Emotions behind Drive-by Download Propagation on Twitter

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Twitter has emerged as one of the most popular platforms to get updates on entertainment and current events. However, due to its 280 character restriction and automatic shortening of URLs, it is continuously targeted by cybercriminals to carry out drive-by download attacks, where a user's system is infected by merely visiting a Web page. Popular events that attract a large number of users are used by cybercriminals to infect and propagate malware by using popular hashtags and creating misleading tweets to lure users to malicious Web pages. A drive-by download attack is carried out by obfuscating a malicious URL in an enticing tweet and used as clickbait to lure users to a malicious Web page. In this paper we answer the following two questions: Why are certain malicious tweets retweeted more than others? Do emotions reflecting in a tweet drive virality? We gathered tweets from seven different sporting events over three years and identified those tweets that were used to carry to out a drive-by download attack. From the malicious (*N=105,642*) and benign (*N=169,178*) data sample identified, we built models to predict information flow size and survival. We define size as the number of retweets of an original tweet, and survival as the duration of the original tweet's presence in the study window. We selected the zero-truncated negative binomial (ZTNB) regression method for our analysis based on the distribution exhibited by our dependent size measure and the comparison of results with other predictive models. We used the Cox regression technique to model the survival of information flows as it estimates proportional hazard rates for independent measures. Our results show that both social and content factors are statistically significant for the size and survival of information flows for both malicious and benign tweets. In the benign data sample, positive emotions and positive sentiment reflected in the tweet significantly predict size and survival. In contrast, for the malicious data sample, negative emotions, especially fear, are associated with both size and survival of information flows.

CCS Concepts: • **Security and privacy → Social network security and privacy**.

Additional Key Words and Phrases: Cyber security, Drive-by download, Malware,Machine learning, Cybercrime

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Over the last decade, online social networks (OSNs) have become one of the most popular platforms on the Internet, attracting billions of users every day. Among the present OSNs, Twitter has emerged as one of the most powerful and widely used platforms, having an active user subscription of around 335 million [30]. Twitter's popularity continues to attract cybercriminals to carry out various cyber attacks. Cyber attacks such as distributed denial of service [32], cross-site scripting [22], Trojan attacks [42] and drive-by downloads [28] continue to be major threats on Twitter.

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Once a user's system is infected, sensitive information is exposed to unauthorised users and their machines can be used to carry out further attacks. Twitter is particularly susceptible due to the 280 character restriction imposed on a tweet. Due to this restriction, a unique resource locator (URL) is automatically shortened, giving cybercriminals the opportunity to obfuscate a URL pointing to a malicious Web server. An attack of this nature is called a drive-by download and accounts for 48% of attacks by exploiting Web-based vulnerabilities [51]. These attacks are not limited to online social platforms but can also we carried out via Social engineering based phishing where the victim may receive an unsolicited email with URLs redirecting to malicious Web sites and upon visitation of these websites a vulnerable system may get infected [36].

In existing research, propagation models for malware are based either on scanning techniques or the topology of a network, where the focus of the research has been on the communication medium [10, 16], social network topology [16] and the relationship [61] exhibited among users. The underlying assumption while building propagation models has been that the malware is self-propagating. However, the research so far has focused on self-propagating malware, such as a worm, or to understand the propagation of spam. In contrast, our research focuses on malware that is not self-propagating; that is, the user has to visit the website containing malicious code in order to get infected. Furthermore, a research gap exists in understanding the propagation of malware based on the Twitter network based on Tweet content. Therefore, this study is novel in that we identify social as well as content factors that contribute to the propagation of tweets containing both malicious and benign URLs during sporting events.

By observing the social and content features of a Tweet, we aim to understand the underlying factors for drive-by download propagation on Twitter. Social factors such as a number of friends or followers, give a social profile of the accounts that propagate malware. Furthermore, from the content of the tweets, we derive features such as emotions and sentiments that affect the propagation of malware. It has been well established that people transfer positive and negative moods to one another [24], in a form of emotional contagion. Through experiments, researchers have shown that emotions representing long-lasting moods like happiness and depression can be transferred through online social networks [17, 24]. Also, one's emotional state can be used to predict emotional states of connected friends. Kramer et al. showed how posting behaviour of a user varied based on the emotional content received [31]. While it is clear emotions do impact posting behaviour, this study extends this work by identifying what emotions affect the the sharing of Twitter content that is designed to propagate malware.

In this paper we uncover factors that cybercriminals use to entice users to retweet content containing a malicious URL. From a corpus of circa 3.5 million tweets collected around seven different sporting events in 3 years, we created a sub-sample and passed it to a high interaction honeypot to identify those tweets that contained malicious URLs. We identified 105,642 tweets containing malicious URLs and 169,178 tweets containing benign URLs. These data were entered into statistical models to estimate the size and survival of 'malicious' information flows. To build our statistical models we derived two dependent variables, size and survival. Size is defined by the number of retweets a tweet receives in the study window, and survival represents the time between the first and last retweet in the same window. Independent variables derived from tweets included social (user characteristics) and content (sentiment and emotion) factors. To the best of our knowledge, this is the first study to identify social and content factors to assess their influence on the propagation of tweets containing malicious or benign URLs in social networks. This paper contributes to the broader literature on malware propagation by:

- Determining if tweets that contain negative emotions are statistically associated with the size and survival of information flows. Furthermore, determining what discrete negative emotions emerge as the most significant;
- Determining if tweets that contain positive emotions are statistically associated with size and survival of information flows.
- Determining if social factors, such as the number of followers a user has are statistically positively associated with the size and survival of information flows;

1 RELATED WORK

Malware Propagation on Traditional Networks:- Researchers have studied malware propagation using a range of different methods. Yu et al. proposed a two-layer malware propagation model for large networks based on epidemiological principles [71]. Similarly, Zou et al. proposed a model based on epidemiology to detect propagation of worms on the Internet [72]. However, their focus was to detect malware at its early propagation stages. Ganesh et al. combined epidemiology and graph theory to understand the malware propagation on networks [19]. They observed that if the spectral radius of the graph of the network studied is higher than the ratio of cure to infection, then average epidemic lifetime is of order *log n*, where n is the number of nodes. However, if the same ratio is greater than the isoperimetric constant of the graph then the average epidermic lifetime is represented by e^{n^a}, where a is a positive constant. Liu et al. combined an epidemic model with transmission theory in order to observe malware propagation in wireless networks [35]. A considerable amount of research has been done to understand malware propagation using epidemiological models in traditional networks [48][43], including wireless and Bluetooth. However, with the growing popularity of OSNs with cybercriminals, attention must turn to propagation that is dependent upon social and content factors.

Malware Propagation on Online Social Networks:- With the emergence of OSNs, new techniques have been developed to exploit the social relationship between users to propagate malware. Earlier research on malware propagation related to social networks focused on the communication medium such as the mobile device [16], Bluetooth [10] or email [68]. Wherein, for example, to observe malware propagation in a mobile network, a social network topology was created using the contacts saved on the user's device to evaluate the speed and severity of random contact worms [16]. Such social networks may have some similarities with online social network graphs, but they differ regarding the amount of data generated and the amount of time a user spends on the network. This abundant data on a user's behaviour opens doors to understand malware propagation using various techniques incorporating social behaviour defined by user relationships. Having compared virus propagation through emails with the propagation of viruses using messages exchanged on Facebook, Fan et al went on to propose malware propagation models based on the application network of Facebook [15]. They investigated two malware propagation strategies, one where the cybercriminal would develop applications designed to carry out attacks or contain vulnerabilities for subsequent exploitation; and the other where a malware is distributed by means of direct messages to users. Their experimental results regarding malicious application showed that even if the malicious application is less popular on the OSN platform, it still has the potential to spread rapidly. Experimenting with user relationships, Sun et al. proposed a human behaviour model based on game theory to describe the propagation of network worms on social networks [61]. Sanzgriri et al. successfully applied epidemiology theory to understand malware propagation on Twitter and showed that even a low degree of connectivity and probability of user clicking links could cause a large degree of malware dissemination [52]. One of the drawbacks of epidemic models is that they lack scalability. To overcome the drawback of epidemic models Wang et al. presented a discrete-time absorbing Markov process to characterise virus propagation [67]. The proposed model was capable of evaluating virus lifetimes in large networks. Their results revealed that the minimum curing probability for a given extinction rate requirement is independent of the explicit size of the network. Thus, one can interpret the extinction rate requirement of a big network with that of a much smaller one, evaluate its minimum curing requirement, and achieve simplifications with negligible loss of accuracy. Yan et al [69] analysed user activity patterns and OSN structure to narrow down the characteristics of malware propagation in OSNs. For their experiments they used real-world locations based on OSN data and conducted analysis from the perspectives of user friendship and activity. Furthermore, they conducted trace driven simulation to observe the initial infection impact, user click probability, social structures and user activity patterns on malware propagation. However, their research assumed that users were active only if they were engaging in certain activities, such as location based check ins, photo updating or posting. Furthermore, they assumed that each user has the same probability of clicking on a malicious URL, which may not be the case in real life, some necessarily being more educated than others. Focusing on user behaviour on OSN, Wang et al proposed a malware propagation model based on user behaviour, mainly looking at user mobility and temporal message processing [66]. One of the key features that they introduced was user mobility as one of the main factors to estimate malware propagation. They incorporated the idea that a user can be mobile and hence the infection rate can change endlessly. In many OSNs, a message recall function was introduced to tackle the malware propagation problem. This feature allowed a user to delete any post that contains a malicious link so that it is no longer accessible to other connected users. However, users were still in the network that had been infected before the message was recalled and they might continue to spread the malware to their connected users. Considering this message recall mechanism Chen et al. proposed a model based on epidemic theory to measure the propagation of infections in a message-recallable OSN [9].

Emotion and Sentiment Analysis on Twitter:- Sentiment analysis is concerned with detecting positive, negative or neutral content in written text. Whereas, emotion analysis is concerned with detecting discrete emotions (e.g. anger, fear, joy, and so on). In Current research sentiments have been used to detect spam. Wang et al. proposed a spam detection model that uses sentiment as one of the features in detection on Twitter [65]. They showed that by using only four features, one could achieve satisfactory results compared to previous tools. Similarly, Hu et al. used a network topology to detect spam showing that the performance of the model increased by the addition of sentiment data [26]. Focusing on the content only, Berger et al. studied emotions expressed in a tweet to identify a relationship between retweeting and emotions [4]. They found that content that evokes high arousal like positive emotion (awe) or in negative emotion (anger or anxiety) has a higher probability of propagation than 'deactivating emotions' such as sadness. In a similar approach, Vosoughi et al. used emotions to explain the propagation of news on social media [64]. They found that news that was false and reflected fear, disgust, and surprise was more likely to be retweeted than actual stories that reflected anticipation, sadness, joy and trust.

Technology and malware are constantly evolving. Models investigating malware propagation have to incorporate new features to tackle the new techniques used by cybercriminals for malware propagation. Content based features such as sentiment have been more often used in models to detect spam [26, 65] than to understand their propagation. Features such as emotions are used to understand the virality of posts on OSNs [4, 64]. Particularly, content containing negative emotions have a higher chance to be shared on OSN than positive emotions [4]. This tactic of using negative emotions to convey a message to a larger audience have been seen in advertisements as well. For example, a series of short films called "The Hire" that evoked negative emotions by including a story line that involved a car chase were created by BMW in order to gain millions of views [5]. This provoked the question of whether cyber criminals were employing similar tactics by creating contagious posts containing negative emotions on OSN to propagate malware. We cannot of course presume to know the the mindset or deliberate actions employed by attackers but we can provide evidence to measure the success of emotions in increasing size and survival of malicious URLs on OSNs.

Even though content-based features are being considered in research, they are limited to understanding the flow of information related to news or to detecting spam. The analysis conducted to understand content sharing on OSN use basic emotions as defined by Ekman [14] that identifies more negative emotion than positive in its six basic emotions (Anger, Fear, Disgust, Sadness, Surprise and Joy). This presents an imbalanced set of positive and negative emotions for analysis. A research gap exist that links emotions and sentiment to malware propagation on OSNs, where the set of emotions used for analysis are balanced in term of positive and negative emotions such as defined by Plutchik [44] (Anger, Fear, Disgust, Sadness, Anticipation, Surprise, Trust and Joy).
To the best of our knowledge this is the first study that correlates emotions expressed in a tweet containing malicious URL with its propagation.

2 DATA COLLECTION AND PREDICTIVE MEASURES

2.1 Data Collection

In 3 years, we collected tweets containing URLs around popular sporting events. The rationale for choosing sporting events was that they are known to attract a large number of social media users, thus increasing the probability of a malicious link being clicked. These events also give cybercriminals an excellent opportunity to lure a large number of people to their malicious Web sites, by enticing users to retweet the link using compelling content, thus propagating the malicious URL. To give an idea of how many users interact online around a sporting event, in 2015 the Copa America recorded 14 billion impressions alone [33] and the 2016 Rio Olympics was the top topic that year - surpassing even the US presidential election [30]. Data for our study were collected from Twitter via the streaming API using the python library Tweepy [49]. We chose Twitter as the online social network for the study because it supports the free collection of 1% of all daily tweets, which was assumed to be of sufficient bandwidth to collect all tweets explicitly mentioning hashtags or keywords describing the sporting events under study. In 3 years, we collected data from seven different sporting events:

(1) Federation Internationale de Football Association (FIFA) World Cup of 2014 : was the 20^{th} FIFA World Cup for men's national football team. It took place in Brazil from 12 June to 13 July 2014 and 32 teams from different countries participated in the event. During this period 642 million tweets were posted on Twitter related to the event and Brazil vs Germany semi-final was the most tweeted about event generating 35.6 million Tweets [55].
(2) The American Football Superbowl 2015: was an American football game played between the American Football Conference (AFC) champion *New England Patriots* and the National Football Conference (NFC) champion *Seattle Seahawks*, to determine the champion of the National Football League (NFL) for the 2014 season. A total of 28.4 million tweets were recorded during the event and it was the most talked about event on Facebook, with 1.36 million people commenting every minute during the event [20].
(3) The Cricket World Cup 2015 : was the 11^{th} men's Cricket World Cup, jointly hosted by Australia and New Zealand from 14 February to 29 March 2015. A total of 14 teams from different countries participated in the event and 3.5 million tweets were recorded during the period event occured [29]. During which the India vs Pakistan match was the most talked about match that generated 1.7 million tweets [58].
(4) Rugby World Cup 2015 was the eighth Rugby World Cup, hosted by England from 18 September to 31 October. A total of 20 teams from different nations participated in the event. The

final between New Zealand vs Australia recorded 560,000 tweets with a highest frequency of 2,900 tweets per second [57].

(5) The American Football Superbowl 2016 : was an American football game played between the AFC champion *Denver Broncos* and the NFC champion *Carolina Panthers*, to determine the champion of the NFL for the 2015 season. A total of 27 million tweets were reported during the event by Twitter and an engagement of 60 million users related to the event was reported by Facebook [21].

(6) The European Football Championships 2016 : was the 15^{th} International men's football championship of Europe organised by The Union of European Football Associations (UEFA). It was held in France from 10 June to 10 July 2016 and a total of 24 teams participated in it. Where England vs Iceland was reported to be the most tweeted about programme, generating 2.1 million tweets during the match [50].

(7) The Olympics 2016 : was an international multi-sport event that was held from 5 to 21 August 2016 in Rio de Janeiro, Brazil. A total of 207 nations participated in the event and it was the most talked about event of 2016, even surpassing the U.S Presidential election [30].

Tweets were captured for each event using the following event related hashtags: *#FIFA2014, #superbowlXLIX, #CWC15, #Euro2016, #Rio2016, #RWC2015, #NFL, #SB50, #SuperBowlSunday.* Table 1 gives the distribution of tweets captured for each sporting event. The minimum sample of 6,111 tweets containing URLs was collected for the Olympics 2016 opening ceremony and the maximum sample of 3.1 million tweets was captured for the European Football Championships 2016. The low number of tweets captured during a few of the sporting events is likely due to the low uptake of the hashtag amongst users chosen for collection. The rationale behind selecting seven events was to the determine whether our statistical findings would generalise beyond a single event.

Table 1. Number of Tweet's captured for each sporting event over a period of three year

Sporting Event	**Year**	**Location**	**Hashtag Used**	**Number of Tweets Captured**
Federation Internationale de Football Association (FIFA) World Cup	2014	Brazil	#FIFA2014	95,000
Circket World Cup	2015	Australia & New Zealand	#CWC15	7,961
Rugby World Cup	2015	United Kingdom	#RWC2015	127,393
SuperBowl	2015	USA	#SB50 #SuperBowlSunday #superbowlXLIXend	122,542
European Football Championship	2016	France	#Euro2016	3,154,605
Olympics	2016	Rio de Janeiro (Brazil)	#Rio2016	6,111
SuperBowl	2016	USA	#SuperBowlSunday #NFL	57,572

During each event, from the collected tweets, a sub-sample was randomly created, and extracted URLs were passed into the Capture HPC [7], a high interaction honeypot set up to identify malicious URLs. This process of visiting website continued for atleast ten days from the date of event, to identify malicious web-pages before they disappear. A malicious URL is defined as those that point to a malicious server or Web site from which a drive-by download is carried out. We chose Capture HPC for our experiment because of the flexibility and support provided in configuring the honeypot.

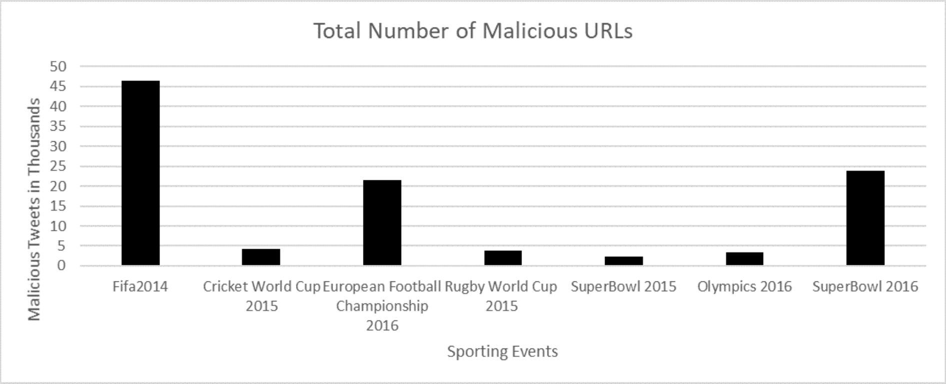
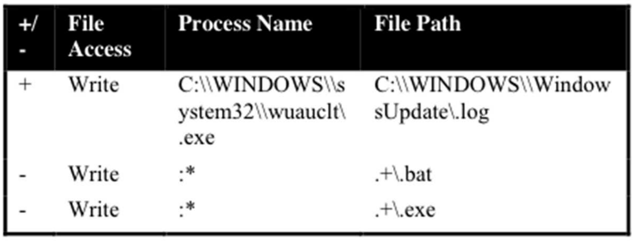


Fig. 1. Number of Malicious Tweet's captured for each sporting event

Furthermore, it is open source making it readily available to the research community. The role of the Capture HPC was to perform dynamic analysis of interaction behaviour between a client machine and that of a Web server based on the URL that is passed to it. Capture HPC operates by visiting each URL that is passed to it through a virtualised sandbox environment - interacting with the Web page for a pre-defined amount of time. At the end of the interaction period Capture HPC determines if any system-level operations have occurred including file, process and registry changes made to the system. Based on these changes it classifies the URL as malicious or benign [46]. The classification is based on three *exclusion lists* that are created based on known file, process or registry entries that are targeted by drive-by download attacks. Figure 2 gives a typical example of rules from a file exclusion list, where each positive symbol indicates that system activity is allowed and a negative symbol means that it is not allowed and is flagged as malicious. For example any *exe* file that is written or created during the visitation of a Web page is not allowed.



+/-	File Access	Process Name	File Path
+	Write	C:\\WINDOWS\\system32\\wuauclt\.exe	C:\\WINDOWS\\WindowsUpdate\.log
-	Write	:*	.+\.bat
-	Write	:*	.+\.exe

Fig. 2. File Exclusion List

One of the biggest challenge faced while analysing URLs pointing to malicious websites was to quickly identify them before they disappear. As, evidence was found in earlier study that these websites were alive for only three days before they disappear/start behaving normally [38] and it took Twitter around three days to suspend 92% of account that were behaving maliciously [62]. Considering the number of tweets posted per minute (on average 350,000 tweets [53]) an epidemic model was built by Giri et al [52] that showed how even a small number of infected users can infect a large number of users on Twitter in a short period of time. Giving us a very short window to analyse and annotate URLs into malicious/benign category. Keeping the short time frame in mind, for our study a data sample of around 300,000 tweets containing both malicious and benign URLs from seven sporting events over three years, including those that were retweeted was randomly selected. By removing the retweets, this dataset was further reduced to 31,171 tweets. This was done to avoid processing duplicate URLs in the honeypot (Capture HPC).

Based on the changes observed in machine activities for a duration of five minutes and by the violation of rules defined in the exclusion list, a total of 6,122 tweets containing malicious URLs and 25,049 tweets containing benign URLs were identified. One of the benefits of using Capture HPC was that it stores the malware sample (executable files, batch file etc) downloaded during visitation and generates a machine activity log during visitation of malicious web-servers. Thus, giving us 6,122 malicious sample across seven sporting events and a malicious log containing millions of rows of machine activity. The collected malware sample when compared to previous studies, like by Moser et al [40] (308 malware sample), Ahmadi et al [1] (806 malware sample) and Naval et al [41] (2,435 malware sample), was a bigger and diverse sample that was collected over a period of three years and was used to built a drive-by download prediction model [28].

Based on previous studies that looked a factors influencing dissemination of information [3, 6], a threshold representing a minimum number of retweets was selected, which further reduced the sample size from 6,122 to 1,137 tweets containing malicious and from 25,049 to 1,187 tweets containing benign URLs. This number only represented nodes/users that initiated the malicious/benign tweet, whereas the total sample size including retweets was equal 274,820 tweets (a total of *N=105,642* tweets containing malicious and *N=169,178* tweets containing benign URLs). When we compared our dataset (274,820 tweets) with those used in previous studies we found a sample of 4,426 malicious URLs that were harvested from a sample of 100,000 messages captured from a Chinese online social network (Weibo) to understand their propagation behaviour was used by Cao et al [8]. Furthermore, we found that in earlier studies either a dataset was generated by means of simulation, for example 10,000 nodes representing Facebook users was considered to understand worm propagation by Wang et al [66] or by gathering real data such that of a network of 65,770 of BrightKite users were used to understand malware propagation [69]. Table 2 and 3 describes the statistics of our sample data for malicious and benign tweets respectively.

2.2 Dependent Measure

We have taken two dependent variables for our experiment to study the effect of malware propagation, *size and survival*. We define size as the number of times a tweet is retweeted (first dependent variable). This is a measure of virality and therefore we assume the more a tweet is retweeted, the greater the risk to other network users if the tweets is malicious. Survival is defined as the duration over which a tweet continues to receive retweets (second dependent variable). Again, if the tweet is malicious, the longer it continues to be retweeted for, the longer the risk to network users remains.

In order to identify the number of retweets a tweet received, we first filtered all the retweets by looking at tweets that had *RT* as the prefix. One of Twitter's features is to prefix each retweet with RT. We then identified all the unique tweets in the dataset and counted the number of times each unique tweet was retweeted. This count for each retweet gives us the size of each tweet's information flow. The sample showed a positive skew (see fig 3) where unique tweets that were retweeted less than five times were found on the far end towards the left-hand side of the distribution. As the main aim of the study was to understand propagation factors, tweets with less than five retweets were removed from the sample, based on research that indicates this is a reasonable cut off for non-trivial information flows [3][6]. The resulting dataset contained *N=1,137* unique malicious tweets and *N=1,862* unique benign tweets that were retweeted at least five times.

For our study, five features representing social factors were derived from the dataset, these were number of hashtags, user mentions in a tweet, number of friends and followers an account had and the age of the account. Number of hashtags were particularly chosen because a recent report

Table 2. Description of Malicious Sample Data *N=1, 137*

Variable	**Range**	**Mean**	**Std. Dev**
Dependent			
Size	5-22,614	86.53	817.19
Survival	0-2850416	218,556.40	483,290.60
Independent			
Social Factors			
Hashtag	0-13	1.90	1.66
Mentions	0-6	1.22	0.93
Friends	0-784,471	3652.78	28614.25
Followers	0-928,4012	168519.50	618537.10
Age of Account	562-1,321	918.25	287.17
Emotion			
Anger	0-3	0.21	0.48
Anticipation	0-7	1.01	1.18
Disgust	0-5	0.27	0.60
Fear	0-5	0.39	0.67
Joy	0-7	0.71	0.95
Sadness	0-3	0.28	0.57
Surprise	0-10	0.44	0.76
Trust	0-5	0.50	0.75
Sentiment			
Negative	0-3	0.19	0.46
Positive	0-4	0.37	0.67

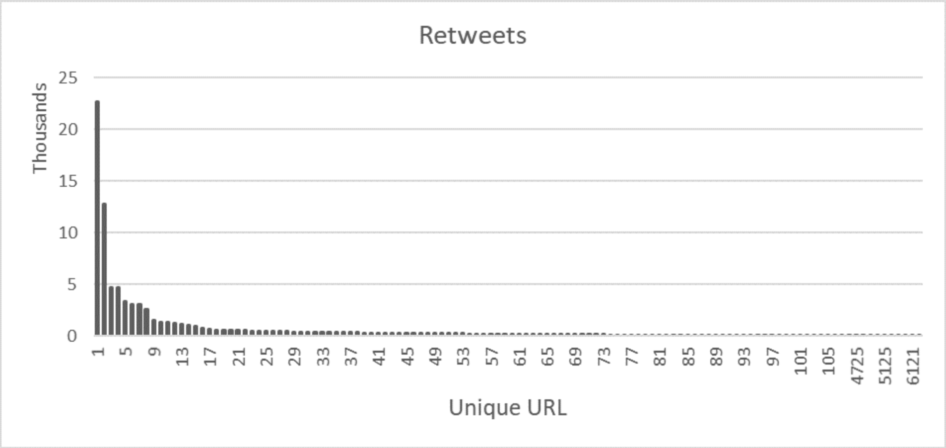


Fig. 3. Number of Tweet's captured with malicious URLs for each sporting event

on the engagement of users on online social platforms revealed correlation between number of hashtags and user engagement [47]. Number of followers and friends have been added as they have earlier been used to understand malware propagation on Twitter [52]. Number of user mentions were used because an adversary could make their post visible to an influential user that has high

Table 3. Description of Benign Sample Data *N=1,862*

Variable	Range	Mean	Std. Dev
Dependent			
Size	5-48,875	90.86	1,160.23
Survival	0-2,896,989	291,628.00	616,751.50
Independent			
Social Factors			
Hashtag	0-12	2.02	1.81
Mentions	0-7	1.00	0.97
Friends	0-481194	2,973.49	16,787.49
Followers	0-12,700,000	143,917.60	761,002.80
Account Age	933-1635	1,200.09	306.50
Emotion			
Anger	0-3	0.07	0.28
Anticipation	0-6	0.21	0.51
Disgust	0-2	0.05	0.23
Fear	0-3	0.09	0.32
Joy	0-5	0.17	0.46
Sadness	0-2	0.08	0.29
Surprise	0-3	0.09	0.32
Trust	0-5	0.22	0.51
Sentiment			
Negative	0-3	0.14	0.39
Positive	0-5	0.34	0.64

number of follower by mentioning them in their post. Similarly, age of account was chosen because it has been used as a parameter to identify tweets containing malicious URLs [28]. Both emotion and sentiment were chosen because they have in the past been used to understand propagation of post [5]. Table 2 and 3 give details of both dependent variables, where the range of size for a malicious tweet was 5 - 22,614 retweets and a mean of 87.53 retweets and the size for a benign tweet was 5 - 48,875 and a mean of 90.86 retweets. For survival, we found a malicious tweet had a range of 0 - 2,850,416 seconds with a mean of 218,556.40 seconds, and a benign tweet had a range of 0-2,896,989 seconds and a mean of 291,628 seconds. The minimum of zero represents rounding down to the nearest second where retweets happened within in milliseconds.

2.3 Independent Features

2.3.1 Social Features.

Based on previous research where social features were used to detect malware on OSNs, we extracted the number of friends, number of followers and age of the Twitter account that posted the initial tweet from metadata. We also calculated the number of hashtags that were included in the tweet and if the tweet contained a mention.

2.3.2 Content Feature.

In addition to the social factors, we derived eight emotions and two sentiment features. The eight emotion features that we derived from the tweet were based on Plutchik's [44] conception of emotion. While others, like Ekman [14] identify six basic emotions (Anger, Fear, Disgust, Sadness,

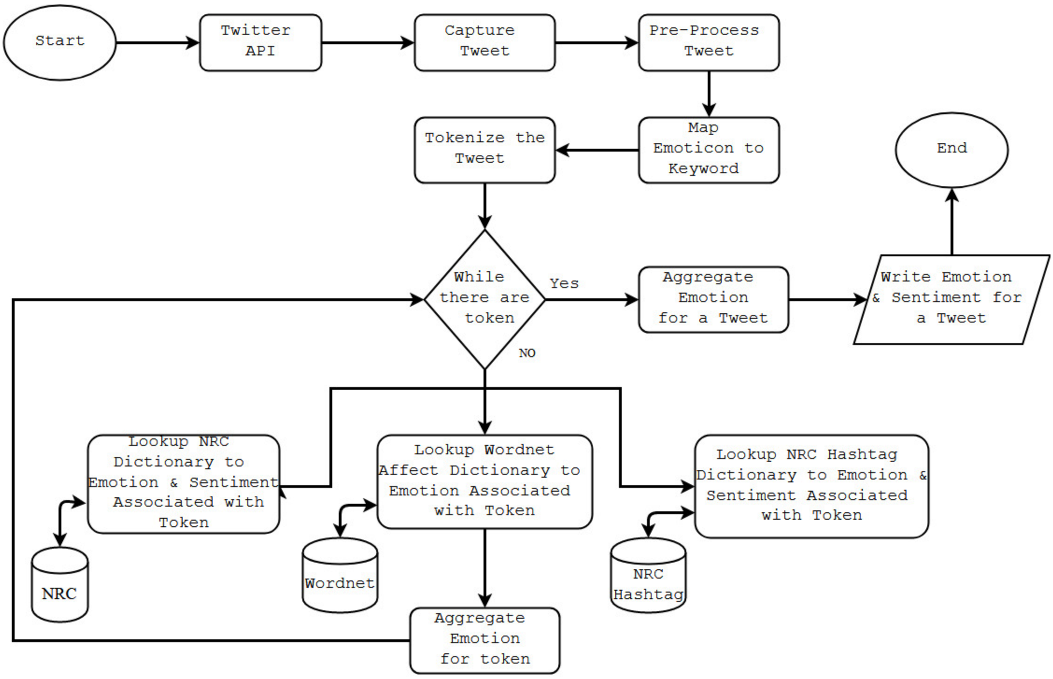

Start
Twitter API
Capture Tweet
Pre-Process Tweet
Map Emoticon to Keyword
Tokenize the Tweet
While there are token
Yes
NO
Aggregate Emotion for a Tweet
Write Emotion & Sentiment for a Tweet
End
Lookup NRC Dictionary to Emotion & Sentiment Associated with Token
Lookup Wordnet Affect Dictionary to Emotion Associated with Token
Lookup NRC Hashtag Dictionary to Emotion & Sentiment Associated with Token
NRC
Wordnet
NRC Hashtag
Aggregate Emotion for token

Fig. 4. Flow Chart of the Emotion and Sentiment Extraction

Surprise and Joy), Plutchik [44] identifies eight (Anger, Fear, Disgust, Sadness, Anticipation, Surprise, Trust and Joy). We do not claim that Plutchik's eight emotions are more fundamental than other categorisations; however, we adopted them because they are well-founded in psychological empirical research, and unlike some other choices, for example, that of Ekman, they are not composed of mostly negative emotions. In addition to the eight emotions, positive and negative sentiment were also included.

A Java-based script was developed to extract the emotion and sentiment of each tweet. The program identifies emotion and sentiment based on keywords using dictionaries containing words associated with each of the eight emotions. These dictionaries were built using the WordNet Affect Lexicon [59] and NRC-Emolex and Hashtag Emotion Corpus [39, 56], that have all been rigorously developed in previous research. In addition to these dictionaries, we used emoticons contained in a tweet to identify appropriate additional emotions.

Figure 4 provides an overview of the core program in the form of a flowchart. The program first reads a tweet from the dataset then pre-processes it by removing stop words and punctuation. It then checks if any emoticons are present and if found it identifies the associated emotion. In the next step the tweet is split into multiple tokens, and for each token (word) the associated emotion is identified using the three dictionaries. As the WordNet affect lexicon represents emotion in a hierarchical structure, a backward mapping of granular emotions was performed onto Plutchik's typology. Finally, we identified the sentiment associated with the tweets.

3 MODEL SELECTION

3.1 Model selection for Dependent variable

The dependent variable size, which represented the number of retweets, is a positive non-zero number (due to the cutoff of 5 imposed). Thus we considered number of statistical count data models. Count data models account for the rate of an event, which in our case was the number of times the tweet was retweeted during the observation period. Typically, the Poisson model is used for count data modelling, where, the model predicts the incidence rate ratio of an event. One of the critical assumptions of the Poisson model is that variance and mean of the dependent variable are equivalent, i.e. there is no over-dispersion.

However, on inspection of our data, we observed the dependent variable size mean and variance were 86.53 and 667,804 respectively for the malicious sample, and 90.86 and 1,160.23 respectively for the benign sample, both indicating over-dispersion. Therefore a negative binomial model was selected. Given the lack of zeros in the dependent variable we used the zero-truncated variant of the negative binomial model (ZTNB).

$$Pr(y_i|y_i > 0) = \frac{(\Gamma(y_i + \alpha^{-1})/y_i!\Gamma(\alpha^{-1}))(\alpha^{-1}/(\alpha^{-1} + \mu_i))^{\alpha^{-1}}(\mu_i/(\alpha^{-1} + \mu_i))^{y_i}}{1 - (1 + \alpha\mu_i)^{\alpha^{-1}}} \tag{1}$$

$$E(y_i|y_i > 0) = \frac{\mu_i}{Pr(y_i > 0)} = \frac{\mu_i}{1 - (1 + \alpha\mu_i)^{\alpha^{-1}}} \tag{2}$$

$$Var(y_i|y_i > 0) = \frac{E(y_i|y_i > 0)}{Pr(y_i > 0)^{\alpha}}[1 - Pr(y_i = 0)^{\alpha+1}E(y_i|y_i > 0)] \tag{3}$$

$$L = \prod_{i=1}^{N} Pr(y_i|y_i > 0) \tag{4}$$

$$= \prod_{i=1}^{N} \frac{(\Gamma(y_i + \alpha^{-1})/y_i!\Gamma(\alpha^{-1}))(\alpha^{-1}/(\alpha^{-1} + \mu_i))^{\alpha^{-1}}(\mu_i/(\alpha^{-1} + \mu_i))^{y_i}}{1 - (1 + \alpha\mu_i)^{\alpha^{-1}}} \tag{5}$$

$$log(\mu_i) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} \tag{6}$$

The zero-truncated models calculate the probability of response variable (size- number of retweets a tweet got) based on positive count data using Bayes's Theorem [23, 25, 37]. Above shows the probability mass function (see equation 1), mean (see equation 2), variance (see equation 3), likelihood function (see equation 4) and response surface (see equation 6) of a zero- truncated negative binomial model. Where $Pr(y_i|y_i > 0)$ is the probability mass function of the zero truncated negative binomial distribution, $E(y_i|y_i > 0)$ is the expectation of zero-truncated negative binomial distribution, $Var(y_i|y_i > 0)$ is the variance of zero-truncated negative binomial distribution, αÌÍ is the over-dispersion parameter, **L** is the likelihood function, μ_i is the estimated retweet count for the i^{th} observation, y_i is the observed retweet count for the i^{th} observation, k is the parameter coefficient of the k^{th} predictor variable ($k = 0$ for intercept), X_{ki} is the value of the k^{th} predictor variable (Hashtag, Mentions, Friends, Followers, Account Age, Anger, Anticipation, Disgust, Fear, Joy, Sadness, Surprise, Trust, Negative, and Positive) for the i^{th} observation.

3.2 Survival model - Cox Proportional hazard regression

Having identified the model to understand the factors behind a retweet, we moved onto identify factors that affected the survival of a tweet containing a malicious URL. Survival analysis involves the modelling of time to event data; in this context, failure to retweet is considered an "event". We conducted survival analysis to analyse the duration of time until users stop retweeting a malicious or benign URL. This allowed us to understand the factors that increase or decrease hazards to survival. For instance, we were interested in identifying if emotions such as anger or fear had any effect on the hazard rate for information flow survival. Put another way, does the lifetime of a tweet (lifetime is defined as the time from the first tweet to last retweet) increase when anger is expressed in textual content? In order to identify explanatory factors to model information flow survival, we chose Cox's proportional hazards model [2]. Cox's model produces a survival function that predicts the probability that a retweet is made in the present time frame for the given values of the predictor variables. Given the predictor variables **X** at a given time **t** the survival function can be defined as $\lambda(t|X)$ where

$$\lambda(t|X) = \lambda_0(t)exp(\beta_1 X_1 + \beta_2 X_2 + ...\beta_n X_n) \tag{7}$$

Based on this, the partial likelihood for X can be calculated using:

$$L(\beta) = \sum_{i:C_i=1} \frac{\theta_i}{\sum_{j:Y_j \geq Y_i} \theta_i} \tag{8}$$

Where for a given tweet i, C_i is an indicator of the time corresponding to the tweet and $\theta_i = exp(\beta_1 X_1 + \beta_2 X_2 + ...\beta_n X_n)$

3.3 Kaplan-Meier estimation

In order to show the impact of survival rate when an emotion or sentiment is detected, we used Kaplan-Meier estimation model to plot the survival function. The generated plot consists of a declining horizontal step. The estimator can be represented by :

$$\hat{S}(t) = \Pi_{t_i<t} \frac{n_i - d_i}{n_i} \tag{9}$$

Where *ni* is the number of tweets that were retweeted and *di* is the number of tweets that failed to be retweet at time *ti*.

4 RESULTS

Table 4 and Table 5 give a summary of the results for the zero-truncated negative binomial models built for our dependent variable size using the malicious and benign datasets. Table 6 and Table 7 give a summary of the results for the Cox proportional hazard regression models for our dependent variable survival. The independent variables are divided into the three categories: social, emotion and sentiment factors. Several statistically significant associations are observed between the predictor and dependent variables. For count data models in place of coefficients the incident rate ratio (IRR) is shown for each predictor. The IRR is derived by the exponentiation of the zero truncated negative binomial regression coefficients, allowing for the interpretation of retweet incidence rates (as opposed to logs of expected retweet counts). We can therefore use the IRR to report the strength of causal associations between certain factors and the information flow size, enabling us to identify quantitatively which factors are more important than others.

In terms of our results, the magnitude of the effect of our variables of interest (emotions, sentiment and social content) on retweets is expressed as a percentage change in the incident rate of a retweet when all other factors in the model are held constant. An IRR of more than one indicates the percentage change in the incidence of a retweet increases, whereas an IRR of less than one indicates the reverse. For example, in Table 4, IRR for Surprise is 1.7851390, which is greater than one. So the percentage change in the IRR is calculated as:

$$\%increase = (IRR - 1) * 100 = (1.7851390 - 1) * 100 = 78.51390\% \tag{10}$$

Which is interpreted as, by holding all other factors constant tweets that contained more words associated with the emotion Surprise were more likely to be retweeted by 78.51390%. Similarly, in Table 4 percentage change in the incident rate for Hashtag (IRR=0.893171), where IRR is less than one, is calculated in the following way

$$\%decrease = (1 - IRR) * 100 = (1 - 0.8931710) * 100 = 10.6829\% \tag{11}$$

Which is interpreted as, by holding all other factors constant tweets that contain higher number of hashtags were less likely to be retweeted by 10.6829%

4.1 Dependent Variable- Size

Table 4. Size model Results for Tweets containing Benign URL

Predictors	IRR	**Std. Err**	Z	**Sig.**
Social Factors				
Hashtag	0.8931710	0.0205727	-4.900	0.000
Mentions	0.6581943	0.0333803	-8.250	0.000
Friends	0.9999995	0.0000045	-0.120	0.907
Followers	1.0000010	0.0000001	9.370	0.000
Age of User Account	0.9993696	0.0001616	-3.900	0.000
Emotion				
Anger	0.9553148	0.2145193	-0.200	0.839
Anticipation	0.7157636	0.1030828	-2.320	0.020
Disgust	0.8145451	0.2109367	-0.790	0.428
Fear	0.8445490	0.1555862	-0.920	0.359
Joy	0.8073432	0.1528402	-1.130	0.258
Sadness	1.0266900	0.2111274	0.130	0.898
Surprise	1.7851390	0.3412885	3.030	0.002
Trust	0.8126954	0.0880218	-1.910	0.056
Sentiment				
Negative	0.5349507	0.0989301	-3.380	0.001
Positive	1.0844390	0.1233625	0.710	0.476

4.1.1 Social Factors.

Benign dataset

Four social factors were statistically significantly associated with the dependent variable size. The number of hashtags and mentions in a tweet both emerged as negatively associated with size. For hashtag IRR was 0.8932, Z was -4.9 and $p<0.00$ (see Table 4). The result shows that for every increase in hashtags within a tweet, that tweet is approximately 11% less likely to be retweeted. Similar results were observed for mentions and age of user account. For mentions, the IRR was 0.6582, Z -8.25, $p<0.00$, and for age of user account IRR was 0.9994, Z -3.9 $p<0.00$. Thus for each increase in user mentions, tweets were 34% less likely to be retweeted. Every increase in age of an account makes it less likely tweets posted by that account will be retweeted by 0.0006%. The older the account, the less likely its benign tweets are to be retweeted. The number of followers a user had was also statistically significant, with IRR of 1.0000010, Z equal to 9.37 and $p<0.00$, thus showing that for every increase in follower numbers, the likelihood of retweet increases. This follows expectations due to increased social capital and therefore exposure of the tweet to more

Table 5. Size model Results for Tweets containing Malicious URL

Predictors	IRR	**Std. Err**	**Z**	**Sig.**
Social Factors				
Hashtag	1.2493	0.0783	3.5500	0.0000
Mentions	0.9678	0.0892	-0.3500	0.7230
Friends	1.0000	0.0000	-0.8600	0.3880
Followers	1.0000	0.0000	2.7300	0.0060
Age of User Account	0.9999	0.0003	-0.4500	0.6540
Emotion				
Anger	0.6585	0.1471	-1.8700	0.0610
Anticipation	1.2971	0.1122	3.0100	0.0030
Disgust	0.9395	0.1492	-0.3900	0.6950
Fear	2.4397	0.3817	5.7000	0.0000
Joy	0.9353	0.0840	-0.7400	0.4560
Sadness	1.3274	0.1731	2.1700	0.0300
Suprise	0.6941	0.0471	-5.3800	0.0000
Trust	0.6883	0.0699	-3.6800	0.0000
Sentiment				
Negative	1.0526	0.2703	0.2000	0.8420
Positive	0.9531	0.1278	-0.3600	0.7200

people.

Malicious dataset

Two variables from the set of independent variables in social factors were statistically significantly associated with the dependent variable size. For hashtags, the IRR was 1.2493, Z 3.55 and $p<0.00$ (see Table 5). This association showed that for every increase in hashtags in a tweet, the chances of retweet are increased by around 25%. We also observed that the number of followers that the person tweeting had, was also statistically significant and we observed IRR of 1.00, Z equal to 2.73 and $p<0.006$. We observed that even though IRR for *followers* was statistically significant, it did not affect the retweeting behaviour(IRR=1).

4.1.2 Emotion and Sentiment.

Benign dataset

Two positive emotions out of the eight primary emotions used as the independent variable were found to be statistically significant. Results showed an IRR of 0.7157636, Z -2.320 and $p<0.02$ for anticipation. For every increase in words relating to anticipation, the tweet was 28% less likely to be retweeted However, for every increase in the emotion surprise, tweets were more likely to be retweeted by 78% (IRR=1.7851390,Z=3.030 and $p<0.02$) when compared to tweets not containing surprise (see Table 4). Among the independent variables in the sentiment set, negative sentiment (IRR=0.5349507,Z=-3.38 and $p<0.001$) was statistically significant, showing that for benign tweets posted during a sporting event, every increase in words containing negative is associated with a 47% reduction in retweet likelihood.

Malicious dataset

Five out of the eight emotions were found to be statistically significant, whereas no significant association was found for sentiment. From the set of negative emotions, fear and sadness were positively associated with size. Where fear has an IRR of 2.4397, Z of 5.7 and $p<0.00$, and sadness has an IRR of 1.3284, Z of 2.17 and $p<0.03$ (see Table 5). In malicious tweets, for every increase in words relating to fear, the likelihood of retweet increased by 143%. For sadness, each increase is associated with a 33% increase in retweet likelihood. Anticipation evokes the feeling of excitement whereas surprise is felt when the unexpected happens and both of them were found to be statistically significant. For anticipation the IRR was 1.2971, Z 3.01 and $p<0.03$ and for surprise the IRR was 0.6941, Z -5.38 and $p<0.00$ (see Table 5). Meaning malicious tweets that contained anticipation were more likely to be retweeted by 30% for each additional word containing this emotion, and those that contained surprise were less likely to be retweeted by 31%. Interestingly, anticipation had a positive association with the number of retweets whereas surprise had a negative association compared to results from benign dataset sample. From the set of positive emotions, trust was observed to be statistically significant. It was observed to have a negative association with information flow, having an IRR of 0.6883, Z of -3.68 and $p<0.00$. We interpret this as meaning for every increase in text representative of trust, malicious URLs spread less by a factor of 31%. . The Bayesian information criterion for the full model was observed to be 10,660.43 and Log-Likelihood to be -5270.41 suggesting a good fit to the data.

4.2 Dependent Variable -Survival

Table 6 and 7 shows the result obtained from the Cox proportional hazards model for both malicious and benign tweets. Considering the diversity of each sporting event regarding the length of playtime (from 90 minutes for a football game to around 480 minutes to cricket match), we wanted to see which information survived longer than 24 hours when the sporting event was over. Therefore, the Cox proportional hazard model was created for the 24 hour time window. Results from the model indicated several statistically significant association between the dependent variable (survival) and our predictive factors. As the model is used to explain the proportional hazards, a positive β indicate an increase in hazard to survival meaning it reduces the survival of information flow and vice versa.

4.2.1 Social Factors.

Benign dataset

Holding all factors constant we found hashtags($\beta = 0.05056, z = 3.01$) and age of account created ($\beta = 0.0012092, z = 12.02$) to be statistically significant and positively associated with hazards to survival. The results showed that benign tweets that contained a higher number of hashtags or are posted by accounts that were recently created have less chance of survival - i.e. will be retweeted for a shorter period than those with less hashtags or with older accounts. We also found user mentions ($\beta = -0.166, z = -4.64$) and number of followers a user have ($\beta = -0.0000002, z = -3.48$) to statistically significant and negatively associated with hazard of survival.

We also found positive sentiment to be statistically significant and associated with decreased hazards to survival. Figure 5 illustrates using Kaplan-Meir survival estimates that benign tweets with higher numbers of positive words have an increased chance of survival over longer periods.

Malicious dataset

Holding all factors constant we found user mentions ($\beta = 0.13513360, z = 3.17$) and a number of followers a user have ($\beta = 0.00000017, z = 2.76$) to be statistically significant in predicting hazard to survival. Both of them were found to be positively associated with hazard of survival. Results showed that the more the cybercriminal uses user mentions in a tweet (e.g. trying to target users) or has an extensive social network (often a sign of bots who buy followers), the more it decreases the chance of survival. A negative association was observed by the number of friends a user has ($\beta = -0.00001060, z = -1.970$), showing more the number of friends a user has the higher the chances of survival of a tweet.

Table 6. Survival Model Results for Tweets containing Benign URL

24 hours Window				
Preictors	**Coef**	**Std. Err**	**z**	**Sig**
Social Factors				
Hashtag	0.0505660	0.0167934	3.010	0.003
Mentions	-0.1661053	0.0357883	-4.640	0.000
Friends	0.0000012	0.0000018	0.660	0.509
Age of User Account	0.0012092	0.0001006	12.020	0.000
Followers	-0.0000002	0.0000001	-3.480	0.000
Emotion				
Anger	0.1982328	0.1531408	1.290	0.196
Anticipation	-0.0820958	0.0956012	-0.860	0.390
Disgust	0.1259461	0.1607216	0.780	0.433
Fear	-0.0869308	0.1282319	-0.680	0.498
Joy	0.3235211	0.1259961	2.570	0.010
Sadness	0.2598578	0.1410289	1.840	0.065
Suprise	-0.2424558	0.1399941	-1.730	0.083
Trust	0.0393096	0.0743090	0.530	0.597
Sentiment				
Negative	-0.1533467	0.1219457	-1.260	0.209
Positive	-0.2803509	0.0833525	-3.360	0.001

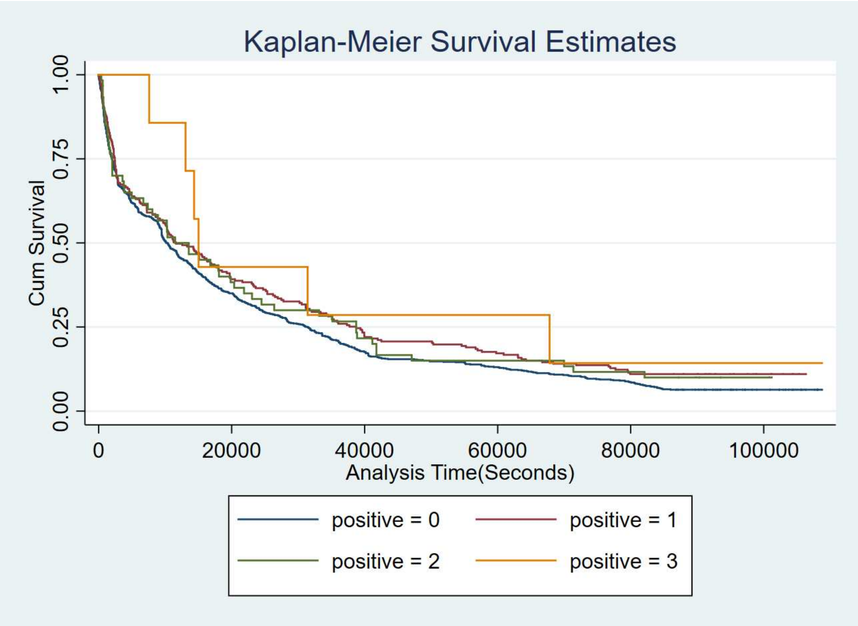


Fig. 5. Survival rate for positive sentiment in benign tweet sample

Table 7. Survival Model Results for Tweets containing Malicious URL

24 hours Window				
Predictors	**Coef**	**Std. Err**	**z**	**Sig**
Social Factors				
Hashtag	-0.02988310	0.02786000	-1.070	0.283
Mentions	0.13513360	0.04256820	3.170	0.002
Friends	-0.00001060	0.00000539	-1.970	0.049
Age of User Account	-0.00008420	0.00014620	-0.580	0.565
Followers	0.00000017	0.00000006	2.760	0.006
Emotion				
Anger	0.35190140	0.09892910	3.560	0.000
Anticipation	-0.02911340	0.04077730	-0.710	0.475
Disgust	-0.00215150	0.07319090	-0.030	0.977
Fear	-0.19202340	0.06798030	-2.820	0.005
Joy	0.01330880	0.04505960	0.300	0.768
Sadness	0.04871910	0.07660280	0.640	0.525
Suprise	0.00820430	0.05620190	0.150	0.884
Trust	-0.04157660	0.06243850	-0.670	0.505
Sentiment				
Negative	0.02373590	0.11119810	0.210	0.831
Positive	0.10034690	0.07497770	1.340	0.181

4.2.2 Emotion and Sentiment.

Benign dataset

Independent variables representing emotion and sentiment in a tweet were derived from the contents of the tweet based on the words it contained. Survival models were built using these independent variables. The results (see table 6) showed that only the positive emotion of joy and positive sentiment were statistically significant in predicting hazard to the survival of the information flow. We observed a positive association for joy ($\beta = 0.3235211, z = 2.570$) indicating that chances of survival reduced if the tweet reflected joy. However, tweets that reflected a positive sentiment showed a negative association ($\beta = -0.2803509, z = -3.360$). Results showed that more positive tweets had a greater chance of survival.

Malicious dataset

Sentiment alone was not found to be statistically significant. However, we found two emotions to be statistically significant in predicting hazard to the survival of information flow. Results showed that anger($\beta = 0.352, z = 3.56$) was positively significantly associated, indicating the chances of survival reduces if the tweet is reflecting anger. However, tweets that reflected fear ($\beta = -0.192, z = -2.82$) showed a negative association indicating that chance of survival of a malicious tweet increases if a cybercriminal posts an intimidating tweet.

Figure 6 illustrates Kaplan-Meir survival estimates for those tweets that reflect the fear emotion. The levels of fear (0-3) represent the number of words related to this emotion in the tweet. The results showed that the more the words associated with fear were used in creating a malicious tweet, the higher were the chances of its survival. Fear spreads longer than any other emotion in malicious tweets.

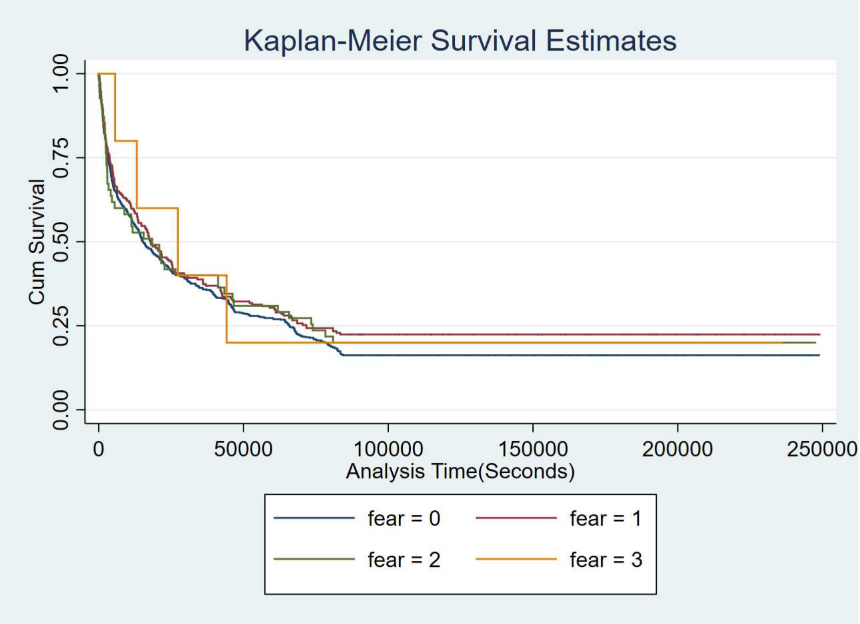


Fig. 6. Survival rate for fear in malicious dataset

5 DISCUSSION

We collected Twitter data around seven sporting events using event-specific hashtags. Sporting events had been chosen specifically because they attracted a large number of users which gave cybercriminals an opportunity to spread drive-by download attacks by obfuscating malicious URLs in tweets. A sub-sample of 274,820 tweets was randomly created from the collected data sample of around 3.5 million tweets, that were preprocessed to remove the retweeted tweets before the unique URL was extracted from them. The resultant sample of 31,171 unique URLs was later passed on to Capture HPC, a high interaction honeypot, that was set up to distinguish malicious tweets from benign. Once a URL was passed to the Capture HPC server, it interacted with the Web server for a limited period and, based on changes made to the client machine, it classified the URL into malicious (drive-by download attack occurring from the endpoint of a URL) or benign. The changes made to the client machine clarified that Capture HPC identified around 6,122 malicious and 25,049 benign URLs. Across all the seven events we identified all the tweets that contained these malicious and benign URLs, including retweets, to understand the propagation of a drive-by download attack on Twitter. The research aimed to identify social and content factors, such as the emotion and sentiment in the tweet, that was associated with the propagation of malicious URLs. With the nature of the sample data in mind, we chose the zero-truncated negative binomial method to model *size* and the Cox proportional hazard model to calculate the *survival* as the dependent variables - and social and content features as the independent variables.

In line with previous research on the virality of news [4, 64] and spam detection [26] in OSNs, several significant associations for emotions and sentiment were revealed between information size and survival. Among the social features, hashtags stood out, being created by users to give context to their post and link them to related topics to reach a targeted audience, increase traffic to their post, and in turn increase interactions and the probability that their tweet will be retweeted. A recent report on the engagement of users on online social platforms revealed that though hashtags provide context and are thus important elements in a post, they reduce user engagement if their number increases beyond a threshold [47]. Interestingly, our results for tweets that contained benign URLs were in line with Clement et al. [47]. Their results show that tweets classified as benign do not engage users' interest and are 11% less likely to be retweeted if they contain more hashtags. This contradicted our finding for those tweets that were classified as malicious. Our results show that malicious tweets were 24% more likely to be retweeted if they contained more hashtags. One explanation for this could be that hashtags which trigger emotional responses are added to tweets to gain popularity or to engage users, as has been shown in earlier work where a relationship was identified between emotion and content sharing [4].

5.1 Re-tweetability of a Tweet

For benign tweets the number of followers of the posting user was positively associated with the chances of them being retweeted (see Table 6). However, though followers were statistically significant in the propagation of malicious tweets, the effect size was very small suggesting cybercriminals do not depend heavily on their followers to propagate malware and may seek other techniques for this purpose, including the use of content features (sentiment or emotion), embedding hashtags that highlight the tweet, or using techniques such as paying for retweets [11, 12] from black market services such as Like4Like [13] or YouLikeThis[45].

Information that is novel attracts people [27] and things that are attractive are worth sharing on online social platforms [4]. Information that is found novel is also considered valuable and surprising. Based on this principle, Berger et al. showed that content on OSNs that evokes high arousal emotions such as *'awe'* have a higher probability of being propagated by the action of sharing [4]. Since the emotion *'awe'* can be derived from the root emotion surprise [59], we found that tweets which were classified as benign and contained keywords associated with surprise were 78% more likely to be retweeted. Even though a higher number of tweets (33% malicious compared to 8% benign) contained one or more keywords associated with the emotion surprise in a malicious dataset, it was not statistically significant for the size of the information flow. This suggests that it was not one of the driving factors behind a high retweet count. Rather, it was negative emotions such as fear and sadness that were found to be statistically significant for the size of the information flow. The results show fear to have the highest incident rate ratio (2.4), meaning that each tweet that reflected fear was 114% more likely to be retweeted. A comparison of sample size revealed that 30% of the tweets from the malicious data sample contained one or more keywords associated with fear compared to 8% from the benign data sample, suggesting that a higher number of words associated with the emotion 'fear' were used in constructing tweets with a malicious link. Even though negative emotion was present in the benign dataset it was not found statistically significant for the size of the information flow in the dataset categorised as benign.

To investigate further the choice of keywords used that helped a tweet to gain popularity or be retweeted, a world cloud (see Figure 7 and Figure 8) was created from the tweets that were categorised as malicious and and tweets that were categorised as benign . On closer inspection words such as "kill", "fight", "shot", "controversy" etc. were frequently observed in tweets that contained malicious URLs. Whereas words such "Team", "love", "happy","good", "enjoy","fun" were found in benign tweets. This suggests that carefully selected words were being used in the formation of these tweets, where a keyword could trigger emotional arousal using negative emotions such as fear, anger, or sadness that could encourage the propagation of malicious tweets. [4, 64]. We further investigated the number of words used in tweets that created emotional arousal and found that tweets that were classified as malicious contained more words associated with emotions than did the tweets classified as benign (see Figure 9).

Even though the collective intensity (total number of words associated with emotions) of positive

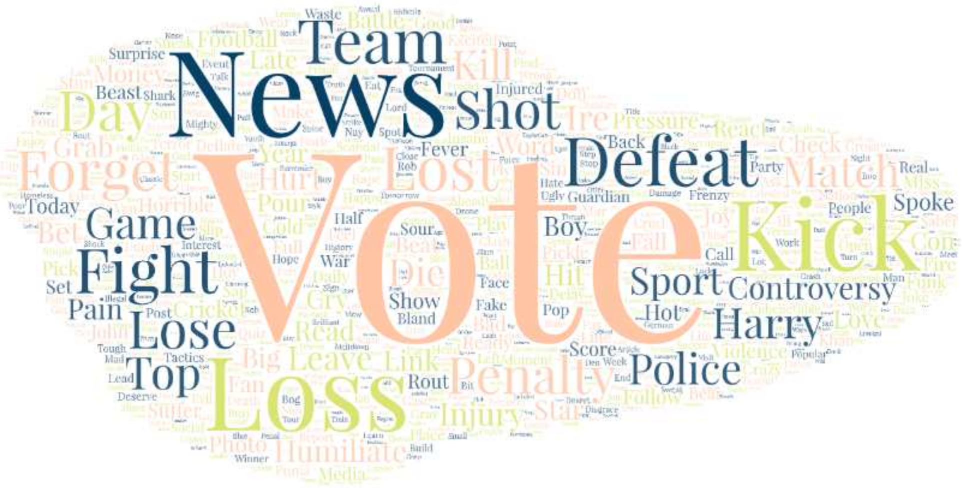


Fig. 7. Word Cloud of Malicious Tweet

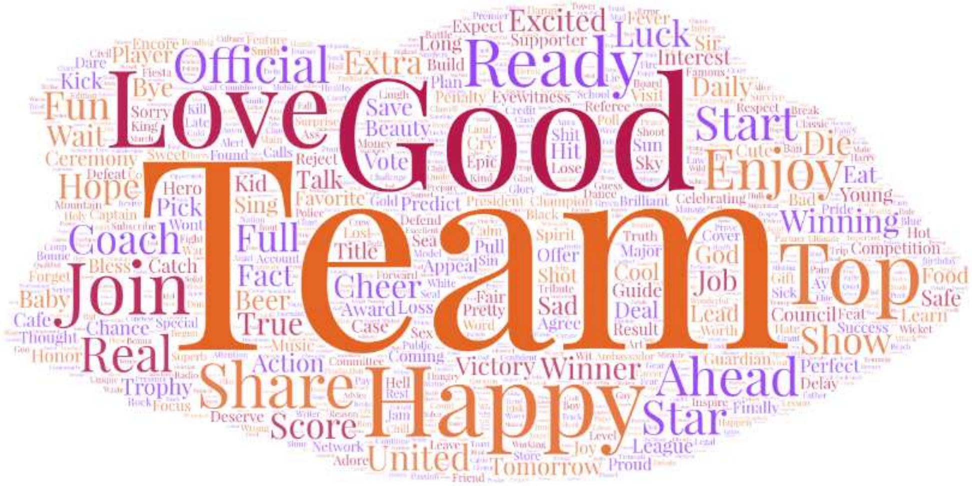


Fig. 8. Word Cloud of Benign Tweet

emotions such as anticipation, surprise, trust and joy were higher than those of the negative

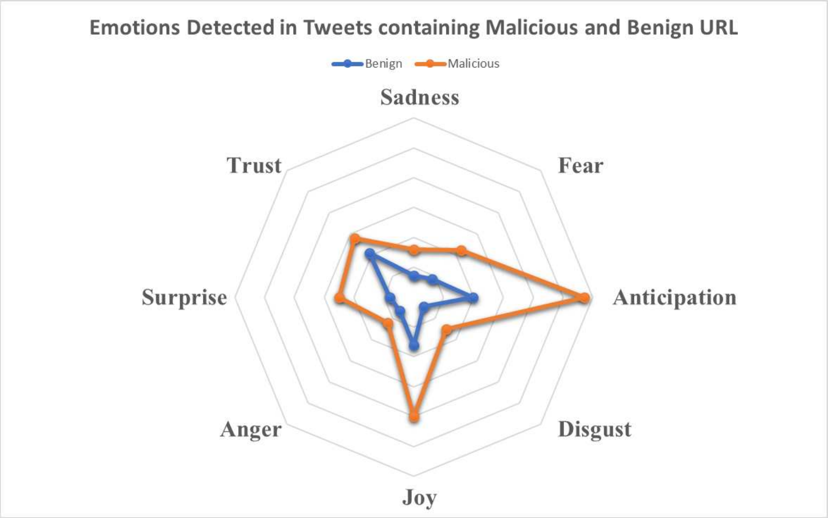


Fig. 9. Emotions captured in those Tweets categorised as malicious (N=1137) and benign (N=1862)

emotions, it was the negative emotion such as fear that were associated with size and the survival of information flow for tweets classified as malicious. This association implies that the associative factors were higher for emotion rather than on *followers* for the propagation of tweets containing malicious links. A similar association was found between content of false news and emotions, where a study showed it was negative emotions that assisted more than positive in propagating fake news [64].

5.2 Longevity of a Tweet

In addition to the ZTNB model built to predict the number of retweets (size) we built a Cox proportional hazard model for both benign and malicious tweets to measure the lifetime of the information flow. A number of social factors were found statistically significant, where the number of hashtags used in a tweet showed similar traits in the size of the information flow. This suggests that as the number of hashtags in a tweet increased, the continued engagement of users was reduced. This is supported by a report on user engagement, that suggested an inverse relationship between number of hashtags in a post and user engagement with that post [47]. However, this trait was seen only in tweets classified as benign and no statistical significance was seen between the survival of a tweet categorised as malicious and the number of hashtags used. Whereas user mentions were statistically significant in both datasets and had an opposite relationship. In the malicious tweets it was positively associated, suggesting that with an increase in user mentions the chances of survival decreased. This is possibly because cybercriminals may misuse the user mention option by mentioning popular users to attract attention to their tweet.

However, the survival of a tweet classified as benign is linked to user mentions and the number of followers, suggesting that users who were mentioned shared a trust relationship with the person mentioning them, thus attracting the retweet as demonstrated in related work where authors showed cybercriminals have exploited the *trust* relationship [18] between users by using accounts that appear trustworthy or by mentioning users in a tweet to aid their propagation. The results for malicious datasets showed a negative association with friends (the more the friends, the higher the chances of survival) and a positive association with followers (fewer followers implying a higher chance of survival), suggesting that malicious tweets from accounts that have a low ratio of followers to friends have a higher chance of survival. This could be one of the tactics employed by cybercriminals to prevent detection, since the follower to friend ratio is identified as one of the key features for flagging an account as malicious [54, 60, 70]. Experimental results show that a tweet categorised as malicious will survive longer if posted by an account that has many friends and uses fewer user mentions. However, these features were not statistically significant for tweets classified as benign.

In terms of emotions that were associated with the survival of a tweet, the results were similar to those on the size of the information flow. For a benign dataset, positive sentiment, which is the emotional effect of the tweet on its reader, was found statistically significant for its survival. This was similar to the size of information flow for benign tweets, where tweets containing emotions with positive associations were likely to be retweeted. Similarly, it was the negative emotions that influenced the survival of a tweet classified as malicious, where, like the size of the information flow, fear stood out from the other negative emotions. Tweets that contained keywords associated with fear were more likely to survive the twenty-four hour window after the sporting event and more likely to be retweeted.

5.3 Security Controls Implemented by Twitter

The approach proposed in this work could extend and complement more technically focused approaches reported in literature. For instance, Twitter has put in place numerous security controls to identify and block malicious URLs. These include their in-house detection software, reporting of malicious URLs by users, third-party vendors and their business partners [63]. When a URL is identified as malicious, a degree of certainty score is given to each URL, based on which a URL can be blocked or a warning can be associated with the tweet. This degree of certainty is defined by Twitter and is dependent on the content of the Web page pointed to by the URL. Despite these security measures, it was discovered by Lee and Kim [34] that Twitter's own algorithm could take up to a day to identify and block malicious URLs. This was achieved by comparing the performance of their model based on URL redirects to the detection algorithm used by Twitter. Similarly, Thomas et al. [62] analysed the behaviour and lifetime of around 80 million spam accounts, the campaigns they execute, and the wide-spread abuse of legitimate web services such as URL shorteners and free Web hosting. Their results show that 77% of accounts spreading spam/malware are suspended within a day, but also that around 145,000 were active for up to a month. These results show that even with Twitter's security measures, there still remains a lag in detecting malicious URLs, which is big enough to expose millions of users to malware over a short period of time. We posit that our approach could significantly speed up this process and reduce the risk to users. Considering the detection lag, lifetime of malicious websites [38] and the number of tweets generated per minute (on average 350,000 tweets per minute [53]), our predictive model [28] only requires a few seconds to determine 'maliciousness'. This could provide a step-change in detection approaches.

6 CONCLUSION AND FUTURE WORK

This study has analysed malware propagation across seven different sporting events covering a diverse group of users. Our results show that there is a statistically significant association between the social and emotional factors derived from a tweet captured during a sporting event. In this paper, it was observed that malware propagation was not strongly associated with the number of followers that a user had. The stronger association was towards content driven features, such as emotions and the choice of words associated with emotions that were used to compose a tweet or create hashtags. Even though the malicious dataset had lower numbers, the cumulative intensity of emotions (see Figure 9) was much higher than in the tweets containing benign tweets. The results showed that tweets that contain malicious links are associated with negative emotions, particularly the emotion fear, for their retweet likelihood (virality) and survival. Whereas, in tweets that are classified as benign, it was the positive sentiment and high arousal emotions such as surprise that were associated with the size and survival of the information flow.

The analysis was conducted solely on the content of the tweet, which was seen by the user. We cannot assume that the user clicked on the URL and visited the Web page before retweeting. Therefore, the Web page content was not considered. We have added this as a consideration for future work, but one would need to be able to determine which URLs were visited, and which were not, which is not trivial. It is important for the rigour of the work that we avoid speculation.

Furthermore, our finding could be used to create a filter to segregate those tweets that contain negative emotions/sentiments as they would have a high probability to be malicious. The aim of the filter would be to reduce the input load to a detection classifier/software. Furthermore, content driven features could also be used to increase the f-measure of drive-by download detection/prediction models such as the one developed by Javed et al. [28]. Also, these attributes could be used to understand social network formed by users posting malicious content. However, development of such filters, understanding social networks or building machine learning models using features associate to propagation would be considered as part of future projects.

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