_j(i) + 1)^{-\delta}|R_j(i)| \quad (2)$$

The parameter γ is not absolutely necessary, but it is used to grant to the quantities $S_j^m(i)$ a value large enough to be meaningful. Similarly, parameter δ does not affect the relative score values in a crucial way, but it is used to allow for fast decaying of older posts. Both parameters do not need complicated tuning, since they are not absolutely necessary; in our experiments, γ and δ are assigned values equal to 4 and 1, respectively. Since a post may receive no comments at all, we add one to the factor that counts the number of comments, to prevent null scores.

Using the definition of scores $S_j^m(i)$, we introduce a new metric *MEIBI*[1] for identifying influential bloggers. The definition of MEIBI follows:

Definition 1. A blogger j has MEIBI index equal to m, if m of his/her $BP(j)$ posts get a score $S_j^m(i) \geq m$ each, and the rest $BP(j) - m$ posts get a score of $S_j^m(i) \leq m$.

This definition awards both influence and productivity of a blogger. Moreover, a blogger will be influential if s/he has posted several influential posts recently.

But an old post may still be influential. How could we deduce this? Only if we examine the age of the incoming links to this post. If a post is not cited anymore, it is an indication that it negotiates outdated topics or proposes outdated solutions. On the other, if an old post continues to be linked to presently, then this is an indication that it contains influential material. Based on the ideas developed

Symbol	Meaning
$BP(j)$	the set of blog posts of blogger j
$bp_j(i)$	i-th blog post of blogger j
$C_j(i)$	the set of comments to post i of blogger j
$R_j(i)$	set of posts referring (have link to) the i-th post of blogger j
$\Delta TP_j(i)$	time interval (in days) between current time and the date that j-th blogger's post i was submitted
$\Delta TP(x)$	time interval (in days) between current time and the date that post x was submitted

Table I
Notation.

[1]Metric for Evaluating and Identifying a Blogger's Influence.

for the MEIBI metric, we work in an analogous fashion. Instead of assigning to a blogger's old posts smaller scores depending on their age, we can assign to each incoming link of a blogger's post a smaller weight depending on the link's age. This idea is quantified into the following equation:

$$S_j^x(i) = \gamma(|C(i)|+1) \sum_{\forall x \in R_j(i)} (\Delta TP(x)+1)^{-\delta} \qquad (3)$$

Based on equation 3 the definition of the *MEIBIX (MEIBI eXtended)* metric is formulated as follows:

Definition 2. A blogger j has MEIBIX index equal to x, if x of his/her $BP(j)$ posts get a score $S_j^x(i) \geq x$ each, and the rest $BP(j) - x$ posts get a score of $S_j^x(i) \leq x$.

The introduction of the MEIBI and MEIBIX generates a straightforward policy for evaluating the influence of both blog posts and bloggers. No user-defined weights need to be set before these metrics provide results, whereas the most sound features of Blogosphere are considered. Moreover, the calculation of the metrics can be performed in an online fashion, since they do not involve complex computation and they do not present stability problem like those encountered when using eigenvector-based influence scores. Note that the developed metrics are similar in spirit with the h-index and its variations (see [14]) that recently became popular in the scientometrics litareture, but the challenges in Blogosphere are completely different: there are comments associated with each blog post, the time granularity is finer, the author of a post is a singe person, the resulting graph might contain cycles, and many more.

There is also the possibility of taking into account the time that each comment was written, but such an extension does not contribute significantly to the strength of the model, since the time-varying interest to the post is captured by the time-weighting scheme to the incoming links, and moreover, it introduces the problem of having to handle two time scales, i.e., days for the links and the posts themselves, and hours or minutes for the comments. In the sequel, we will evaluate the effectiveness of the proposed metrics to a real-world dataset, comparing it with its only competitor [2].

IV. Experimental evaluation

The evaluation of the methods proposed here, but in general, of a lot others developed in the context of information retrieval, is tricky, because there is no ground truth to compare against; things are more challenging in this case, since there is only alternative [2] to contrast with. Nevertheless, we firmly believe that our evaluation is useful and solid as long as the proposed methods reveal some latent facts that are not captured by the competitor and by some straightfoward methods, which result in different rankings for the final influential bloggers. In the sequel of this section, we first describe the real data we collected for the experiments, and then present the actual experiments and the obtained results.

A. Data characteristics

Millions of blog sites exist. The Technorati[2] blog search engine claims to have indexed more than 115 million blogs. Since it is impossible to crawl the entire Blogosphere to obtain a complete dataset, it is essential to detect an active blog community that provides blogger identification, date and time of posting, number of comments and outlinks. The Unofficial Apple Weblog[3] (TUAW) is a community that meets all these requirements; the same source of data was used also in [2]. Although we use data from only one blog, the proposed methods can be appplied to every blog community having characteristics similar to these of TUAW. We crawled[4] TUAW and collected approximately 160 thousand pages, from which we extracted 17831 blog posts authored by 51 unique bloggers. This accounts for approximately 350 posts per blogger on average. Moreover, the posts received totally 269449 comments (15 comments per post on average); only 1761 posts (ratio 10%) were left uncommented. To obtain the incoming links to each blog post, we used the Technorati API[5]. Apart from the number of the incoming links, we also retrieved the date that the referring post was submitted and its author's name. This information is necessary for the calculation of the MEIBI and MEIBIX metrics. From the total 17831 blog posts, only 4586 of them had incoming links. Table II depicts the time distribution of both the blog posts and the incoming links.

Year	Posts	Posts with inlinks	Inlinks
2008	3676	3653	53204
2007	4497	662	259
2006	4354	186	18
2005	4307	77	1
2004	997	8	0
Total	17831	4586	53575

Table II
TIME DISTRIBUTION OF POSTS AND INLINKS.

It is interesting to note, that 80% of the total posts which have received at least one incoming link (3653 posts out of the total 4586), were submitted within the year 2008. Consequently, either TUAW was not so popular before 2008 and the bloggers were unaware of the information published there, or the posts submitted before 2008 were of medium or low quality, so that only a few other bloggers referred to them. Hence, time-aware influence metrics which measure time difference in days, are indeed necessary to differentiate between influential bloggers.

We investigate also the temporal distribution of the incoming links for a blog post measuring the intermediate

[2]http://technorati.com
[3]http://www.tuaw.com
[4]First week of December 2008.
[5]http://technorati.com/developers/api/cosmos.html

time between the date a post was submitted and the date it received each of the incoming links. The results are depicted in Table III. Almost half of the total inlinks were received (published) the same day that the post was submitted. Only a percentage of 2.3% of all inlinks are dated one or more years after the publication of the post. These results prove the necessity of time-aware metrics for the identification of the influentials; since the posts are influential for a few days, *it is not particularly useful to identify influentials for the whole lifetime of the blog site, but it is more substantial to identify the now-influential bloggers of the blog site*.

Age	Inlinks	Percentage
0 days	26346	49,2%
1 day	13470	25,1%
between 1 and 7 days	6653	12,4%
between 7 and 30 days	2406	4,5%
between 30 and 60 days	928	1,7%
between 60 and 365 days	2523	4,7%
over 365 days	1249	2,3%
Total	53575	99,9%

Table III
THE AGE OF THE INCOMING LINKS WITH RESPECT TO THE PUBLICATION DATE OF THE POST THEY CITE.

B. Identifying the influential bloggers

In this subsection we apply the proposed methods on the acquired dataset. Apart from the proposed methods, we also examine a naive method which ranks the bloggers by using only their activity, i.e., number of published posts – the activity index, one ranking method which is a straightforward adaptation of a method coming from the bibliometric literature – the h-index [14] (we call these two methods as the plain methods), and a more sophisticated method, proposed in [2].

We divide the experimentation into three parts: in the first part, we compare the influential bloggers indicated by the proposed methods, to the bloggers found by the plain methods. We use the entire dataset as a baseline experiment, examine whether temporal considerations are worthy examining; in the second part, we compare the influential bloggers indicated by the proposed methods, with those found by the influence-flow method using the posts published in November 2008, to prove that even for small time intervals the rankings are different; finally, we examine the temporal evolution of the influential bloggers identified by the proposed methods during the year 2008, to examine whether the most influential bloggers lose their lead in influence and strengthen even more the necessity for temporal considerations.

1) The new methods vs. the plain ones: Table IV includes the ten most influential bloggers based solely on their activity (i.e., productivity) measured by the number of posts they have published in TUAW. We also provide the dates that the first post (fourth column) and the last post (fifth column) of each blogger was published. Although *S. McNulty* is ranked first, he has not submitted any posts during the last 4.5 months. A similar observation of inactivity holds also for other top-10 influential bloggers, like *D. Chartier* who is inactive in the last 3.5 months and *C.K. Sample, III*, who has no posts in the last 1.5 year. Recall, that both *S. McNulty* and *D. Chartier*, were ranked among the top-5 influential bloggers with the information-flow method ([2, Table 1]).

	Bloggers	N	First	Last
1	S. McNulty	3037	06/01/2005	31/07/2008
2	D. Caolo	2242	07/06/2005	04/12/2008
3	D. Chartier	1835	26/08/2005	30/08/2007
4	E. Sadun	1560	09/11/2006	26/09/2008
5	C.K. Sample III	1057	01/03/2005	05/06/2006
6	M. Lu	1043	13/12/2006	04/12/2008
7	L. Duncan	954	19/09/2004	23/01/2007
8	C. Bohon	793	24/02/2004	04/12/2008
9	M. Rose	793	29/11/2006	05/12/2008
10	M. Schramm	648	07/06/2007	04/12/2008

Table IV
BLOGGERS RANKING BASED ON THE NUMBER OF POSTS SUBMITTED (ACTIVE BLOGGERS).

Table V presents a ranking of the ten most influential bloggers when the h-index [14] metric is used; recall that this metric examines the number of posts of each blogger and the number of incoming links to each posts, awarding both productivity and influence. The third column of Table V displays the value of the h-index metric for each blogger and the next two columns show the total number of posts he/she has submitted in TUAW and how many of them have been cited by other posts respectively. Finally, the last column illustrates the total number of incoming links that all the posts of a blogger have received.

	Bloggers	h	Posts	Cited	Inlinks
1	E. Sadun	31	1560	489	5759
2	C. Bohon	29	793	676	9439
3	M. Schramm	25	648	339	4322
4	R. Palmer	25	354	354	4809
5	M. Rose	24	793	364	4222
6	D. Caolo	23	2242	459	4907
7	M. Lu	23	1043	397	4282
8	S. McNulty	23	3037	334	3212
9	B. Terpstra	22	226	223	3013
10	C. Warren	22	133	112	1605

Table V
BLOGGERS RANKING BASED ON THE H-INDEX.

Comparing Table V to Table IV, some significant differences derive. These differences justify that productivity

and influence do not coincide. The most active blogger, *S. McNulty* is ranked 8^{th} when the ranking is done in decreasing h-index order. According to the h-index metric, the most influential blogger is *E. Sadun* who has 31 articles that has at least 31 incoming links each. *E. Sadun* is the fourth most active blogger in TUAW, though she has posted nothing in the last 2.5 months. Although she has been inactive recently, she is still the most influential according to the h-index metric. This proves that the h-index can indicate the most influential blogger, but cannot identify bloggers who are *both* influential and active.

In the sequel, we apply the two proposed metrics MEIBI and MEIBIX in our dataset. The ranking of the bloggers according to the MEIBI metric is displayed in Table VI.

	Bloggers	m	C_j
1	C. Bohon	49	14745
2	R. Palmer	46	9916
3	S. Sande	36	7246
4	E. Sadun	34	32432
5	M. Rose	30	13499
6	M. Schramm	30	12838
7	C. Warren	28	4857
8	D. Caolo	27	27985
9	M. Lu	25	17966
10	B. Terpstra	17	3770

Table VI
BLOGGERS RANKING BASED ON THE MEIBI INDEX.

The data displayed in Table VI indicate that the blogger whose posts were the most influential recently, is *C. Bohon*. This is partially explained by the fact that 676 out of the total 793 posts, have received 9439 references; it is the highest number of incoming links among the other bloggers. Furthermore, all posts have been commented 14745 times.

On the other hand, *E. Sadun*, the most influential blogger according to the h-index metric, falls in the fourth position; considering the fact that she has remained relatively inactive in the past 2.5 months, this is a satisfactory result. *R. Palmer* and *S. Sande* occupy the second and third position respectively. All top-three bloggers have submitted posts within December 2008. This is an indication that the MEIBI index not only identifies the most influential bloggers, but also the most active. It is a metric that suits very well to our case, as Blogosphere changes rapidly and our metric manages to keep track of these changes by handling the ages of the posts and the comments that they receive.

Table VII presents the most influential bloggers according to the MEIBIX index. One may detect several similarities between Table VI and Table VII. The most active blogger of TUAW, *S. McNulty*, is not among the top-10 influential bloggers when the ranking is performed according to either MEIBI or MEIBIX. This indicates that although *S. McNulty* is undoubtedly an active blogger, he has not submitted influential posts recently. Table V though, reveals that the blogger in question, is the 8^{th} most influential when the ranking is determined by the plain h-index metric.

	Bloggers	x
1	C. Bohon	48
2	R. Palmer	47
3	S. Sande	37
4	E. Sadun	33
5	C. Warren	30
6	M. Rose	29
7	M. Schramm	27
8	M. Lu	26
9	D. Caolo	25
10	B. Terpstra	15

Table VII
BLOGGERS RANKING BASED ON THE MEIBIX INDEX.

Finally, we computed the correlation of the rankings produced by h-index, MEIBI and MEIBIX by using the *Spearman's rho* metric. The results (Table VIII) indicate that MEIBI and MEIBIX produce similar rankings, but both of them diverge from the h-index ordering significantly.

Methods	ρ
h-index – MEIBI	0.478788
h-index – MEIBIX	0.321212
MEIBI – MEIBIX	0.951515

Table VIII
CORELLATION OF RANKINGS

2) The new methods vs. the influence-flow method: For the comparison of the proposed metrics against the basic competitor, i.e., influence-flow method [2], we select a subset of the real data in order to be fairer. It was obvious by the experimentation of the previous paragraphs, that the inactivity has a dramatic effect upon the final ranking. The real question concerning the usefulness of the proposed methods is whether in a small period of time, say a month, these methods would provide different rankings than those of the influence-flow method. Thus, we selected to work upon the blog posts of November 2008 only. For comparison purposes, we present in Table IX the top-10 of active (most productive) bloggers during November 2008 as this ranking is provided by the TUAW site itself.

In Table IX we present the most influential bloggers for November 2008 as they are provided by the influence-flow method and the MEIBI and MEIBIX metrics. Neither MEIBI nor MEIBIX generate rankings that agree with the TUAW ranking of bloggers. TUAW concerns *R. Palmer* as more influential than *S. Sande*. On the other hand, MEIBI concerns *R. Palmer* and *S. Sande* to be equally influential. The former has authored more posts which received more

	Bloggers	N	Inlinks	C_j
1	C. Bohon	47	508	556
2	R. Palmer	42	339	491
3	S. Sande	34	354	177
4	M. Schramm	29	203	166
5	D. Caolo	20	163	178
6	M. Rose	19	138	154
7	B. Terpstra	15	103	87
8	C. Warren	8	80	331
9	M. Lu	8	71	248
10	V. Agreda	5	30	42

	Blogger
1	C. Bohon
2	R. Palmer
3	M. Lu
4	C. Warren
5	D. Caolo
6	C. Ullrich
7	S. Sande
8	M. Rose
9	V. Agreda
10	Jason Clarke

	Blogger	m
1	C. Bohon	26
2	R. Palmer	20
3	S. Sande	20
4	D. Caolo	17
5	M. Schramm	16
6	M. Rose	13
7	M. Lu	8
8	B. Terpstra	7
9	C. Warren	7
10	V. Agreda	4

	Blogger	x
1	C. Bohon	27
2	S. Sande	20
3	R. Palmer	19
4	D. Caolo	18
5	M. Schramm	16
6	M. Rose	13
7	M. Lu	8
8	B. Terpstra	7
9	C. Warren	7
10	V. Agreda	4

Table IX
BLOGGERS RANKING ACCORDING TO: TUAW (LEFT). INFLUENCE-FLOW MODEL (CENTER). MEIBI AND MEIBIX (RIGHT).

comments, whereas the latter's posts although fewer, have been referenced more times by other posts. The ranking produced by MEIBIX positions *S. Sande* into the second place, higher than *R. Palmer*. We could state that MEIBIX is more sensitive to the number of incoming references than MEIBI.

Comparing the rankings produced by the proposed methods with the ranking according to the influence-flow model, we can state that this model assigns to *C. Bohon* the first position of the list. The model concerns *R. Palmer* as the second most influential blogger for the period of November of 2008 and agrees with TUAW. Despite *S. Sande* has published more articles that received more incoming links, *M. Lu*'s posts have attracted more comments. Hence, we conclude that *M. Lu* is primarily influential inside the TUAW community, whereas *S. Sande* has published influential posts that stimulated other bloggers to refer to them.

D. Caolo has authored less posts than *S. Sande*. Although his articles attracted both less comments and inlinks, the influence-flow model assigns him a higher rank than *S. Sande*. Obviously, the model's determination of influential bloggers, by taking into consideration only the best post and discarding all others, leads to erroneous rankings.

The *Spearman's rho* metric was used to compute the correlation of the rankings of Table IX. The results illustrated in Table X, reveal that MEIBI and MEIBIX produce rankings that diverge significantly from the one generated by the influence-flow model.

Methods	ρ
TUAW – influence-flow model	0.284848
TUAW – MEIBI	0.948485
TUAW – MEIBIX	0.939394
influence-flow model – MEIBI	0.418182
influence-flow model – MEIBIX	0.357576
MEIBI – MEIBIX	0.987879

Table X
CORELLATION OF RANKINGS

3) Temporal evolution of the rankings produced by MEIBI and MEIBIX: Finally, it is interesting to examine how the rankings generated by the proposed metrics vary over time. Figures 1 and 2 depict the top-10 influence rankings of the bloggers in the past 11 months (from January 2008 to November 2008), when MEIBI and MEIBIX are applied respectively. The columns in Figures 1 and 2 represent the progression of time, whereas the rows contain the bloggers, ordered according to the time they were recognized as influential. Therefore, the (i, j)-th cell stores the rank of the i^{th} blogger in the j^{th} time window. The dash symbol signifies that the particular blogger was not among the top-10 of that period.

	Jan 2008	Feb 2008	Mar 2008	Apr 2008	May 2008	Jun 2008	Jul 2008	Aug 2008	Sep 2008	Oct 2008	Nov 2008
Erica Sadun	1	2	1	2	1	4	3	4	2	-	-
Scott McNulty	2	10	8	6	6	3	4	-	-	-	-
Cory Bohon	3	1	2	1	2	1	2	1	3	2	1
Dave Caolo	4	8	5	3	5	5	6	5	6	7	4
Mike Schramm	5	4	4	9	9	8	7	6	5	5	5
Brett Terpstra	6	5	7	7	8	-	-	7	8	9	8
Christina Warren	7	6	-	8	-	7	9	-	7	8	9
Mat Lu	8	3	6	4	3	6	8	8	9	6	7
Michael Rose	9	7	3	5	-	-	-	9	10	3	6
Nik Fletcher	10	9	9	10	-	-	-	-	-	-	-
Chris Ulrich	-	-	10	-	-	-	-	-	-	-	-
Robert Palmer	-	-	-	-	4	2	1	2	1	1	2
Steven Sande	-	-	-	-	7	9	5	3	4	4	3
Joshua Eliis	-	-	-	-	10	10	-	-	-	-	-
Gilles Turnbull	-	-	-	-	-	-	10	10	-	-	-
Victor Agreda, Jr.	-	-	-	-	-	-	-	-	-	10	10

Figure 1. Influential bloggers' blogging behavior over 2008, according to MEIBI.

MEIBI and MEIBIX produce similar rankings; MEIBIX is more affected by the number of incoming links, whereas MEIBI assigns better scores to the posts that attracted more comments.

Studying the blogger rankings fluctuation over time, composes a valuable tool for distinguishing bloggers that have been influential for a very long or very short time. The former can be considered as more influential, as compared to the latter which are proved more trustworthy. Certainly, many other categories of bloggers can be derived from the

retrospection of their activity through time and many potential applications can be developed using these categories.

	Jan 2008	Feb 2008	Mar 2008	Apr 2008	May 2008	Jun 2008	Jul 2008	Aug 2008	Sep 2008	Oct 2008	Nov 2008
Erica Sadun	1	2	1	3	1	4	3	4	2	-	-
Scott McNulty	2	-	8	6	5	3	4	-	-	-	-
Cory Bohon	3	1	2	1	2	1	2	1	3	2	1
Dave Caolo	4	7	4	2	7	5	6	5	7	7	4
Brett Terpstra	5	5	7	7	6	-	-	7	9	9	7
Christina	6	6	-	8	-	6	9	-	6	8	9
Mat Lu	7	4	5	5	3	7	7	8	10	6	8
Michael Rose	8	8	3	4	-	-	-	9	8	3	6
Mike Schramm	9	3	6	9	8	8	8	6	4	5	5
Nik Fletcher	10	9	9	10	-	-	-	-	-	-	-
Chris Urlich	-	10	10	-	-	-	-	-	-	-	-
Robert Palmer	-	-	-	-	4	2	1	2	1	1	2
Steven Sande	-	-	-	-	9	9	5	3	5	4	3
Joshua Ellis	-	-	-	-	10	10	-	-	-	-	-
Giles Turnbull	-	-	-	-	-	-	10	10	-	-	-
Victor Agreda	-	-	-	-	-	-	-	-	-	10	10

Figure 2. Influential bloggers' blogging behavior over 2008, according to MEIBIX.

V. Conclusions

The Blogosphere has recently become one of the most favored services on the Web. Many users maintain a blog and write posts to express their opinion, experience and knowledge about a product, an event, and several others comment upon these opinions. This "participatory journalism" of blogs has such an impact upon the masses that Keller and Berry [9] argued that through blogging "one American in tens tells the other nine how to vote, where to eat and what to buy". Therefore, a significant issue is how to identify such influential bloggers, because commercial companies can turn the influentials to become their "unofficial spokesmen", innovative business opportunities related to commercial transactions and traveling can be developed capitalizing upon the influentials, and so on.

This article investigated the problem of identifying influential bloggers in a blog site and proposed two new methods that provide rankings of the influentials. The main motivation for the introduction of these methods is that the closely relevant, competing methods have not taken into account temporal aspects of the problem, which we argue are the most important ones when dealing with spaces like the Blogosphere, which is highly volatile and doubles in size every six months.

The first proposed metric, termed MEIBI, takes into consideration the number of the blog post's inlinks and its comments, along with the publication date of the post. The second metric, MEIBIX, is used to score a blog post according to the number and age of the blog post's inlinks and its comments. The metrics can be computed very fast because they do not involve complex recursive definitions of influence, and in addition they do not use tunable parameters which are difficult to set. Therefore, they can be used in an online fashion for the identification of the *now-influential bloggers*.

These methods were evaluated against the state-of-the-art influential blogger identification method, namely that reported in [2], utilizing data collected from a real-world community blog site. The obtained results attested that the new methods are able to better identify significant temporal patterns in the blogging behaviour, and reveal some latent facts about the blogging activity.

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