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THE FIERY, THE LOVELY, AND THE HOT - ANALYSIS OF ONLINE VIRAL PHENOMENA IN SOCIAL MEDIA

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Research paper

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Abstract

Social media, such as Facebook and Twitter, offer new ways of communication for companies, politicians, or celebrities to get in direct touch with their customers, the public, or fans. Thereby, online posts undergo different information diffusion processes. While the majority of posts vanishes in the vast flood of data, single posts – called buzzes – receive an extraordinary attention and become viral. Previous research indicates that different types of buzzes, i.e. firestorms, lovestorms, and hot topics, exist. However, researchers have not yet distinguished between them in their analyses. This study examines firestorms, lovestorms, and hot topics by analysing variables describing their characteristics and comparing them. Drawing on a manually classified data set of more than 60,000 Facebook posts, we emphasise that a differentiation between the buzz types is necessary for future analyses. We underline that content-related variables, like the mean comment's length, are useful to describe firestorms and hot topics. Temporal variables, like the activity within the first hours, help to distinguish firestorms from lovestorms and hot topics. User-related variables, like the number of new participating users, are good predictors for all three buzz types while engagement variables, such as comments, likes, and shares, yield surprising differences among the three types.

Keywords: Information Diffusion, Firestorms, Lovestorms, Hot Topics

1 Introduction

In these days, online social media constitute a major part of our lives. Among others, companies, politicians and their parties, public figures, and celebrities use social media channels as a new way of direct communication with customers, citizens, supporters, and fans. Some of their online posts do not find much attention, while others spread exceptionally far so that lots of people talk about them online or offline and even news agencies might pick them up – posts that have become viral. The topic of virality has found its way into academic literature, too. Based on prior work, we generally refer to such viral posts as buzzes (Lesot et al. 2012; Deusser et al. 2018). Buzzes are specific posts, behaviours, or topics that initially spread on social media and that suddenly draw surprising and extraordinary attention. Posts can contain texts, videos, or pictures and obtain online reactions such as likes, comments, as well as shares and sometimes offline reactions such as people participating in events or buying certain items. Usually, this extraordinary attention lasts for a few days or weeks and in rare cases even for a few months. Right at the beginning there are mostly no news agencies involved, however in the further course of reactions to the post, single media outlets might report on the buzz later.

Research focusing on information diffusion processes found that not every buzz is the same (e.g., Cvijikj and Michahelles 2011; Deusser et al. 2018). For example, Deusser et al. (2018) indicate that different types of buzzes exist which refer to firestorms, lovestorms, and hot topics. So far, on the one hand, researchers either focused on one single buzz type – firestorms (e.g., Pfeffer et al. 2014; Drasch et al. 2015), lovestorms (Ács and Pagh 2017), or hot topics (e.g., Bun and Ishizuka 2002) – without considering the respective others. On the other hand, most researchers have treated buzzes alike in their studies and did not further analyse the different buzz types (e.g., Berger and Milkman 2012; Deusser et al. 2018). Within this study, we differentiate between firestorms, lovestorms, and hot topics to enrich existing literature on information diffusion and social media research since these buzz types can undergo various diffusion processes. This differentiation can also help to explain contradicting findings in previous literature: some say that positive content makes a post go viral (Berger and Milkman 2012), some claim that negative content spreads better (Hansen et al. 2011), and others emphasise that both positive and negative contents have viral effects (Stieglitz and Dang-Xuan 2013). Different underlying buzz types may explain these contrasting findings, which encompass different characteristics affecting virality. Furthermore, because of the great importance of buzzes, e.g. for profitable online advertising placements (Berger and Milkman 2012), especially researchers in the computer science field analysed how to detect them based on various variables (e.g., Tsur and Rappoport 2012; Deusser et al. 2018). But here, too, for various parties it might not only be interesting to identify buzzes in general but to detect the more specific buzz types.

The objective of this study is to examine the three buzz types – firestorms, lovestorms, and hot topics – by analysing variables derived from theory, which describe their characteristics as well as their commonalities and differences. Firestorms (Pfeffer et al. 2014, p. 118) are "the sudden discharge of large quantities of messages containing negative WOM [= word-of-mouth] and complaint behaviour against a person, company, or group in social media networks. In these messages, intense indignation is often expressed, without pointing to an actual specific criticism." For example, the food company *Barilla* became the target of such a firestorm in 2013 when *Barilla*'s chairman offended homosexuals in an interview and continued to do so in his following Facebook post meant as an apology (Facebook 2013). Lovestorms (Ács and Pagh 2017, p. 2) are "a persistent wave of expressions of sympathy and compassion. Lovestorms seek to emphasise, develop and echo the positive stories on a specific topic by spreading positive messages across several social media platforms." For example, the brand *Honey Maid* obtained several lovestorms for different commercials integrating messages that human interactions should be based on love, respect, and compassion (e.g., Facebook 2015a). Hot topics are topics that are frequently discussed over a period of time (Bun and Ishizuka 2002). They trigger heated discussions and reappear regularly, e.g. regarding the topic of obesity (Facebook 2016a) or political questions concerning refugees (Facebook 2016b) or participation in military offensives such as in Syria (Facebook 2015b). In contrast to firestorms, hot topics contain rather valid facts instead of false allegations or rumours (Pfeffer et al. 2014).

We choose an exploratory approach as above all lovestorms and hot topics have not been studied in academic literature very extensively yet. We apply logistic regressions on a manually classified data set of more than 60,000 posts from 77 different public Facebook pages. Our results emphasise that content-related variables, such as the mean of the comments' length, are good predictors for firestorms and hot topics. Temporal variables, like the activity within the first hours, are useful to identify hot topics and lovestorms. User-related variables, such as the number of new participating users, reveal significant results for all buzz types. Engagement variables underline rather surprising results as comments, likes, and shares differ significantly concerning the underlying buzz type.

This study valuably contributes to information diffusion literature and social media research. We enrich previous literature on virality by distinguishing between different buzz types and describing their characteristics. Thereby, we shed light on why researchers found contrasting results regarding which pieces of online content go viral and underline the importance and need for differentiating between different buzz types in future research. Our results are of practical importance as well since they help various parties to identify different buzz types to meet their interests. For example, social media managers may be interested in all buzz types – to prevent their organisations from firestorms, use lovestorms for their advertising strategies, and react upon hot topics to take their positions.

The remainder of this article is structured as follows: Section 2 gives a brief overview of existing literature focusing on the characteristics of buzzes in general and studies referring to firestorms, lovestorms, and hot topics. In Section 3, we present the data and methodology we used in this study. Section 4 summarises the results which we extensively discuss by referring to extant literature in Section 5. Finally, in Section 6, we present the conclusions of our study.

2 Literature Review

Buzzes and their different types underlie the general concept of information diffusion processes. Especially regarding social media, the topic of online information diffusion has attracted many researchers within the last decades. Above all, researchers concentrated on identifying and understanding variables that drive information diffusion in social networks to explain why some online contents get more attention than others (e.g., Berger and Milkman 2012; Stieglitz and Dang-Xuan 2013). However, so far, researchers did not distinguish between different buzz types (e.g., Berger and Milkman 2012; Deusser et al. 2018) although several results indicate that buzzes are not the same and should therefore not be treated alike. For instance, Lesot et al. (2012) emphasise that some buzzes relate to rumours, while Cvijikj and Michahelles (2011) find that some, e.g. relate to disruptive events or popular topics. Just recently, Deusser et al. (2018) gave examples for buzzes which actually represent the three different buzz types. Based on their findings, we are the first to differentiate between firestorms, lovestorms, and hot topics, as well as to examine them and compare them among each other. Hitherto, a few studies have focused on each buzz type only separately. Examining all three buzz types allows us to learn more about the specific diffusion processes of each type. This may help us to explain the contradictory findings regarding the drivers for virality and to detect each type based on its specific characteristics in order to align strategic decisions and activities. We further depart from existing studies by taking into account a manually classified data set of more than 60,000 posts from various public Facebook pages. We analyse easily accessible variables which describe the characteristics of the three buzz types as well as their commonalities and differences. Thereby, we show the importance of differentiating between different buzz types. Especially, concerning the contrasting findings regarding the question whether positive or negative content goes viral, such a differentiation may help to explain these findings. In the following, we first focus on studies concentrating on different variables to describe buzzes. Second, we draw on the few extant studies regarding firestorms, lovestorms, and hot topics.

In general, researchers analysed buzzes referring to content-related variables such as the sentiment (Berger and Milkman 2012; Stieglitz and Dang-Xuan 2013), bursty keywords (Mathioudakis and Koudas 2010), hashtags (Tsur and Rappoport 2012), or visual characteristics of images (Guerini et al. 2013). In addition, there are several studies including metadata, such as user-related, temporal, and engagement variables, in order to analyse information diffusion processes in different contexts. They, e.g. refer to age, gender, and view count (Feroz Khan and Vong 2014), date and time of uploaded content (Deza and Parikh 2015), or the number of likes and comments (Deusser et al. 2018). Moreover, there are studies taking into account both content-related variables and variables from metadata such as the number of hashtags and the number of followers and followees (Suh et al. 2010), the sentiment of hashtags and the number of users and tweets (Ma et al. 2013), as well as vocabulary diversity and number of retweets (Zubiaga et al. 2015). Yet, the presented studies only considered buzzes in general and did not distinguish between different buzz types.

Existing literature regarding firestorms, lovestorms, and hot topics lacks specific variables which are easily accessible and describe the single types in an online environment. Furthermore, particular characteristics are missing to compare the three buzz types among each other. For example, Stich et al. (2014) draw on a complex friendship network to model the spread of negative electronic word-of-mouth (eWOM) and the conditions causing firestorms by including user-related variables, such as if they are hubs, bridges, or fringes, as well as content-related variables, such as if the eWOM is negative or positive. Pfeffer et al. (2014) described firestorms among others by "network clusters" and "lack of diversity" but they do not derive specific variables that they can test empirically. Drasch et al. (2015) developed an "Online Firestorm Detector" in order to automatically detect online firestorms in real time. However, to determine whether an online firestorm becomes likely, the authors only draw on the volume of total and negative eWOM checking if it exceeds a certain threshold. Besides, they evaluate their artefact by only referring to one firestorm.

Literature regarding lovestorms and hot topics is rather scarce. Ács and Pagh (2017) were the first to study lovestorms. Their aim was to generate lovestorms, in contrast to firestorms, by diffusing positive aspects in order to increase reputation and drive societal change. Nevertheless, they did not empirically examine the characteristics of lovestorms. Their attempt to find differences and similarities between lovestorms and firestorms also needs to be scientifically verified. They stated that lovestorms were not as widespread as firestorms and that both had an external trigger. Further scientific literature regarding the phenomenon of lovestorms does not exist up to now. Hence, our study contributes intriguing new insights to a relatively new stream of literature considering the topic of lovestorms.

Regarding academic literature on hot topics, above all, studies exist aiming at the extraction of hot topics. Bun and Ishizuka (2002) concentrated on identifying hot topics for weekly news reports. Therefore, they referred to two major variables: (1) the number of terms that occur in an article and (2) the number of articles from different news agencies that contain those terms. Chen et al. (2007) extended the study by taking into account temporal and engagement variables such as continuity and popularity. Zhang and Li (2010) applied their idea and enhanced the system from solely hot topic extraction to the functions of question clustering and trend analysis. Yet, there are no studies identifying hot topics on Facebook pages based on different variables in the context of social networks.

3 Data and Methodology

In order to identify and examine variables characterising firestorms, lovestorms, and hot topics as well as describing their commonalities and differences, we analyse the temporal courses of the different buzz types and non-buzzes before we apply logistic regressions on a manually classified data set. Thereby, we first estimate a model to describe buzzes in general. In a second step, we take this model and change the dependent variable according to the different buzz types. Thus, we are able to analyse and describe the statistical characteristics of each type and compare them among each other.

3.1 Data Collection and Classification Process

For our data collection, we used a self-developed crawler that uses the Facebook Graph API in order to collect metadata from public Facebook pages. In total, we gathered data from 77 Facebook pages in the period from the page's existence until the end of August 2016. The collected pages belong to famous persons like politicians, musicians, athletes but also rather unknown people as well as public institutions, companies, political parties, fire and police departments from various countries in Europe, the United States, Canada, Australia and New Zealand. In order to be sure that a buzz occurred on a given page, we selected the pages through daily checks on news aggregation websites, such as news.feed-reader.net that report on buzzes having occurred on a given page, from December 2015 until August 2016. The metadata include easily available information which we can access without any given limitations by Facebook. They represent the number of page likes and the name of the page, information on the posts of each Facebook page, the number of likes, shares and comments of a post and the ID of a user who wrote a comment to a post.

In order to ensure enough time for the activity on a buzz to develop, we cleaned the data by including only posts that were older than two weeks. Finally, our data set consisted of 60,355 posts. First, these posts were manually classified as buzzes and non-buzzes by four coders based on the initially presented definition of buzzes as the coding criteria. All four coders classified more than one fourth of the data in order to check their reliability. At least two coders classified the remaining posts.

In order to verify the intercoder reliability, we rely on the tetrachoric correlation coefficient, which is a measure specifically designed for binary data (Carroll 1961; Divgi 1979). The coefficient's value of 0 means no agreement and a value of 1 means perfect agreement. Generally, researchers regard ratings with values above .7 as strong associations. As we can see in Table 1, the correlations between two coders are always higher than the considered threshold value. In order to prevent any misclassification, the author went through the cases of disagreement and decided whether a post was a buzz or not. After this classification process, our data set consisted of 169 buzzes. In a second step, the author analysed these 169 buzzes in order to classify them as firestorms, lovestorms, and hot topics based on the definitions given in the introduction as the coding criteria. In the end, our data set comprised 25 firestorms, 77 lovestorms, and 67 hot topics.

Coders 1 & 2	Coders 1 & 3	Coders 1 & 4	Coders 2 & 3	Coders 2 & 4	Coders 3 & 4
n = 18,872 r = .8571 *	n = 41,923 r = .9063 *	n = 20,920 r = .7212 *	n = 10,680 r = .9231 *	n = 10,680 r = .9223 *	n = 10,680 r = .9370 *
n = number of posts both coders classified; r = tetrachoric correlation score; * = $p < .01$					

Table 1. Overview of intercoder reliability measures between all pairs of coders

3.2 Operationalisation

The dependent variables “buzz”, “firestorm”, “lovestorm”, and “hot topic” are dichotomous. Thus, “buzz” is either 1 and represents a buzz given the definition in the introduction or “buzz” is 0 and represents no-buzz as the definition does not hold true. The same applies to the different buzz types. Given the available data, we derive the independent variables from theory and assign them to the four categories (1) content-related, (2) user-related, (3) temporal, and (4) engagement variables. Table 2 gives an overview of the descriptions of these variables and their descriptive statistics.

Variable Category	Variable	Variable Description	Mean	SD
content-related variables	*postPositivity*	difference between the percentage of positive and weighted negative words in a post	.014	.089
	commentsPositivity	difference between the percentage of positive and weighted negative words in the comments	.022	.071
	meanCommentLength	$\frac{\text{aggregated number of words of each comment}}{\text{total number of comments on a post}}$	9.741	12.602
user-related variables	*newUsers*	$\frac{\text{users commenting on a page for the first time}}{\text{all users commenting on the post}}$	.356	.284
	repeatUsers	$\frac{\text{users commenting on a post more than one}}{\text{total number of comments on a post}}$	.181	.184
temporal variables	*firstHoursComments*	$\frac{\text{number of comments within the first two hours}}{\text{average number of comments on the page}}$	.340	1.348
	hoursPeakActivity	$\sum_{i=1}^{3} \text{hours of i}^{\text{th}} \text{ highest number of comments}$	320.377	466.584
engagement variables	*comments*	$\frac{\text{number of a post's comments}}{\text{number of pagelikes}}$	.0009	.066
	likes	$\frac{\text{number of a post's likes}}{\text{number of pagelikes}}$	.004	.034
	shares	$\frac{\text{number of a post's shares}}{\text{number of a post's likes}}$	.164	1.192

Table 2. Descriptions of the independent variables and their descriptive statistics

Content-related variables. As suggested by previous literature, we consider content-related variables to examine both the content’s sentiment (e.g., Berger and Milkman 2012; Stieglitz and Dang-Xuan 2013) and the content’s length (e.g., Tsur and Rappoport 2012). To obtain the sentiment of Facebook posts and comments, we employ the SentiStrength tool which is extremely suitable for short informal texts as we can often find them on Facebook (Thelwall et al. 2010). Following Berger and Milkman

(2012, p. 3), we use the positivity criterion defined as the "difference between the percentage of positive and negative words" as it is an excellent score to measure the span of the emotions expressed in a text. Compared to scores that represent the overall emotion within a text, the positivity score avoids a bias towards a high contrast in the emotional information. Given the Pollyanna hypothesis (Boucher and Osgood 1969), there is a bias in human language towards the usage of positive words. For example, Pfitzner et al. (2012) confirm this fact and among others Guzman et al. (2014) incorporate this aspect by weighing the negative words with the factor 1.5. So do we and obtain "postPositivity" representing the weighted positivity value for each post and "commentsPositivity" representing the weighted positivity value for all comments given to one post. Regarding the content's length, we calculated the variable "meanCommentLength". For every post, *meanCommentLength* indicates the aggregated number of words of each comment divided by the total number of comments given on a post.

User-related variables. Following existing studies (e.g., Zubiaga et al. 2015; Deusser et al. 2018), we employ two variables with regard to users' involvement. On the one hand, we distinguish between old and new users. Old users represent users who commented on a given Facebook page before. New users are users who comment on a certain page for the first time. We calculated the variable "newUsers" standing for the percentage of new users commenting on a specific post. On the other hand, we include "repeatUsers" in our model to consider whether one user commented on a post or the related comments more than once divided by the total number of comments a single post received.

Temporal variables. In order to incorporate the temporal course of buzzes as suggested by several researchers (Tsur and Rappoport 2012; Stieglitz and Dang-Xuan 2013; Deusser et al. 2018), we take into account two variables. One represents the activity within the first hours of a post's publication and the other variable refers to a post's peak activity. Following Cvijikj and Michahelles (2011), "firstHoursComments" reflects the number of comments within the first two hours after the related post was published. We divide this number by the average number of comments a post receives on the given page. By including the average number of comments on a page, we respect the fact that buzzes are rare cases because non-buzzes are the vast majority of posts on a given page. With "hoursPeakActivity" we refer to previous findings (Cvijikj and Michahelles 2011) and incorporate the hours of peak activity in terms of the number of comments on a post. We calculate this variable by cumulating the number of hours that has passed after a post's publication for the three hours of maximum activity.

Engagement variables. Other researchers analysing buzzes used variables to cover the engagement such as the number of retweets, likes and comments (Tsur and Rappoport 2012; Feroz Khan and Vong 2014; Deusser et al. 2018). Although they represent rather obvious characteristics describing buzzes, we still examine them as we are highly interested in how they characterise the different buzz types. Looking at the number of page likes in our data set, we see that "smaller" (around 1,000 page likes) and "larger" Facebook pages (more than 12 million page likes) exist. Thus, for a small Facebook page, posts receiving just a few comments or likes can already be extraordinary to that page. Yet, posts on a large Facebook page may always receive this small number of comments or likes which does not make them extraordinary. Therefore, we divide the number of comments and likes by the total number of page likes and obtain the variables "comments" and "likes", respectively. We are also highly interested in how the number of shares behaves regarding the different buzz types. A variable representing the number of shares divided by the number of page likes would correlate with the other two engagement variables. Hence, we decided to consider a variable "shares" reflecting the number of shares divided by the number of likes. Like this, we do not have any correlation problems and do not risk to bias our model due to multicollinearity but still have the chance to draw conclusions regarding a post's shares.

3.3 Model

Classifying posts as buzzes or non-buzzes, as firestorms or non-firestorms, as lovestorms or non-lovestorms, and as hot topics or non-hot-topics, we always have a dichotomous outcome variable. Hence, we estimate several logistic regression models (Peng et al. 2002). The logistic regression estimates the likelihood of occurrence of the outcome variable depending on different explanatory variables. The following equation describes this regression approach:

$$z = \alpha + \beta_1 * postPositivity + \beta_2 * commentsPositivity + \beta_3 * meanCommentLength + \beta_4 * newUsers + \beta_5 * repeatUsers + \beta_6 * firstHoursComments + \beta_7 * hoursPeakActivity + \beta_8 * comments + \beta_9 * likes + \beta_{10} * shares$$

where α is the Y intercept and the βs are the regression coefficients. α and β are estimated by the maximum likelihood method.

However, modelling the likelihood of occurrence is not based on a linear regression approach but on a logistic function which is as follows:

$$\pi(Y) = \frac{e^z}{1 + e^z}$$

where π denotes the probability of the outcome variable Y, which depending on the considered case either represents buzz, firestorm, lovestorm or hot topic and e represents Euler's number.

4 Results

First of all, we present some descriptive evidence of our analyses. Figure 1 depicts the temporal courses of the different buzz types in terms of their comments, which gives a first impression on their commonalities and differences.

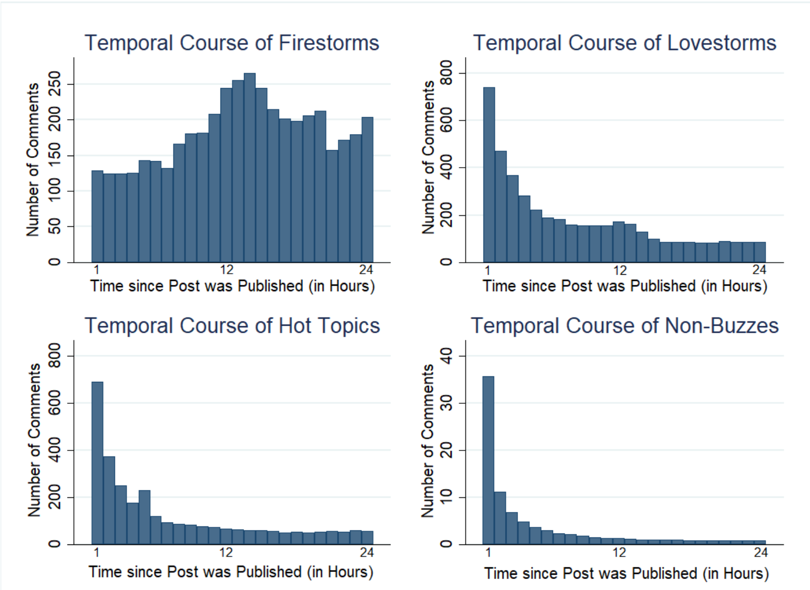

Figure 1. Average temporal course of different buzz types and non-buzzes

	Lovestorms	Hot Topics	Non-Buzzes
Firestorms	chi^2 = 5.321 ** chi^2 = 6.651 ***	chi^2 = 10.404 *** chi^2 = 8.984 ***	chi^2 = 8.556 *** chi^2 = 19.690 ***
Lovestorms	–	chi^2 = .165 chi^2 = .01	chi^2 = 62.096 *** chi^2 = 118.350 ***
Hot Topics	–	–	chi^2 = 95.389 *** chi^2 = 123.643 ***
Slope represented by upper chi^2, *Intercept* represented by lower chi^2; ** $p < .05$, *** $p < .01$			

Table 3. Results of the Kruskal-Wallis test showing the significant commonalities and differences between firestorms, lovestorms, and hot topics in terms of their temporal course

After estimating logarithmic functions to approximate the comments' course of time for firestorms, lovestorms, hot topics, and non-buzzes, we apply the Kruskal-Wallis test (Kruskal and Wallis 1952) (see Table 3). We find that firestorms and non-buzzes both significantly differ from the three respective others regarding the slope and the intercept. Lovestorms and hot topics do not significantly differ from each other which means that they follow a similar temporal course. While lovestorms, hot topics, and non-buzzes decline within hours, firestorms usually reach their peak activity after 12 hours on average. Lovestorms and hot topics generally receive most comments within the first hour after the post has been published. Non-buzzes also receive the majority of their comments within the first hour, but with a much lower intensity. Now, we turn to our econometric modelling. We first check the correlation among the explanatory variables and find that none of the correlations exceeds critical values (see Table 4 for details).

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	*postPositivity*	1								
(2)	*commentsPositivity*	.123***	1							
(3)	*meanCommentLength*	–.038***	–.115***	1						
(4)	*newUsers*	–.015***	.046***	.141***	1					
(5)	*repeatUsers*	.008**	–.075***	.212***	.210***	1				
(6)	*firstHoursComments*	.002	.008*	.027***	.127***	.086***	1			
(7)	*hoursPeakActivity*	–.074***	–.049***	–.204***	–.372***	–.370***	–.142***	1		
(8)	*comments*	–.004	–.005	.006	.017***	.012***	.032***	–.008**	1	
(9)	*likes*	.010**	.001*	.007	.064***	.023***	.136***	–.055***	.198***	1
(10)	*shares*	–.033***	–.034***	.014***	–.046***	–.008**	.006	.022***	.015***	.003
* $p < .1$, ** $p < .05$, *** $p < .01$										

Table 4. Correlation matrix for the independent variables

In the following, we report the results of our logistic regression models. We measure the quality of the estimated models by referring to the Pseudo R^2 and measures for relevance such as accuracy, precision, and recall which are based on the related classification tables. Table 5 summarises all the models that we estimated for the dependent variables “buzz”, “firestorm”, “lovestorm”, and “hot topic”.

	Model for Buzzes	Model for Firestorms	Model for Lovestorms	Model for Hot Topics
postPositivity	.878 (.687)	1.204 (2.071)	–.239 (1.153)	.930 (1.023)
commentsPositivity	–3.431** (1.526)	–6.550*** (1.037)	2.847** (1.279)	–7.389*** (1.004)
meanCommentLength	.0245*** (.003)	.031*** (1.037)	–.028 (.237)	.032*** (.003)
newUsers	6.948*** (.539)	7.947*** (1.861)	7.434*** (.720)	8.122*** (.643)
repeatUsers	.637 (574)	4.711*** (.795)	–1.685** (.797)	2.700*** (.539)
firstHoursComments	.085*** (.033)	–.026 (.0446)	.099*** (.018)	.083*** (.019)
hoursPeakActivity	–.640 (.432)	–.085 (–.10)	–.156 (.470)	–3.953* (2.137)
comments	45.183*** (9.450)	54.389*** (9.981)	–3.760 (3.427)	–5.155 (3.787)
likes	29.725*** (6.367)	–11.238*** (2.884)	5.114*** (1.788)	1.777 (2.308)
shares	.237*** (.068)	.037 (.180)	.157** (.064)	.229*** (.075)
constant	–11.046*** (.468)	–15.247*** (1.454)	–10.754*** (.682)	–12.530*** (.510)
Pseudo R^2	53.20 %	65.93 %	36.41 %	33.73 %
	n = 60,355; * $p < .1$, ** $p < .05$, *** $p < .01$; robust standard errors in parentheses			

Table 5. Summary of the estimated models of buzzes and their different types

First of all, we present the results for the “buzz” model, which yields a Pseudo R^2 of 53.20 %. Regarding the content-related variables, the results indicate that the *postPositivity* is not significant, whereas the *commentsPositivity* is significantly negative ($p < .05$). Thus, the more negative words the comments of a post contain the more likely it is that this post is a buzz. The *meanCommentLength* is significantly positive ($p < .01$), meaning that a post is more likely a buzz if the number of words in the related comments increases. With regard to the user-related variables, the results highlight that *newUsers* is significantly positive ($p < .01$) while *repeatUsers* is insignificant. Thus, the higher the number of new users commenting on a post, the more likely it is that these posts are buzzes. When focusing on the temporal variables, we can see that *firstHoursComments* is significantly positive ($p < .01$), i.e. the more comments a post receives within the first two hours after the posting, the more likely it is that a post is a buzz. However, the *hoursPeakActivity* variable is insignificant. Regarding the engagement variables for the classification of buzzes, the results are all significantly positive ($p < .01$) which is not surprising since adding these variables confirms parts of the definition on which the human classifiers based their classification. All in all, the results show that (1) the higher the number of comments in relation to the number of page likes, (2) the higher the number of likes in relation to the number of page likes, and (3) the higher the number of shares in relation to the number of likes, the more likely it is that a post is a buzz. Yet, these engagement variables are more illuminating when comparing firestorms, lovestorms, and hot topics among each other. In summary, compared to non-buzzes, buzzes have a more negative sentiment, users write longer comments while at the same time more new users participate in the discussion. Furthermore, buzzes yield more comments within the first hour as well as more comments, likes, and shares in total.

Secondly, for the firestorm model, we obtain a Pseudo R^2 of 65.93 %. The model shows that two content-related variables, i.e. *commentsPositivity* and *meanCommentLength*, are both significant ($p < .01$). *CommentsPositivity* has a negative sign, meaning that a post is more likely a firestorm if the number of negative words in comments increases which underlines its definition and is rather unsurprising. *MeanCommentLength* is significantly positive yielding that the more words users use in the comments the more likely it is that this post is a firestorm. The *postPositivity* remains insignificant. Regarding the users involved in these discussions, we can clearly see that the number of new users and the number of users commenting on a post more than once are significantly positive ($p < .01$). The temporal variables are both insignificant for firestorms. Considering the engagement variables, we find that comments are significantly positive ($p < .01$) and it is more likely that a post is a firestorm if the likes significantly decrease ($p < .01$), while the number of shares is insignificant. Thus, compared to the other buzz types and non-buzzes, firestorms are clearly characterised by negative comments. Besides, an intense discussion is going on, attracting a lot of new users and repeat users. A high number of comments and a low number of likes is typical of firestorms.

Thirdly, the model representing lovestorms yields a Pseudo R^2 of 36.41 %. Concerning the content-related variables, *commentsPositivity* is significantly positive ($p < .05$), while the *postPositivity* and the *meanCommentLength* are insignificant. Hence, a post is more likely to be a lovestorm if the number of positive words in the comments increases. The number of new users commenting on a given post is significantly positive ($p < .01$), whereas the number of *repeatUsers* is significantly negative ($p < .05$). Thus, it is more likely that a post is a lovestorm if the number of users is higher and if there are more users commenting on the post just once but not multiple times. Moreover, lovestorms receive a very high number of comments within the first two hours after the posting, as the variable *firstHoursComments* is significantly positive ($p < .01$). The second temporal variable *hoursPeakActivity* is insignificant. Regarding the likes and shares, we see both the *likes* ($p < .01$) and the *shares* ($p < .05$) have a positive influence on lovestorms. On the one hand, the probability of classifying a post as a lovestorm rises with the number of likes compared to the pagelikes. On the other hand, the higher the number of shares is in relation to the likes a post receives, the more likely it is that a post is a lovestorm. The number of comments does not have an influence on lovestorms. Compared to the other buzz types and non-buzzes, lovestorms’ comments are characterised by a positive sentiment. Many new users react on a lovestorm once, but not multiple times, which above all takes place within the first hours after the lovestorm has been published. Furthermore, lovestorms obtain a high number of likes and shares.

Fourthly, we take a look at the model for hot topics, which results in a Pseudo R^2 of 33.73 %. With regard to the content-related variables, we can see that a significantly negative *commentsPositivity* ($p < .01$) indicates a higher probability for a post being a hot topic. The *meanCommentLength* is significantly positive ($p < .01$), yielding that a post is more likely to be a hot topic if the number of negative words in the comments increases. The *postPositivity* is insignificant for hot topics as well. Telling from the user-related variables, hot topics are characterised by a significantly positive number of both new users ($p < .01$) and users commenting on a specific post more than once ($p < .01$). This means that a post is more likely to be a hot topic the higher the number of both new users and repeat users is. Regarding the temporal variables, we find a significant positive effect for *firstHoursComments* ($p < .01$) meaning that hot topics receive most of their comments within the first two hours. The *hoursPeakActivity* is negative but only slightly significantly ($p < .1$), so that we can only derive a weak association. The earlier three maxima of comments per hour are reached, the more likely it is that a post is a hot topic. However, we have to take into account this relation carefully when discussing the results. The shares are also significantly positive ($p < .01$), so that we can draw the conclusion that the higher the number of shares is in relation to the likes a post received, the more likely it is that a post is a hot topic. The other engagement variables are insignificant for hot topics. In comparison to the other buzz types and non-buzzes, hot topics receive comments with a rather negative sentiment and are lively discussed drawing a high number of new users who also comment on the post more than once. Most comments are given within the first hour after the post has been published and the attention on hot topics declines rather quickly. A further characteristic of hot topics is their high number of shares.

4.1 Robustness Checks

To control for the robustness of our model, we apply the following checks. As we are dealing with rare case events yielding from the imbalance between buzzes and non-buzzes, the standard logistic regression as we apply it may have problems with these rare case events. That is why we use the *relogit* function to estimate our model again since it can explicitly deal with such rare cases (King and Zeng 2001). By comparing the initial results to the ones taking into account the fact that our data set contains rare cases, we can tell whether our results are robust. Our estimated *relogit* models reveal exactly the same results for the buzz model as we obtained with the logit model, which leads us to the conclusion that our results are stable. To further underline the robustness of our model, we control for the categories of the respective Facebook pages – i.e. politics, public figures, companies etc. We obtain the same significant results as in the initial model emphasising that the model is stable.

5 Discussion

Our results reveal, that buzzes are best described by user-related and temporal variables. The content-related variables do not seem to be essential and the significance of the engagement variables is present but not as surprising as for the different buzz types. For firestorms, lovestorms, and hot topics the engagement variables show unexpected and differing results. For all of them user-related variables are of vital importance, whereas content-related variables are only important for firestorms and hot topics and temporal variables only play a crucial role for lovestorms and hot topics. In the following, we further discuss the obtained results. Table 6 summarises these findings.

Content-related variables. As *postPositivity* is neither significant for buzzes nor the different buzz types, we can conclude that the sentiment of a post does not have any influence on whether this post becomes viral. Thus, in practice it may be difficult to evoke a buzz on purpose by its content's sentiment. Interestingly, the sentiment of the comments has a significant influence on buzzes and on their types and contributes to a post's virality. As outlined in the introduction, in academic literature, there is no consensus on whether positive or negative sentiments make an online content go viral. Besides, researchers claim that the information diffusion in social networks does not depend on the sentiment of a post but on physiological arousal (Berger 2011) and emotionally charged content (Pfitzner et al. 2012; Stieglitz and Dang-Xuan 2013). Berger and Milkman (2012) find content that evokes awe, anger, or anxiety to be more viral. These contrasting findings might be due to the underlying buzz types.

Firestorms and hot topics entail rather negative whereas lovestorms contain rather positive sentiments. Content that evokes awe could represent a lovestorm, content evoking anger could refer to a firestorm, and content evoking anxiety could signify a hot topic. Regarding the *meanCommentLength*, we find that firestorms and hot topics are both significantly positive. People express their feelings concerning the fact and the discussions that provoked a firestorm (Johnen et al. 2018), which might result in comments with a rather high number of words. The same may hold true for hot topics because people discuss different facts and communicate their views (Holt 2004). Hence, in order to detect the different buzz types in real-time, practitioners could analyse the content of comments by monitoring the sentiment scores as well as the number of words used in the comments as first two good indicators.

Variable Category	Variable	Buzzes	Firestorms	Lovestorms	Hot Topics
Content-Related Variables	*postPositivity*	n. s.	n. s.	n. s.	n. s.
	commentsPositivity	–	–	+	–
	meanCommentLength	+	+	n. s.	+
User-Related Variables	*newUsers*	+	+	+	+
	repeatUsers	n. s.	+	–	+
Temporal Variables	*firstHoursComments*	+	n. s	+	+
	hoursPeakActivity	n. s.	n. s.	n. s.	–
Engagement Variables	*comments*	+	+	n. s.	n. s.
	likes	+	–	+	n. s.
	shares	+	n. s.	+	+

Table 6. Overview of significant characteristics of buzzes and their different types

User-related variables. *NewUsers* reveal significantly positive effects regarding buzzes and the different buzz types which is similar to the results of Zubiaga et al. (2015). They find that across their four classes of different trending topic types the number of users is uniformly distributed and the number of new users is considerably high. Likewise, Bruns and Stieglitz (2012) state that especially new users comment on posts of rather special events. Researchers focusing on firestorms also report that mostly new users contribute to the reactions to a post (Lamba et al. 2015). Others show that a few users help the different buzz types to become viral and further users join in commenting on a given post (Asur et al. 2011; Zubiaga et al. 2015). Engaging such previously passive users might also be encouraged by media agencies reporting on the firestorms or lovestorms (Einwiller et al. 2016; Johnen et al. 2018).

The *repeatUsers* does not have any significant explanatory power regarding buzzes. But, it is significantly positive regarding firestorms and hot topics as well as slightly significantly negative for lovestorms. Bruns and Stieglitz (2014) found that only a small number of users contributes to hashtags, concluding that this might be due to existing community structures. Hence, a group of people might also have developed who have similar opinions in terms of a firestorm and discussing certain hot topics intensively. Besides, Holt (2004) shows that the largest participation in discussions is given when people debate different viewpoints as it is the case for hot topics. Considering a post that deals with a controversial topic, which is mostly true for the considered hot topics, many users will actually engage in discussing competing or alternative ideas resulting in a higher number of repeat users. Regarding firestorms, researchers find that people have to stimulate the need to join the attack if they feel that their sense of morality is violated (Eisenberg 2000; Lindenmeier et al. 2012). Thus, we conclude that the stronger one's perception of a moral violation is, the more likely a person comments on a firestorm repeatedly. In the case of lovestorms, we assume that not much discussion takes place so that people comment on such posts only once in order to express their emotional arousal.

In practice, *newUsers* is a sound variable to detect buzzes in general. However, to distinguish between the buzz types further user-related variables should be considered. Especially for firestorms, practitioners should look at the *repeatUsers* to adapt their social media strategies for the case that these users are either repeatedly denunciating public figures or companies, or actually trying to defend them.

Temporal variables. *FirstHoursComments* describes lovestorms and hot topics pretty well. This means that in the first two hours after a post is published, lovestorms and hot topics significantly gain a very high number of comments compared to the number of average comments given to posts on the considered Facebook page. This result confirms the temporal courses illustrated in Figure 1: lovestorms and hot topics obtain most of their comments within the first hours. Szabo and Huberman (2010) confirm these findings by highlighting that very popular content follows a right-skewed distribution. Compared to further results of their study, both lovestorms and hot topics might reflect content that naturally has a limited time period in which it interests people. Other researchers report similar outcomes showing that people lose their interest in prominent stories after a few hours (Wu and Huberman 2007; Yang and Leskovec 2011; Asur et al. 2011), which might especially hold true for lovestorms. Falkinger (2007) states that this can be due to habituation or competition from new posts.

HoursPeakActivity shows a weak significance for hot topics meaning that people's interest and attention fades more quickly concerning hot topics since the sum of the hours receiving the three highest numbers of comments is significantly low. This might be due to the fact that contents of hot topics reoccur more often, e.g. regarding discussions about refugees. The number of comments quickly rises but lacking further excitation reactions, the post decays shortly after its publication. Yang and Leskovec (2011) illustrate different temporal courses of memes which they investigated in their study. They find that there are memes with different temporal behaviour, e.g. ones where the peak lasts for less than one day and others where the peak lasts longer than one day. We can complement their study by suggesting that lovestorms and hot topics belong to the example described first and firestorms to the latter one as people slowly draw their attention to firestorms and their interest in them lasts longer.

From a practical point of view our results suggest that an early detection is of vital importance for lovestorms and hot topics so that, e.g. social media managers can quickly react to such a post due to its short popularity span. Concerning firestorms, a reaction is not as quickly needed as for the other buzz types since they generally last longer. This is in line with literature giving advice on how to react to firestorms and stating that responsible persons should rather take their time to formulate an expressive and argumentative message than reacting too quickly with a low quality response (Beşer et al. 2016).

Engagement variables. In general, there has been much research to understand why people engage with different forms of content (e.g., Katz 1959; Muntinga et al. 2011; Feroz Khan et al. 2014). Our results can valuably contribute to this stream of research as we find surprising differences when examining the underlying buzz types. Researchers state that emotional aspects of the content may determine whether people react to it or not (Heath et al. 2001). We have seen that the buzz types refer to various emotional aspects and complementing the assumption of Heath et al. (2001), we can conclude that firestorms, lovestorms, and hot topics encourage different forms of engagement. In practice, these engagement variables can be used in detection systems as solid indicators to distinguish between the different buzz types. Considering firestorms, our results show that they are best described by comments, representing the most elaborate way for engagement according to Bonsón et al. (2015). Thus, people take their time, especially to comment on firestorms. Berger and Milkman (2012) report that people discuss their emotional experiences with others as it might be the case when commenting on firestorms characterised by an aggressive tonality (Johnen et al. 2018). Furthermore, Pfeffer et al. (2014) find that the volume of communication is one characteristic of firestorms, which also confirms the significantly high number of comments in our results. Lovestorms are signified by the two most popular and easiest types of engagement – according to the descriptions of likes and shares by Bonsón et al. (2015). Thus, compared to firestorms, lovestorms do not evoke people to reveal their emotional experiences within comments, but through liking and sharing a certain post. Researchers find that above all people like and share socially and emotionally charged content to reduce dissonance or to deepen social connections (Festinger et al. 1956; Peters and Kashima 2007; Brandtzaeg and Haugstveit 2014) as it might be true for lovestorms. Hot topics are best described by a high number of shares. People share a post if it represents similar views to theirs or contains useful, interesting, and surprising content (Berger and Milkman 2012; Stieglitz and Dang-Xuan 2013). As hot topics reflect discussions where different points of view are debated or new facts come to light, people might find them interesting and share them. In contrast to firestorms, hot topics are rather characterised by solid discussions where people explain their opinions based on facts rather than on emotionally driven accusations against others, which might potentially be based on rumours. Hence, people may be more careful in terms of just making comments on a given post, which might explain the insignificance of *comments* for hot topics. These people can prefer to share hot topics to validate and engage with others (Boyd et al. 2010).

6 Conclusion

Public figures, companies, politicians and many others use social media as a new way of communicating with their customers, fans, or citizens. They publish a vast amount of posts. Some of these posts become very popular and go viral whereas others do not. This study focused on these particular posts termed buzzes. So far and to the best of our knowledge, we are the first to analyse different buzz types. In existing literature, researchers have treated buzzes alike, although some indications yielded the existence of different buzz types. Such a differentiation between the three buzz types, namely firestorms, lovestorms, and hot topics is imperative to analyse diffusion processes in more detail and to explain contrasting findings in literature. Besides, various parties are not only interested in buzzes in general but in their more specific types. The objective of this study was to examine the three buzz types by analysing variables which describe their characteristics as well as their commonalities and differences. We applied logistic regressions on a manually classified data set of more than 60,000 posts of almost 80 different public Facebook pages. Our results underline that the content-related variables characterise firestorms and hot topics, while the temporal variables describe lovestorms and hot topics the best. For example, firestorms differ from lovestorms and hot topics regarding their temporal course as their activity continues over a longer period. User-related variables show commonalities among the three types and the engagement variables surprisingly reveal further differences.

This study contributes to existing literature on information diffusion and social media research. We enrich previous literature by distinguishing between different buzz types and describing their characteristics. By showing that firestorms, lovestorms, and hot topics have commonalities and differences, we emphasise that there is a strong need to take into account these different types in future research in order to improve analyses by avoiding false implications. For example, our results may help to explain contrasting findings regarding the question whether positive or negative content makes posts go viral. We find that this might be due to the corresponding underlying buzz types so that depending on the type all findings may hold true. Our study also entails practical contributions as our results may help various parties, such as governments, politicians, or organisations to identify different buzz types to meet their interests. For example, social media managers might want to detect firestorms in order to prevent their organisations from further harm. They might also be interested in incorporating lovestorms in their advertising strategies or marketing campaigns, such as Delta Airlines did in their on-board security video (Youtube 2016). By reacting upon hot topics they might want to take their positions concerning a controversial issue. Moreover, journalists may want to report on different buzz types in their news articles. Others might be interested in joining discussions of hot topics in order to debate their viewpoints and draw attention to their institutions, parties, or campaigns.

The limitations of this study and potential avenues for future research are the following. As this study only concentrates on Facebook, future studies can analyse whether our findings hold true for other social media platforms, such as Twitter or Instagram, as well. Generally, as this study entails an exploratory approach, there is a need for further studies to validate our findings. Moreover, this study may also provide the fundamental results for building a detection system for buzzes and their different types. Therefore, further variables may also be included that help to describe the characteristics of the different buzz types. Future work may include semantic analyses of the posts and their comments to obtain better classification results. This also entails further practical improvement as only relevant posts might be reported to responsible persons – e.g., with regard to particular discussions of hot topics, certain keywords within a lovestorm, or competitors' names being included in firestorms. Besides, it might be interesting to focus on the users who drive the virality of certain posts and to examine if and how the users differ regarding firestorms, lovestorms, and hot topics.

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