Time-Sensitive Analysis of Value Based Micro-blogs

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Manuscript submitted April 25, 2017; accepted October 14, 2017.
doi: 10.17706/ijeeee.2018.8.2.105-111

Abstract: Social Media have become a major component of today's society. Value-based blogs make billions of dollars a year from web-based commercial markets which have become increasingly attractive entities for investors. This research will focus on how to evaluate a blog's value and how to make the invested money valuable. The purpose of the study aims to identify the time-sensitive curve of the amounts of visitors, so that business users who are interested in commercial marketing of social media could optimize their returns of investments by investigating the relationship between time of a post and its influences. In this research, the influences are measured by three parameters, including Likes count, Reprint count and Comments count. The results indicated that in addition to the content of a post, the following activities catch followers' attention: (1) encouraging them to reprint and make comment, (2) mentioning influential people in posts by using "fans economy", and (3) creating product-related topics.

Key words: Time sensitive analysis, fans economy, social media.

1. Introduction

The loyalty of fans or followers to websites is reflected by their visits and these visits are derived from a well-placed ad banner or pop-up showing a piece of chat, news, virtual-reality life [1], thought, image sharing, or information on an internet platform [1]. Inside this online community, views on a picture or an attention grabbing post typed by a well-known celebrity gives a more entertaining and interesting aspect through browsing the web.

As smart phones become a major form of mobile platform, social apps are developed and many lives have been changed leading to social times from a friendly physical gathering to 24/7 virtual existence [1]. These apps include micro-blogging networks such as Twitter and Weibo, video-sharing applications such as YouTube, image-sharing applications such as Instagram, map applications such as Google Map and Baidu Map, and social networking applications such as Facebook and WeChat.

Most value-based micro-blogs or celebrity posts have unpredictable efficacy, the more views on a page more value to it. So, the number of fans or reviewers a page indicates the popularity it receives. Commercial market prefers to monitor the amounts of views [2]. Followers pay to a business and the business returns payments to the endorsed bloggers and celebrities. How do businesses evaluate the monetary value of the sponsored celebrities and pay them appropriately? Most commercial ads' payments depended on follower's numbers. However, there is a problem. Many commercial companies could not find pertinent standards to evaluate posts. Moreover, to solve the problem, this research can help companies to find the best time to post information about products or service. This research focuses on analysis on well-received blogs and the actions of social media celebrities. Through continuous observations, we plotted the levels of social-media activities and came up with the influence levels for different time periods. Particularly, this research used Sina Weibo as a main app for this time-sensitive analysis of value based micro-blogs.

2. Literature Review

Sina Weibo recorded post times and made a report (Fig. 1) named habit time of users' daily posts on Weibo. The report stated that from "5:00 onwards, micro-blog users began to rise to 12:00 to reach the first peak, followed by a slight decline in the afternoon 1:00 to 2:00. After 3:00, micro-blog volume of visits increased slightly. At 7:00 pm, the posts volume again rose faintly. At 10 pm, it had reached the peak, then began to decline." (data.weibo.com/report) This description showed daily activities changing over time, including activities from individuals or businesses users. The purpose of this study is to help businesses to improve their user participation in accordance to user data. Therefore, we can use this record as a reference to help with marketing strategies. Researchers also studied time series data relate to followers behaviors reflecting micro-blog contents [3]. For example, Zhang (2015) studied public responses to "the MOOC Movement" in China [3]. The author examined the time series of micro-blogs in massive open online courses (MOOC) [3]. The author charted public responses to "the MOOC Movement" in China (Fig. 2) [3].

Fig. 1 and 2 show that time is a factor influencing the user traffic flow significantly [3]. There are some parameters to evaluate user participation. These parameters are shown by the numbers of forwards, comments, and likes. These three variables suggest user participation directly to the posts. About the number of views, micro-blogging has a function to record the read views of posts. The variable has a correlation with the number of followers. We could use this variable to evaluate users' participation. Some feedbacks are created passively from users, for sometimes micro-blogging users could their see these posts pushed up by micro-blogging system; in other words, this variable is quite different from other active variables, like forwards, commenting, and clicking "like". These active variables could directly indicate that the micro-blog users have participated with posts.

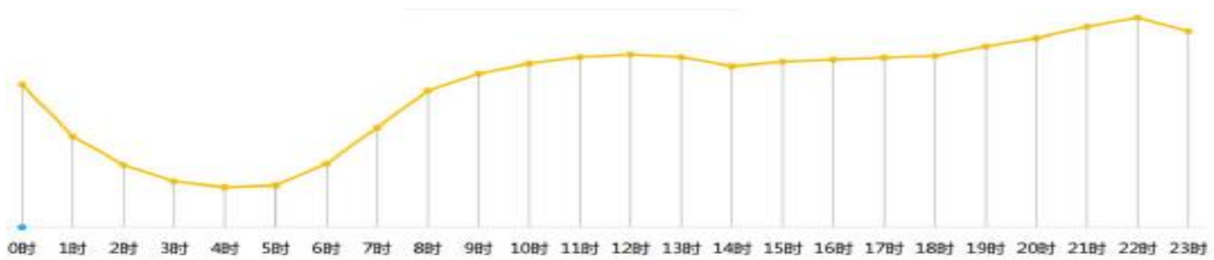


Fig. 1. Time and flow change (Sina Wei 2012).

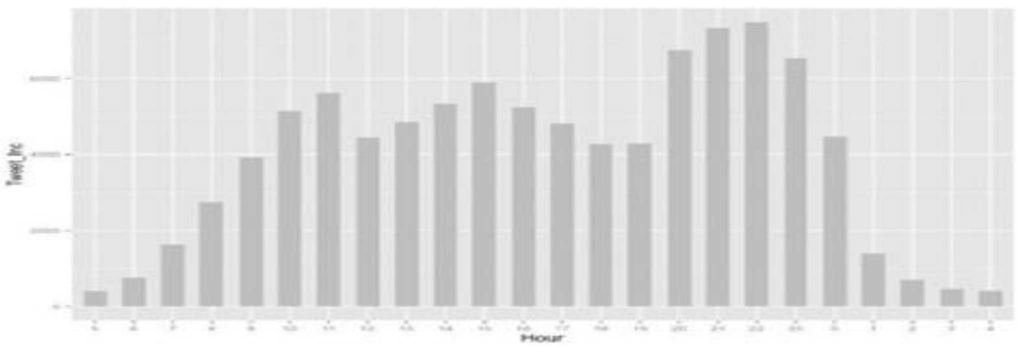


Fig. 2. The MOOC movement (Zhang, J. 2015)

3. Methodology

This research used big data methods and statistical tools to analyze data and generate the observation report. The case study and analysis can bring the basic knowledge from to test our hypothesis. Regarding the time of a post, it is a hypothesis that there is correlation between a celebrity's participation and the users' leisure time (Fig. 1&2). The matched peak time of posts were around 12:00PM, 5:00PM, and 10:00PM. We directly used these time periods as research experiments. Days were separated into weekdays and weekends since the leisure times were fairly different. Therefore, the focus group were composed by different time periods and days.

Object sample: Choosing the object would be the very important section for the purpose of this study. We chose one user from Sina micro-blog called "Weibo" with the user's name as "Ideological Focus". It was the object sample. This user was chosen because the person had an astounding 16 million followers which provided enough data to study the reposts, comments and likes.

This user updated posts frequently and from 6:00am to 1:00am every day. Using the diligent updates of this individual's micro-blog as an example, we are able to continually record the three parameters. The huge volume of data also provided choices about times of posts.

Sample group: From the Sina report, the samples' ages were from 17 years old to 33 years old, who composed of an 83% of main micro-blog users following the subject's posts [4].

Data: The majority of data collected were from online resources and public reports. The bigger the volume of the data, the more stable the conclusions are [5]. For example, these posts usually have hundreds of forwards, comments, and thousands of likes. When we recorded these comments following time periods, each time period had many comments. However, compared with other industries, such as clothes, tourism, soft drink, food, books, and cosmetics, mobile phone brands had an obvious advantage of amounts of followers, comments, reposts and likes.

Progressing: We collected user data by dividing them to three groups，including lottery draw, adding spokesman' name, and adding self-made topics [6]. For these three strategies, we divided posts into three parameters (i.e. Likes, Reposts, and Comments). Then we analyzed their time-sensitive values through Minitab.

4. Case Study and Analysis

1	repost	comment	Likes
2	2709	749	10612
3	1004	330	2056
4	2272	1012	9031
5	3562	745	7453
6	4729	914	5956
7	3570	331	3466
8	3647	1027	6551
9	4092	779	7803
10	2173	499	3015
11	3610	457	3759
12	523	139	1160
13	579	592	2962
14	2516	3272	8135
15	2046	1681	8665
16	3824	1588	10258
17	809	859	1006
18	261	2437	2727
19	240	178	700
20	2587	437	6644
21	480	415	1520
22	563	101	896
23	4013	1726	6505
24	145	102	1150
25	3806	613	5238
26	28	43	277
27	1071	607	7900
28	451	584	1854
29	2275	351	3661
30	2187	1754	7041
31	138	135	1071
32	2830	404	7754
33	3005	329	2394
34	1691	746	5858
35	167	50	736
36	4046	1721	12207
37	8010	279	5520
38	6104	2081	5962
39	3100	1342	6491
40	4621	857	5742
41	8577	2191	23422

Fig. 3. Sample blog activities.

We picked our objects randomly from a high volume month. For example, after choosing November, 2016, as the object month, we began to divide days into two groups, including weekdays and weekends. In this month, there were 20 weekdays and 8 weekends, and we could find 20 posts on weekdays at each time period. Time periods started from 6 am to 1am. Each period had 20 objects. After counting the number of three parameters in each hour, we took these 20 numbers as a group and calculated the mean and median of this group. Furthermore, we compared these means and medians of all the groups in this sample. We came up with a conclusion about the best time to post a message in weekdays. Then we used the same way on weekends as well.

Data Collection: It is impossible for the individual user to know when the users click "Like" on the posts, because there is no clue on the posts. Therefore, the first thing we need to do is to verify the correlation between the repost count and the like count. We randomly chose the posts of "Ideological Focus" on the 24th of November, 2016, as the sample in Fig. 3

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	1	349506792	349506792	35.42	<0.0001
Error	38	374985208	9868032		
Total	39	724492000			

Model Summary

S	R-sq	R-sq(adj)
3141.34	48.24%	46.88%

Coefficients

Term	Coef	SE Coef	T-Value	P-Value
Constant	1683.8	795.1	2.12	0.0408
repost	1.4482	0.2433	5.95	<0.0001

Regression Equation

Likes = 1683.8 + 1.4482 repost

Fits and Diagnostics for Unusual Observations

Obs	Likes	Fit	Resid	Std Resid		
36	5520	13284.0	-7763.98	-2.77	R	X
40	23422	14105.1	9316.88	3.41	R	X

R Large residual
X Unusual X

Fig. 4. Simple regressions between likes and reposts.

Minitab Verification: Fig. 4 is simple regression between Likes and Reposts. From this Figure, we could see that there is positive correlation between Like count and Repost count. Since *P*-value<0.0001<0.05, we deny the hypothesis that there is no correlation.

For comment count, it is very hard to count, because the time of comments is disorganized. We used Minitab to verify the correlation between the Like count and the Comment count (Fig. 5).

Simple Regression: Likes versus comment

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	1	247260248	247260248	19.69	<0.0001
Error	38	477231752	12558730		
Total	39	724492000			

Model Summary

S	R-sq	R-sq(adj)
3543.83	34.13%	32.40%

Coefficients

Term	Coef	SE Coef	T-Value	P-Value
Constant	2488.9	859.2	2.90	0.0062
comment	3.3549	0.7561	4.44	<0.0001

Regression Equation

Likes = 2488.9 + 3.3549 comment

Fig. 5. Correlation between like and comment count.

From the Figure, we could see there is correlation between Likes and comments. Therefore, we could use the repost count as the variable for this study.

The following items show the details of choosing data:

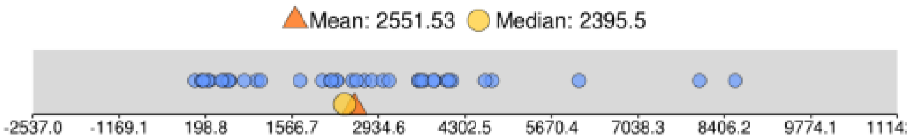
Content of posts is a vital factor to influence the final numbers of Repost, Comments, and Likes. Therefore, we choose the Repost counts of posts as close as possible, which could help us to reduce the error, which is caused by other reasons, like the quality of posts, unexpected forwarding by an influential user, posts which are referred to hot topics.

From the Posts' time limited efficacy, we avoid choosing posted from the most recent days. It is obvious that the numbers of Repost, Comments, and Likes still have a slight rise. Therefore, we choose the sample posts which posted several days ago.

From the Sample, for weekdays and weekends, we should choose different samples respectively. For weekdays, we could choose a day from Monday to Friday. For weekends, we could choose Saturday or Sunday.

Aimed to the first detail, we could select our sample and find a relatively better interval of Repost count.

The 6th Figure is to show the mean and median of sample1.

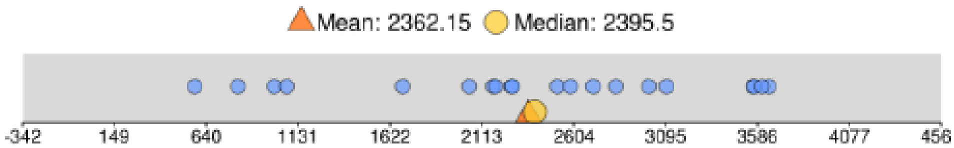


Descriptive Statistics:

Sample Size	Mean	Standard Deviation	Minimum	1st Quartile	Median	3rd Quartile	Maximum	IQR
40	2551.53	2067.11	28.00	575.00	2395.50	3686.75	8577.00	3111.75

Fig. 6. Mean and median of deleted sample.

Form the Fig. 6, we could find that the minimum is just 28 and the maximum is 8577 comments, which suggest that there is huge variance between contents of posts. And for 1st Quartile and 3rd Quartile, there is still big variance between them. Therefore, we should delete some data which are too small or too huge. For this sample, I choose to delete Repost count which is less than 1st Quartile 575 or more than 3rd Quartile 3686.75 comments. Fig. 7 shows the new median and mean of deleted sample.



Descriptive Statistics:

Sample Size	Mean	Standard Deviation	Minimum	1st Quartile	Median	3rd Quartile	Maximum	IQR
20	2362.15	951.83	579.00	1957.25	2395.50	3028.75	3647.00	1071.50

Fig. 7. New median and mean of deleted sample.

We could see the variance between 1st Quartile and 3rd Quartile has a big decrease. Then we could use the new interval between 1st Quartile and 3rd Quartile as the random of Repost count for choosing the posts.

According this interval, we randomly choose posts of weekdays from the account “Ideological Focus” to compose Fig. 8.

posting time	amount of forwrding	interval	Num of interval	num/min
6:05	2878	6:05-7:00	361	6.56/min
7:05	2769	7:05-8:00	1408	25.6/min
8:03	2631	8:03-9:00	1081	18.96/min
9:00	3105	9:00-10:00	1528	25.47/min
10:03	2965	10:03-11:00	923	16.19/min
11:06	2475	11:06-12:00	629	11.65/min
12:06	2773	12:06-13:00	1305	24.17/min
13:04	2902	13:04-14:00	1106	19.75/min
14:05	2807	14:05-15:00	962	17.49/min
15:05	2970	15:05-16:00	1028	18.69/min
16:06	2751	16:06-17:00	1124	20.81/min
17:00	2307	17:00-18:00	1024	17.07/min
18:07	2940	18:07-19:00	1340	21.27/min
19:13	2040	19:13-20:00	843	17.94/min
20:13	2126	20:13-21:00	1021	21.72/min
21:03	2169	21:00-22:00	923	15.38/min
22:35	2789	22:35-23:00	624	24.96/min
23:15	1787	23:15-24:00	789	22.54/min
0:08	3203	0:08-1:00	1132	21.77/min
1:03	3024	1:03-2:00	463	8.12/min

Fig. 8. Time-flow and interval number.

The peak times are 7:00 Am, 9:00Am, 12:00 Am, and 10:00 Pm and 11:00pm. This table has weekdays. We can run the same cycle for weekends as well.

The procedure would be the same as done for the optimal time.

Lottery draw has an important impact on users' participation because the motivations of people are from the belief that everyone could be lucky [7]. And lottery draw on Micro-blogs is at no cost. Adding names of other celebrities in posts is an effective way to obtain more participation from their followers.

Adding self-made topics is a kind of fans-economy. These brands are famous in China, but it is hard to say that there is strong association between customers and brands or products.

5. Conclusion

It is well known that internal reasons of posts are prime things for these users. These internal factors inlcude the number of followers, the influence of individual or business, the content of posts, the quality of posts. The purpose of the study is to help the micro-blog user to explore and analyze some strategies, such as launching lottery draw in posts, choosing the best time to post, adding names of other celebrities in posts, adding self-made topics.

Regarding the best time to post in this study, it should be within four time periods, 7:00 Am,9:00Am,12:00 Am, or 10:00 PM. This time schedule is just an initial conclusion. From this initial conclusion, we could find that at different times the frequency of users' participation in micro-blogging are different. So there is a correlation between leisure time and user' participation on posts.

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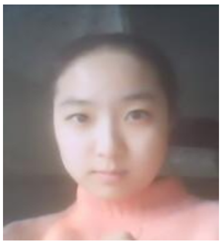

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