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Article

The Role of Multimedia Content in Determining the Virality of Social Media Information

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Abstract: The paper provides empirical evidence supporting the assumption that content plays a critical role in determining the virality, *i.e.*, the influence, of social media information. The analysis focuses on multimedia content on Twitter and explores the idea that links to multimedia information increase the virality of posts. In particular, we put forward the following three main hypotheses: (1) posts with a link to multimedia content (photo or video) are more retweeted than posts without a link; (2) posts linking a photo are more retweeted than posts linking a video, and (3) posts linking a video raise more sentiment than posts linking a photo. Hypotheses are tested on a sample of roughly two million tweets posted in July 2011 including comments on Berlin, London, Madrid, and Milan relevant from a tourism perspective. Findings support our hypotheses and indicate that multimedia content plays an important role in determining not only the volumes of retweeting, but also the dynamics of the virality of posts measured as speed of retweeting.

Keywords: social media; influence; virality; microblogging; multimedia

1. Introduction

Social media have a strong impact on the way users interact and share information. The process through which users create and share opinions on brands, products, and services, *i.e.*, the electronic word-of-mouth (eWOM) is gaining increasing attention. In the online context, the eWOM has been transformed from a communication act that takes place in a private one-to-one context to a one-to-many complex interaction. This represents the most powerful aspect of the eWOM. The reach of information sharing through eWOM can be both broad and fast. Companies know that controlling the dynamics of information sharing is very difficult. This need for improving control is one of the reasons why there is a growing interest in understanding how the structure of a social network can affect the dynamics of user interaction and information sharing.

Several previous studies have focused on the role of influencers, *i.e.*, nodes with a central position in the network. In particular, microblogging platforms such as Twitter are the focus of a wide range of studies that aim at understanding how messages spread inside the social network and how the role of the message author impacts on message reach. Microblogging networks are more and more used by companies as a communication medium for the promotion and engagement of customers. An emerging paradigm for the study of social networks as a communication medium is the attention economy [1]. This paradigm starts from the observation that brands are involved in a competition for gaining the attention of possible customers. While on traditional media attention can focus not only on content, but also on the way a message is conveyed, on social media content plays a more central role [2]. Content is even more central with microblogging, as the shortness of messages compels users to focus on the core of the information that they want to share. On Twitter, the standard size of a message limited to 140 characters is roughly the typical size of headlines and encourages users to produce content that are easy to consume.

Our claim is that, while the information shared by influencers has a broader reach, the content of messages plays a critical role and can be a determinant of the social influence of the message irrespective of the centrality of the message's author. We make a distinction between influence and influencers. While nodes are influencers depending on their centrality in the social network, influence is the actual impact of messages, which depends not only on the structure of the network, but also on the ability of message content to raise attention. Studying how content spread within social networks can be useful for explaining why some trends are followed more quickly and successfully than others, thus providing an invaluable input to business intelligence. The concept of influence can provide more accurate insights on how companies can leverage social media to strengthen their brand's reputation.

In this paper, we put forward a set of hypotheses supporting the claim that the content of messages plays a critical role and can be a determinant of the social influence of the message irrespective of the centrality of the message's author. In this paper, we focus on multimedia content as an important characteristic of online communication patterns. We put forward the following three main hypotheses: (1) posts with a link to multimedia content (photo or video) are more retweeted than posts without a link; (2) posts linking a photo are more retweeted than posts linking a video, and 3) posts linking a video raise more sentiment than posts linking a photo. Hypotheses are tested on a sample of roughly two million tweets posted in July 2011 including comments on Berlin, London, Madrid, and Milan relevant from a tourism perspective.

The remainder of this paper is structured as follows. Section 2 presents related research and highlights the innovative aspects of this work. Section 3 discusses our research hypotheses, while Section 4 reports testing results. Finally, Section 5 draws some conclusions and presents future research directions.

2. State of the Art

The study of social networks began in 1908 with Simmel who has built the first theory that interprets social phenomena [3]. In 1934, Moreno was the first to propose a formal representation of social networks as a combination of nodes and arcs [4]. Then, Harary and Cartwright [5,6] applied the concept of the graph theory to social networks that were called sociograms. With the introduction of directed arcs between nodes they were able to explain complex social patterns.

At the end of the 1930s, two different schools of thought emerged. The sociocentric approach [7] focused on identifying subgroups of people within the same network and understanding the relationships between subgroups. The egocentric approach was focused on the study of the whole community. This latter approach [8–10] emphasized the importance of social networks as a means to share knowledge and information. In particular, Milgram introduced the concept of the six degrees of separation [10], which attempted to demonstrate the idea of what he called "small world phenomenom," particularly interesting in understanding the power of eWOM.

Freeman focused on the definition of important nodes in a network and related metrics [11]. In this respect, microblogging has created new opportunities. Jansen *et al*. [12] have examined Twitter as a form of electronic word-of-mouth for sharing consumer opinions concerning brands. They investigated the overall structure of tweets and sentiment trends. In The Million Follower Fallacy [13], with a very large Twitter data set consisting of about six million users and considering the indegree (*i.e.*, the number of followers) metric to measure the importance of users, authors analyse the correlation between indegree and mentions and retweets. The conclusion of this work is that user's popularity has a little effect on the actual attention from other users measured by retweets and mentions. Galuba *et al*. [14] track 15 million URLs exchanged among 2.7 million users over a 300 h period in Twitter and propose a propagation model that predicts which users are likely to mention which URLs in their tweets. Similarly, Suh *et al*. [15] present a comprehensive propagation model including a broad database of tweets associated with a wide range of metadata. Their findings show that URLs and hashtags have strong correlation with the number of retweets.

A recent study in the context of the Ecology Web Project [16] focuses on the influence of a set of 12 very popular users, based on an in-depth analysis of their posts and corresponding responses. Users were divided into three clusters, *i.e.*, celebrities, news, and social media analysts. The authors of this study found that celebrities have the largest number of followers and are able to produce significant volumes of responses with a very low effort (*i.e.*, activity). Social media analysts can reach the highest values of influence if their responses are weighed by the number of followers; however, these high values are reached only with a very high effort. Finally, news has the greatest ability to have their contents forwarded by other users.

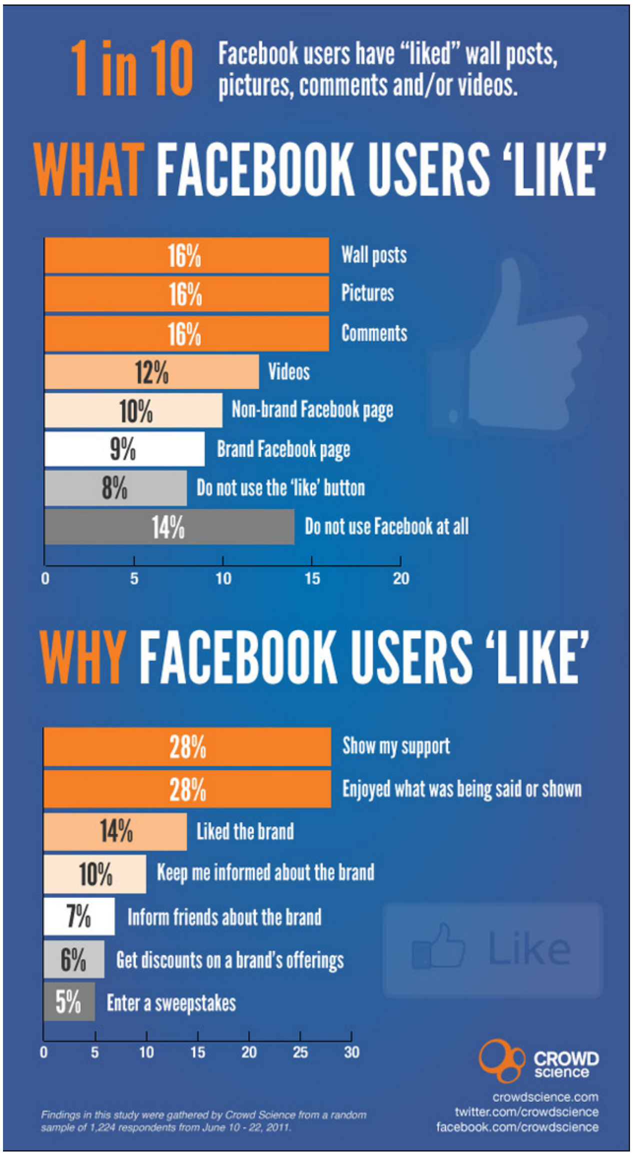
Other researches [17,18] found that the propagation of a message on Twitter is greater if a twitterer is more influential, measuring influence by means of the PageRank algorithm [19]. Due to the nature of this algorithm, the authors observed a high reciprocity among follower relationships. In contrast, it has also been found that overall reciprocity is low in Twitter [13].

3. Research Hypotheses

In this paper, we still focus on Twitter, but we address multimedia content as an important characteristic of tweets. Regarding multimedia content, a qualitative analysis conducted by Crowd Science [20] on Facebook in 2011 shows how posts with multimedia content, especially pictures, receive a significantly higher number of *likes* (see Figure 1). To the best of our knowledge, the literature does not provide similar studies focusing on Twitter. To fill this literature gap, we put forward the following research hypothesis aiming at verifying whether this finding is valid with Twitter:

H1: Tweets with a link to multimedia content (photo or video) are more retweeted than posts without a link.

Figure 1. Multimedia and Facebook likes [20].



In our second hypothesis, we make a distinction between videos and photos. As a general observation, we posit that photos convey a more immediate message, as they do not involve a sustained attention to be understood. The literature provides evidence highlighting the virality of shorter videos, irrespective of technical issues related to bandwidth and devices [21]. In general, shorter videos are recognized to be more viral [22]. Conversely, longer videos require more motivation to be viewed and, from a technical standpoint, are more demanding in terms of bandwidth and more restrictive on the set of enabled mobile devices. Photos are more accessible, require limited time and resources to be downloaded, can be viewed on any mobile device, and have been proved to have a longer persistence in people's memory [23]. These considerations lead us to the following hypothesis:

H2: Tweets linking a photo are more retweeted than posts linking a video.

On the other hand, there is general agreement in crediting a greater emotional impact to videos [21–26]. Videos can serve as a powerful communication vehicle that can be made more impactful by designing the right combination of color, content, lighting, and movement of an image. These characteristics are used extensively by professionals on web sites and advertisements to draw attention and leave a lasting emotional impression. Compared to videos, photos provide more limited design options, with a generally lower emotional impact. We focused on the sentiment of posts to characterize the emotional impact of content. This leads to our third hypothesis.

H3: Tweets linking a video raise more sentiment than tweets linking a photo.

Note that hypotheses H1–H3 are expressed in terms of volumes of posts. Similar considerations can be made to reformulate hypotheses H1–H3 in terms of speed of retweeting. Hypothesis H1 posits that volumes of retweeting are greater for tweets linking multimedia content, as this type of content is broadly recognized to be viral. However, virality has both a volume and a time speed dimension. For example, Wallsten notes how the speed with which viral videos cross the boundaries of one's circle of direct friends is far reaching in a very short time frame, compared to more traditional forms of communication based on broadcasting [27].

H4: Tweets with a link to multimedia content (photo or video) receive more retweets per time unit than posts without a link.

Following a short URL linking to a photo is clearly faster than following a link to a video. Previous studies from cognitive sciences indicate that the emotional status of individuals changes rapidly with a sequence of images [28]. It has been demonstrated that images embedded in a video create an unconscious permanent reaction when they are not consistent with the storyline underlying the video stream. This technique is adopted in psychology to recall traumatic events [29] or in education to stimulate reactions and reduce feedback time [28]. Overall, previous studies indicate that the time required to obtain a reaction is shorter for images compared to other forms of communication and, in particular, videos [30].These considerations lead us to the following hypothesis.

H5: Tweets linking a photo are retweeted more quickly than posts linking a video.

In H6, we mitigate H5 by positing that videos show faster dynamics compared to photos when they demonstrate capable of raising sentiment. As noted before, videos can have a stronger emotional impact. When they do, they raise sentiment. We now focus on videos that have raised sentiment, as expressed by the comments attached to the posting or reposting of their URLs. This subset of videos may have the capability of raising more interest than pictures and, thus, receive more attention in terms of retweets per time unit. Photos have been found to be more accessible and more likely to be remembered, but also less viral [31]. Our next hypothesis states that viral videos have faster dynamics compared to photos.

H6: Among tweets with sentiment, tweets linking a video receive more retweets per time unit than tweets linking a photo.

4. Empirical Testing

Hypotheses are tested on a sample of approximately two million tweets posted in July 2011 including comments on Berlin, London, Madrid, and Milan relevant from a tourism perspective. Analyses have been limited to tweets written in the English language. Retweets are roughly 270,000 out of our total sample. We have clustered our sample by grouping all retweets of a post with the original post. In this way, we have obtained 110,000 clusters. The number of retweets per cluster ranges from 8515 to one, with mean value equal to two.

We have divided clusters into two sets, the first including clusters where the original tweet has a link to multimedia information, the second including tweets without a link or linking other types of content. Then, we have made a distinction between photos and videos by automatically detecting links to the most common sources of images, including Flickr, Instagram, TwitPic and Yfrog, and videos, including TwitVid, TwitCam, YouTube, and Vimeo. This process resulted in 1627 clusters of tweets linking photos and 586 clusters of tweets linking videos.

A descriptive analysis of the samples highlights the presence of many zeros, *i.e.*, the distributions of our samples are right-skewed. Following a common rule of thumb, we preliminary tested the medians of the distributions. We adopted the Wilcoxon-Mann-Whitney (WMW) test because of its recognized effectiveness [32].

We have run a WMW test of the distributions associated with tweets containing a link to multimedia content and tweets without a link. The descriptive statistics of the samples are reported in Table 1. The WMW test (z = 5,765, p = 0.000) shows that there are significant differences between the two distributions. Often this statistic is used to compare a hypothesis regarding equality of medians. Since the U statistic (and the normalized version, z) tests whether two samples are drawn from identical populations, equality of medians follows as a consequence.

Then, we have run a *t-test* on the mean value of retweets in our sample sets. Results are reported in Table 2.

Table 1. Descriptive statistics of our sample.

Cluster	N	Mean	Standard Deviation	Standard Error Mean
No Link	74,294	1.550	34.937	0.128
Photos and Videos	2,213	2.770	26.390	0.561

Table 2 shows how the *t-test* indicates that the difference of the mean value of retweets with and without links to multimedia information is statistically significant (p = 0.033). We can conclude that there is a statistically significant difference between the mean number of retweets for posts that link multimedia information and posts that do not link multimedia information. This means that the hypothesis 1 is supported by our data.

Table 2. *T-test* for equality of mean values (H1).

t	*df*	*Significant (2-tailed)*	*Mean Difference*	*Standard Error Difference*	*95% Confidence Interval of the Difference*	
					Lower	*Upper*
−2.137	2,448.788	0.033	−1.230	0.575	−2.358	−0.101

Table 3 shows the mean value and standard deviation of the number of retweets of posts linking photos compared to posts linking videos. Clearly, posts linking photos are retweeted five times more than posts linking videos.

Table 3. Descriptive statistics of our sample.

Cluster	**N**	**Mean**	**Standard Deviation**	**Standard Error Mean**
Photos	1,626	3.520	30.707	0.762
Videos	586	0.730	2.889	0.119

A WMW test (z = −3,628, p = 0.000) shows that there are significant differences between the two distributions. The results of *t-test* reported in Table 4 support hypothesis 2.

Table 4. *T-test* on retweeting of posts linking photos *vs*. videos (H2).

T	*df*	*Significant (2-tailed)*	*Mean Difference*	*Standard Error Difference*	*95% Confidence Interval of the Difference*	
					Lower	*Upper*
3.620	1,702.950	0.000	2.790	0.771	1.278	4.302

In order to test the third hypothesis, we used a semantic analysis tool [33] to select tweets that express opinions on Milan city, *i.e*., tweets carrying sentiment (either positive or negative). Opinions have been classified according to the Anholt model [34], providing a set of city brand drivers relevant from a tourism perspective, e.g., arts and culture, services and transports, food and drinks, *etc*.

Table 5 shows the mean value and standard deviation of the number of tweets with sentiment (positive or negative) linking photos compared to posts linking videos. Clearly, posts linking videos raise more sentiment than posts linking photos.

Table 5. Descriptive statistics of our sample.

Cluster	N	Mean	Standard Deviation	Standard Error Mean
Photos	159	3.383	9.212	0.730
Videos	83	4.060	4.575	0.502

Because of the small sample available for validating the third hypothesis, we adopted the Kolmogorov–Smirnov (KS) test instead of the Wilcoxon-Mann-Whitney. Indeed, for very small samples the KS test is preferable to the Wilcoxon-Mann-Whitney test, while the latter is preferred for large samples [35]. The KS test (D = 1,372, p = 0.040) shows that there are significant differences between the two distributions. The results of t-test reported in Table 6 support hypothesis 3.

Table 6. *T-test* on sentiment of posts linking photos *vs*. videos (H3).

t	*df*	*Significant (2-tailed)*	*Mean Difference*	*Standard Error Difference*	*95% Confidence Interval of the Difference*	
					Lower	*Upper*
−2.063	1,405.219	0.039	−0.245	0.119	−0.479	−0.012

The same dataset has been used to validate the hypotheses about the speed of retweeting. We have calculated the time (in seconds) elapsed between each original tweet and its retweets. A Kendall's Tau correlation test [36] was run to determine the relationship between the volumes and the speed of retweeting. A small, positive correlation was found between the volumes and the speed of retweeting, with high statistical significance (τ = 0.231, p = 0.002). This small correlation supports the need for testing hypotheses 4–6.

Table 7 shows the mean value and standard deviation of the retweeting times of tweets linking multimedia content compared to posts without a link. Cleary, the mean values of the two sets of tweets are considerably different.

Table 7. Descriptive statistics: multimedia *vs*. no link (speed of retweeting).

Cluster	N	Mean	Standard Deviation	Standard Error Mean
No Link	114,809	412.580	206.274	0.609
Photos and Videos	6,141	283.180	169.649	2.165

The results of *t-test* reported in Table 8 support hypothesis 4.

Table 8. *T-test* on speed of retweeting of post linking multimedia *vs*. no link (H4).

t	*df*	*Significant (2-tailed)*	*Mean Difference*	*Standard Error Difference*	*95% Confidence Interval of the Difference*	
					Lower	*Upper*
57.539	7,147.067	0.000	129.395	2.249	124.986	133.803

Table 9 shows the mean value and standard deviation of the retweeting times of tweets linking photos compared to tweets linking videos. Data show that posts linking photos are retweeted more quickly than posts linking videos.

Table 9. Descriptive statistics: photos *vs*. videos (speed of retweeting).

Cluster	**N**	**Mean**	**Standard Deviation**	**Standard Error Mean**
Photos	5,716	274.590	166.682	2.205
Videos	425	398.780	167.058	8.104

The results of *t-test* reported in Table 10 support hypothesis 5.

Table 10. *T-test* on speed of retweeting of post linking photos *vs*. videos (H5).

t	***df***	***Significant* (*2-tailed*)**	***Mean Difference***	***Standard Error Difference***	***95% Confidence Interval of the Difference***	
					Lower	***Upper***
−14.788	488.892	0.000	−124.194	8.398	−140.695	−107.693

Finally, Table 11 shows the mean value and standard deviation of the retweeting times of tweets with sentiment (positive or negative) linking photos compared to posts linking videos. As in the previous case, posts linking photos are retweeted more quickly than posts linking videos.

Table 11. Descriptive statistics: tweets with sentiment linking photos *vs*. videos (speed of retweeting).

Cluster	**N**	**Mean**	**Standard Deviation**	**Standard Error Mean**
Photos	234	332.190	212.080	13.864
Videos	36	429.890	197.001	32.834

The results of *t-test* reported in Table 12 support hypothesis 6.

Table 12. *T-test* on speed of retweeting of post with sentiment linking photos *vs*. videos (H6).

t	***df***	***Significant* (*2-tailed*)**	***Mean Difference***	***Standard Error Difference***	***95% Confidence Interval of the Difference***	
					Lower	***Upper***
−2.741	48.363	0.009	−97.697	35.641	−169.343	−26.050

5. Conclusions and Future Works

This paper provides general evidence supporting the idea that content plays a critical role in determining the virality of posts on social media. While previous literature focuses on social media influencers, we stress the distinction between influencers and influence. The idea that content matters is interesting in that it suggests that social media users are not passive consumers of information, but are opinionated and think autonomously as opposed to delegating decision-making to social influencers only. Users' autonomous opinion-making processes represent a key factor in (a) encouraging an attention towards the quality of shared content and (b) making social media less prone to bias and manipulation.

Interestingly, the characteristics that make content more viral do not seem to be straightforward. In previous research [37], we have provided evidence supporting a complex relationship between sentiment and virality. Negative tweets have been shown to have a higher probability to be retweeted, but dynamics of retweeting similar to that of positive and neutral tweets. In this paper, we have focused on multimedia content. We have found that multimedia content contributes to the virality of tweets. However, photos and videos trigger different dynamics of retweeting. As cited by Logan [38], MacKay suggested that information should be defined as "the change in a receiver's mind-set, and thus with meaning" [39]. Our findings seem to support the idea of subjectivity of meaning as the emotional impact of content is found to play a role in determining both the extent and the speed of information sharing on Twitter.

In the last years, cities are trying to become smarter, using technology to enhance their citizen's life and to attract tourists by advertising their services. Twitter seems to be a powerful tool to build a city brand reputation and, thus, to achieve an effective rebranding. Scharl *et al*. [40] have shown that social media coverage and sentiment influence a tourism destination image. Our results seem to confirm these insights.

Our analyses are limited to tweets written in the English language. Moreover, our dataset is limited to well-formed tweets, as per Twitter's double arrow icon [41]. Future work will extend this research to a broader dataset and to social media different from Twitter. In particular, future research will address other indicators of virality, such as speed and reach of information. We will also revisit the concept of influencer by applying our metrics of influence to the selection of a sample of social media users to be analyzed across different social media.

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