Location impact on source and linguistic features for information credibility of social media

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Abstract

Purpose Social media platforms provide a source of information about events. However, this information may not be credible, and the distance between an information source and the event may impact on that credibility. Therefore, an understanding of the relationship between sources, physical distance from that event, and the impact on credibility in social media needs to be addressed.

Design/methodology/approach In this paper, we focus on the impact of location on the distribution of content sources (informativeness and source) for different events, and identify the semantic features of the sources and the content of different credibility levels.

Findings The study found that source location impacts on the number of sources across different events. Location also impacts on the proportion of semantic features in social media content.

Research limitations/implications This study illustrated the influence of location on credibility in social media. The study provided an overview of the relationship between content types including semantic features, the source, and event locations. However, we will include the findings of this study to build our credibility model in the future research.

Practical implications - The results of our study provide a new understanding of reasons behind the overestimation problem in current credibility models when applied to different domains: such models need to be trained on data from the same place of event, as that can make the model more stable.

Originality/value Our study investigate several events -including crisis, politics and entertainment- with steady methodology. This gives new insights about the distribution of sources, credibility and other information types within and outside the country of an event. Our study further used the power of location to find alternative approaches to assess credibility in social media.

Keywords Social media, Credibility, Information source, Location, Semantic analysis, Statistical analysis.
Paper type Research paper.

INTRODUCTION

Social media is an important source of information, particularly about national and international events. Facebook and Twitter users get their primary news from social media (66% and 59% respectively) (Gottfried and Shearer, 2016). Eighty-five percent of Twitter posts have news-based content (Kwak, Lee, Park, and Moon, 2010). In crisis situation, such as the Japan earthquakes, Twitter posts give alarms faster than a national new agency (Sakaki, Okazaki, and Matsuo, 2010).

However, the credibility of social media content about an event is a major concern. Studies show that fake news and rumors spread on Twitter during events, such as the Chile earthquake in 2010 (Mendoza, Poblete, and Castillo, 2010) and Hurricane Sandy in 2012 (Gupta, Lamba, Kumaraguru, and Joshi, 2013). These rumors spread quickly and are difficult to detect in timely manner thereby having a negative impact on decision making (Oh, Agrawal, and Rao, 2011).

Social media “noisy content” mixes information with high and low credibility. So, assessing information credibility is challenging. While many sources are likely to contribute information about an event, some are more credible than others. Credibility of information can be measured through knowledge about the source. For example, identifiable news sources will be more credible than anonymous sources.

Users in social media research are generally classified based on their location as local or remote. Local users are able to get first-hand information from the event site and are called eyewitness. Remote users share information about the event from a distance. Eyewitnesses are most likely to give first hand information about the event; however, many limitations exist for such accounts (see related work section). Increasing the number of credible sources that can be used to find credible information is essential in order to assess social media information quality.

Knowledge that a source is local or remote can help enhance credibility assessment. First, we can estimate level of credibility of sources in each location. Second, local people are able to understand and interpret the event in terms of geographic cultural and political impacts. Currently, it is common practice for traditional stakeholders (e.g. national press) to contact via social media sources who are close to the place of event to get an update (Dailey and Starbird, 2014). So, information coming from the same region of the event is likely to be richer than remote content.

The language of tweets generated from the same event's region differs from language of tweets from outside that region (Morstatter, Lubold, Pon-Barry, Pfeffer, and Liu, 2014; Kumar, Hu, and Liu, 2014; Cheng, Caverlee, and Lee, 2010). Previous research on social media shows that content of the same credibility level (whether credible or not) shares common practice (Castillo, Mendoza, and Poblete, 2013). At the same time previous research present the overestimation of prediction in current credibility models when apply in different domain (Boididou, Papadopoulos, Kompatsiaris, Schifferes, and Newman, 2014; Aker, Zubiaga, Bontcheva, Kolliakou, Procter, and Liakata, 2017). However, no study has investigated the effect of location on the behavior of different sources and credibility content.

The research questions that we investigated in this paper are:

- What are the types of sources expected in different events from both in- and outside the country of events?
- How linguistic features differ among sources of different type, credibility level, and location?

Related Work

In this section, we review the research in the areas of credibility, linguistic, information source and user location in social media. All of these areas are related to this research, and for each one of them we show the research gap in relation to our work.

Microblog Credibility

Credibility research in social media has diverse directions based on the Methods used. Research has considered tweets' content by choosing a number of content, user and network-based features (Castillo et al., 2013; Gupta, Kumaraguru, Castillo, and Meier, 2014). Other research has focused on the content features such as the sentiment of tweets and then used those features to train the model to predict the credibility of a tweet (Mitra, Wright, and Gilbert, 2017b; O'Donovan, Kang, Meyer, Höllerer, and Adali, 2012). Other research has used the source of the tweet, "tweet's author," to assess credibility, (Ghosh, Sharma, Benevenuto, Ganguly, and Gummadi, 2012; Gupta and Kumaraguru, 2012). An overview of the rumor detection and credibility research in social media have been well studied (Zubiaga, Aker, Bontcheva, Liakata, and Procter, 2017).

Rumors about an event and their spreading have been studied (Zeng, Starbird, and Spiro, 2016; Aker et al., 2017; Kwon, Cha, Jung, Chen, and Wang, 2013; Qazvinian, Rosengren, Radev, and Mei, 2011). Detecting the rumor is achieved by analysis of linguistic features, sentiment and part-of-speech (POS) tagger. Recent work shows that credibility prediction models can not be generalized for different events (Boididou et al., 2014; Aker et al., 2017), as the accuracy of the classifiers drop when apply on event for different domain.

Credibility and linguistic features

Studying the linguistic features related to different credibility level in the web has been studied, Popat, Mukherjee, Strötgen, and Weikum (2016, 2017) presented an approach to identify true and false textual claim. They studied the linguistic styles of documents related to such claim by using a set of lexicons. It assumes that language of a high credible article is unbiased and objective, while subjective language relate to low credible articles. Also, they include the reliability of the web-source of the article. They found the effectiveness of using the language features with with other factors to identify the credibility of a given claim. Horne and Adali (2017) compared between the real and fake news, they found a significant differences between them in structure of title and other language features. Moreover, in large scale study for true and false news distributed between 2006-2017 on Twitter, found significant differences in language features of user response to false and true news (Vosoughi, Roy, and Aral, 2018). Also, the linguistic features were found to be important factor in identifying the experts in Twitter (Horne, Nevo, Freitas, Ji, and Adali, 2016). The language of a tweet is influenced by user's location (Cheng et al., 2010; Han, Cook, and Baldwin, 2014), including the linguistic features with other factors like location in social media credibility models can enhance the prediction overestimation in the exist models (Boididou et al., 2014).

Information Source

Considering the source of information is a critical part of assessing its credibility. In social media, many researchers have attempted to categorize users into high and low credibility sources to be able to reach credible information. Users post tweets varying from globally well-recognized organizations to locally popular community organizers (De Choudhury, Diakopoulos, and Naaman, 2012), and from specialists in such a domain to fake accounts that steal the identity of other people. Consequently, the quality of information is hugely diverse; finding the users who have highly relevant and credible information about such an event as the source of information is challenging. Methodologies to find authentic sources in social media are different; for example, using the topical content and network structure to rank users based on credibility in a given topic (Canini, Suh, and Pirolli, 2011).

Other research has included user-related data such as tweet content and user profile to build their models in addition to using the social media experts groups. These groups are in the nature of topical expertise directories, such as lists and skills membership on Twitter and Linked-in respectively (Wagner, Liao, Pirolli, Nelson, and Strohmaier, 2012; Bhattacharya, Ghosh, Kulshrestha, Mondal, Zafar, Ganguly, and Gummadi, 2014; Ghosh et al., 2012; Bastian, Hayes, Vaughan, Shah, Skomoroch, Kim, Uryasev, and Lloyd, 2014). For example, lists in Twitter are an organizational feature created by user to group experts in such topics. Previous research has classified users as high and low based on their topical expertise and local authority and expertise (Cheng, Caverlee, Barthwal, and Bachani, 2014). However, all these research were limited by focusing on the information source of a general topic and not for a particular event which may be limited by time and location, such as crisis events. Also, these research limited by their methodologies which rely on geolocation information.

User and Event Location

Using the location of an event to predict content credibility is an important factor. During events, social media platforms often provide the first alarm: people start sharing information about what is happening. Users from the same event location share specific and accurate information while those further from the event location share general content (Kumar, Morstatter, Zafarani, and Liu, 2013).

Users posting information for a particular event from the same or proximate area of an event are known as "eyewitnesses", they are presumed to have accurate information. Many research has attempted to reach eyewitness authors, such as (Diakopoulos, De Choudhury, and Naaman, 2012; Olteanu, Vieweg, and Castillo, 2015),but there are many limitations to those studies: (a) very few users who are witnesses to an event share information on social media (Truelove, Vasardani, and Winter, 2014), (b) Witness users are defined via GPS coordinates attached to the tweets; however ($\sim$ 1%) of tweets in Twitter are geo-tagged (Morstatter, Pfeffer, Liu, and Carley, 2013). To date, there has been no research studying the impact of the distance between user and event locations on the credibility of the information.

METHODOLOGY

We followed the next steps to complete this study:

1) We defined the number of dimensions to classify the social media message at time of events: Location, informativeness, source and credibility.
2) We collected Twitter data for sets of events occurring between 2016-2017 using Twitter API. These events were taken from three different topics, entertainment, politics and crisis.
3) We ran set of crowd sourcing tasks to evaluate and characterize these messages: each event had 1200 tweets.
4) We analysed the interaction between type of author location and his/her messages' characteristics based on the message's informativeness, the used source, credibility and the semantic of the message.

Location dimension

Our research questions have three main components: location, source and credibility of social media content. We categorized the tweets of each event based on physical distance between the source and the event location, and then we used crowd source to annotate tweets' informativeness and sources.

Previous research found that the tweets from the same area of event are different from tweets remote from that area (Morstatter et al., 2014). Moreover, the behavior of users in Twitter differ between countries, mainly they are different of using four main features, hashtags, URLs, mentions, and retweets (Poblete, Garcia, Mendoza, and Jaimes, 2011).

We examined to the interrelation of user location with the type and quality of messages during different events. Other research was interested to find eyewitnesses to different events, where he/she is the most likely to give the first-hand and credible information about the event. However, in many cases determining the eyewitness is hard and many weaknesses in the exist research (Truelove et al., 2014). Users location can be used to find credible information but not necessarily from eyewitness.

So, we build on the hypothesis that being a local user might increase the credibility of information. Our definition of the author's proximity to the event location is that is within the same country in which the event is occurring, similar to (Kumar et al., 2013), while remote users are those who are outside that country. Then to evaluate the impact of distance to the event, we compare the two categories (local and remote) according to different content types.

We classified tweets of each event into two categories, local and remote tweets. To complete that, there are two ways to determine users' location in Twitter, by using GPS coordinates associated with tweets at the time of post. However, the geo-tagged tweets are (<%1) (Morstatter et al., 2014). The other way to determine tweet location is through user profile location which is entered by users. In this research we followed the second option as did many other researchers (Sakaki et al., 2010; Mislove, Lehmann, Ahn, Onnela, and Rosenquist, 2011; Thomson, Ito, Suda, Lin, Liu, Hayasaka, Isochi, and Wang, 2012; Poblete et al., 2011; Kumar et al., 2013). We did not include the automated GPS information because location changes as users are often moving continuously. In this work we are interested in the home country of the user and not in current location:, we prefer the user profile location as it more accurately reflects the home country of the user.

Hecht, Hong, Suh, and Chi (2011) found 66% of Twitter's users had a valid geographical location, 16% had empty locations and only 18% had invalid locations. So, the profile location field is free text which can include not the geographic location entered by users. To determine a user's home country and then to classify them to one of the two location classes (local and remote), we took the following steps:

Local: For defining a user's location inside the country of event, we used country name in different format, for example, for the event in United kingdom we used all different formats as used in Geonames [1]. Also, we used the large cities of each country of event, a Wikipedia entry was used to define the large cities of each country.

Remote: For users outside the country of event, we used the list of all countries' names in different formats (without names of the country of event). Also, we used the list of top 100 largest cities (excluding the cities of the country of event), where the user is located in one of them to be classified as a remote user. The same methodology has been used by (Magdy, Darwish, Abokhodair, Rahimi, and Baldwin, 2016).

Content dimension

To assess the content broadcast during different events we reviewed the previous research that analyzed social media content and credibility, we created set of categories that had been included in other research (Olteanu et al., 2015; Starbird, Palen, Hughes, and Vieweg, 2010; Vieweg, Hughes, Starbird, and Palen, 2010; Gupta and Kumaraguru, 2012; Imran, Elbassuoni, Castillo, Diaz, and Meier, 2013). These categories are bit broader to fit with different events, the large number of messages in this kind of studies, and the limitation of using crowd-source workers to complete annotations,

Informativeness

In this step we assess the status of tweets' informativeness to the event. This process is subjective task since it depends on the person seeking the information, and the context of the event to understand the implications. For this dimension we followed the precedents of (Vieweg et al., 2010; Gupta et al., 2014), to measure how a tweet gives understanding about the situation. The following criteria were used.

- Related to the event and informative: when a tweet includes information about the situation and helps a reader to understand what is happening.
- Related to the event, but is not informative: when a tweet includes information about the situation but doesn't help one to understand what is happening.
- Not related to the event.
- Not applicable.

Source

When people get an update of an event in social media they look for the source of information, which is a main concern for the quality of the shared information.

The users contributing on social media are diverse and distributed as individuals or organizations, and each category has sub-categories. So we select the sources that are always included in different events; the sources were also included in previous research (Olteanu et al., 2015; Lotan, Graeff, Ananny, Gaffney, Pearce, et al., 2011; Thomson et al., 2012).

For this dimension, we developed a categorization schema based on the following types of sources.

- Government: information published by official (State or local body).
- Businesses: information published by profit-making companies or agencies.
- Non-profit organization: information that publish by non-profit organization.
- Traditional media: information publish by news agencies.

1. http://www.geonames.org/

EVENT NAME	COUNTRY	YEAR	POSTS	USERS	ACTIVE USERS
Apple Event	US	2016	1407577	771081	106067
Search keywords:#AppleEvent					
Summer Olympics	Brazil	2016	3094539	1404981	236962
Search keywords: #Rio2016					
Oscar Academy Award	US	2017	3133296	1463300	274144
Search keywords: #Oscar #Oscar2017					
Italy Earthquake	Italy	2016	512798	320306	30177
Search keywords: #ItalyEarthquake #PrayForItaly					
London Attacks	UK	2017	303884	212765	16564
Search keywords:#LondonAttacks #Prayforlondon #Londonstrong #Westminster					
Cyclone Debbie	Australia	2017	89954	33129	6292
Search keywords:#debbie #cyclone #CycloneDebbie #tcdebbie Qld Queensland cyclone #BigWet					
Presidential Debate	US	2016	5443507	1819068	355895
Search keywords: #debatenight					
Presidential Election	US	2016	1295766	892094	77903
Search keywords: #ElectionDay #ElectionNight #USElection2016					

TABLE 1: The events description used in this research.

- Journalists: associated with an organization or a freelance journalist.
- Eyewitnesses.
- Politicians.
- Academics,specialists, researchers.
- Digerati.
- Celebrities.
- Outsiders: ordinary or non-identified sources.

Credibility assessment

Assessing the credibility of the information is subjective process, in this research we used the common methodology used by the most of social media credibility research (Castillo, Mendoza, and Poblete, 2011; Castillo et al., 2013; Gupta et al., 2014). We asked annotators to label the tweets based on the credibility into one of the following categories:

- Definitely Credible.
- Seems Incredible.
- Definitely Incredible.
- I can't Decide.

The credibility definition was used in this research and was provided to the annotators is- "offering reasonable grounds for being believed" [2] and then give an explanation for each category. The criteria for a tweet to be a credible is to be a fact, informative, not a personal point of view (Castillo et al., 2011; Shariff, Zhang, and Sanderson, 2014). We noticed "seems not credible" in pilot test a kind of replication with "seems credible" as both of them indicate the tweet is credible and not credible, we only keep one of them to enforce evaluators select from the other options as in (Castillo et al., 2011; Gupta and Kumaraguru, 2012).

DATA COLLECTION

The goal of this paper is to the informativeness and sources in different locations at the time of an event, and the impact of location on studying credibility in social media. For the purpose of the experiment we collected data of different events having different topics. For each event we identified the most used keywords and hashtags that were used during event window time. We then submitted them to Twitter streaming API [3], to crawl event-related tweets. These tweets were most likely to be representative of the discussion of the event in Twitter. Table 1 provides information about the users' and tweets' number for each event. We collected events in the same way as was used by (Vieweg et al., 2010; Thomson et al., 2012; De Choudhury et al., 2012). In this study we only include the active users who had three or more tweets about the event (most of users only has one tweet), similar to (Vieweg et al., 2010; Starbird and Palen, 2010; Thomson et al., 2012). This threshold for sampling was taken to reduce the noise by capturing active users.

We used crowd sourcing to complete the annotation process of informativeness and source. The crowds' workers were given instructions how to complete each task,including the event name with short description and the link

2. http://www.merriam-webster.com/dictionary/credible. This definition was used by most of the previous credibility research such as (Castillo et al., 2011). So, applying this definition on our research, a given tweet is said to include credible information, when annotator believe the truthfulness of tweet's information.

3. https://dev.twitter.com/streaming/overview

to an outside source to read about the event in more detail. This is further detailed in the following subsections. Also, we gave examples about each event to help them understand the task. We used CrowdFlower platform to complete the tasks [4].

Characteristics of the tasks

For all tasks in this study we included those tweets that were written in English. The crowdsourced workers were from the same country as the event except that when there were not enough workers we included workers from neighboring countries. We followed this procedure because the local workers are more likely to understand the situational awareness of the event, understand the dialects, locations, entities and the culture of overall place of event. Moreover, as crowd flower platform guidelines, 40 to 50 tweets for each event and task where annotated by the research team. Any worker with less than 80% agreement from the annotated tweets was classified as untrusted. A trusted judgment by a trusted worker took a mean of 8 seconds for informativeness task, in the source task took 22.75 seconds to be completed, while the trusted judgment in the credibility task took 18 seconds. The overall agreement between workers judgments for 100 randomly-selected tweets by the platform in the informativeness task is 72.5% , 81.2% for the source task and 81.24% for the credibility assessment. For each tweet in all tasks we collected at least three judgments, and the final label was calculated by the majority.

For each step of annotation which includes 1200 tweets for a single event in each task (informativeness, source or credibility) was completed by about 15-25 workers, each worker was limited by 300 judgments for each task and can't exceed this limit as recommended by the crowd sourcing platform.

The first classification task was to define the event-related tweets. Some tweets may contain event keywords but they are unrelated to the event. So, for each event we annotated 600 related tweets from each location type selected randomly. For all events, we labeled tweets until we passed the limit and kept only the related tweets (informativeness and not), and then classified them based on their source and credibility.

Evaluation of the tasks

Subjectivity in the classification process like tweets' content might affect results, especially in large scale studies such as ours. To evaluate the effect of this subjectivity in our results, we followed the methodology used by (Olteanu et al., 2015). Independently, two coders of the research team labeled 100 tweets selected randomly from all events. They classified the tweets based on informativeness and source type. The coders have a full background about all events, read the tweets as displayed on Twitter, they visited links (if any) within a tweet and the author profile of the tweet.

We apply Cohens' Kappa (k)to measure the inter-agreement between the two coders, the k formulated as:

$$k = \frac{Pr(a) - Pr(e)}{1 - Pr(e)}$$

Where Pr(a) is the number of times that the coders agree and Pr(e) is the probability that the coders agree by chance (Carletta, 1996). The results are (K = 0.80) for the informativeness task and (k = 0.89) for source task. Both values indicate substantial and excellent agreement between coders' labels.

We followed that by comparing labels of the tweets that both coders agree with labels provided by workers of crowd source. The result of informativeness is (k = 0.77), source is (k = 0.79) and (k = 0.81) for credibility. The results also show substantial agreement in all tasks. Next, we checked the agreement between each author individually with workers. This includes the labels with no agreement between the two authors. The results also indicates high agreement as well: (k= 0.78 and 0.64) for informativeness, (k =0.79 and 0.72) for source and (k =0.80 and 0.74) for credibility task.

From the previous experiment we can note that crowd source workers provide a reliable set of collective labels in social media labeling tasks. This conclusion similar to the previous studies which used crowd sourcing for labeling (De Choudhury et al., 2012; Diakopoulos et al., 2012). We received 28800 labels (8 X 1200 X 3) for each task informativeness, source and credibility.

RESULTS

In this section we present the analysis that we performed on the data received from the crowd source workers. We first present the distribution of the content across locations. Then we study the proportion of the linguistics features among different sources and credibility levels, and the impact of other factors (location and topic) on the tweets' linguistic distribution.

4. https://www.crowdflower.com/

	All	SD all	Local	SD local	Remote	SD remote	P two locations
Government	330	57.078	201	34.668	129	22.931	*
Non_Profit	258	36.394	158	22.05	100	15.005	
Business	141	13.917	62.0	5.946	79.0	8.543	**
Traditional_Media	2090	130.001	777	60.523	1313	78.991	**
Eyewitness	8.00	1.309	4.00	1.069	4.00	1.069	
Journalist	625	69.221	374	46.775	251	22.557	**
Academic	78.0	6.319	38.0	4.496	40.0	3.586	
Politician	256	49.702	154	24.33	102	26.612	*
Digerati	259	26.104	143	14.446	116	12.259	
Celebrity	328	35.21	160	18.189	168	17.542	
Ordinary	5227	222.014	2729	122.092	2498	108.39	*

TABLE 2: The overall sources, and the sources' distribution across the locations, *< 0.05, **<0.001.

Content vs. Location dimensions

We begin by presenting the content distribution for each content type and then the content categories across locations.

Informativeness

The distribution of messages that were found to be related to the event (including the first two categories) was on average 91%. The proportion of related messages based on location had a similar ratio, the average of local related messages was 88%, while the average of remote messages was 91%. The effect of distance on the related messages is therefore weak.

The informative messages (only the first category of the informativeness task was considered) gave an average 46% , similar to (Gupta et al., 2014). The effect of distance to event location on informativeness of tweets was high; the percentage of informative remote tweets were higher than local tweets; the average was 43% in local location, while it was 49% in remote location. This indicates that tweets from outside the country of an event post more informative information than those within that country.

Sources

Table.2 shows the numbers of sources, and their distribution in local and remote locations from all events. For each source we present the proportion in both location categories, we apply sign test (Gibbons and Chakraborti, 2011) to see whether the distribution of sources are different between the two locations. Also, we show the proportion of each source category across topics.

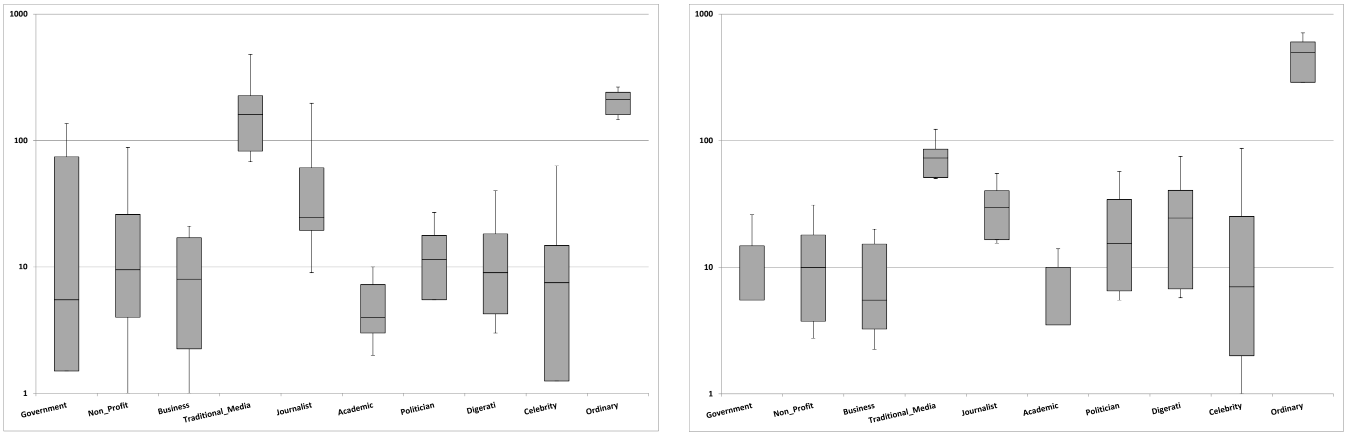
- *Government*: 3.4% of sources in all events are government, they count 4.2% of local and 2.7% of remote sources (the remote sources are found in crisis event to support a foreign country, or in "Rio2016 Olympic" supporting their national team) , p<0.05. As expected the government sources in the country of event are higher than those in outside. Government accounts in entertainment, politics and crisis were 3.3% 0.3% and 5.7%, respectively.

- *Non_profit organization*: 2.7% of all sources in this study are NGOs, 3.3% of them are locally and 2.1% are remotely, p>0.05. The distribution of these sources differ between topics: 4.1% in entertainment; 1.2% in politics and 2.3% in crises.

- *Business*: we found 1.5% are business sources, the local business sources are 1.3%, while the remote business sources are 1.6%, p<0.001. The entertainment events were include in the highest number of business sources 3% comparing to the politics 0.7% and crisis 1%.

- *Traditional and Internet media*: These form the second largest source by 22%. The traditional sources used locally is 16% compared to 27% remotely, p<0.001. The traditional sources in crisis events are 29%, entertainment events 22% and politics events are 11% . The number of traditional sources used by remote users is higher than those used by local people in almost all events: "the Cyclone Debbie" occurred in Australia 2017 was the event with greatest traditional media sources by 44%.

- *Journalist*: 6.5% of sources in all events are journalists, with 8% locally and 5%remotely, p<0.001. The journalists in crisis events were the largest group by 8%, followed by entertainment 6% and then politics 4%. Then number of journalist sources was the highest in two events: the Summer Olympics 2016 recorded 11% and Cyclone Debbie 2017 recorded 19%.



(a) Related and informative.

(b) Related but not informative.

Fig. 1: The informativeness status of each source type.

- *Academic and researcher*: 1% of sources belong into researcher and academic, and their distribution is the same 1% locally and remotely, $p>0.05$. The distribution of this source between the two locations is almost the same in all events in different topics.

- *Eyewitness*: In our results the eyewitness sources were the least estimated sources with <1%. That is because this type of source is most likely related to crises events with diffused and progressive nature (Olteanu et al., 2015).

- *Politician*: 3% of sources are politician, with local sources 3% and remote sources measuring 2%, $p<0.05$. Of course, the largest proportion of this source type will be in political events with 8% and the “US Presidential Debate” was the event with the largest political sources by 13% of the event sources.

- *Digerati*: the proportion of digerati source is 3% , and their distribution locally and remotely are 3% and 2% respectively, $p>0.05$. Digerati are those people with most closely related to technology and blogging 4% in both entertainment and politics, while it was only 1% for crisis.

- *Celebrity*: Celebrities count 3.4% of sources from all included events. 3% of local and 4% of remote sources are celebrities, $p>0.05$. As with digerati, celebrities as a source have larger proportion of users: 5% on both entertainment and political events of their sources compared to only 2% in crisis events.

- *Ordinary*: among all source categories, the ordinary source provides the largest sources 54%. The ordinary source locally is 57% and 52% remotely , $p<0.05$. The results indicate that ordinary individuals are the majority of sources in most of events. This finding concurs with those of (Lotan et al., 2011; Olteanu et al., 2015; De Choudhury et al., 2012). In time of crisis, 50% of sources are ordinary and there is a large difference in the distribution of these sources locally 54% and remotely 45%, compared to events in entertainment 52% and politics 67%. However, “Cyclone Debbie" was an event with few ordinary sources: 18%. “Cyclone Debbie” was expected for a while before it happened, and this affected substantial part of Australia.

Source vs informativeness: Figure.1 presents the interaction between the sources and the informativeness, for example, Figure.1a shows the sources distribution with the first informativeness category (Related and informative). While in Figure.1b, we see the distribution of the source in the second informativeness category (Related but not informative). Eyewitness wasn’t included due to small sample size (only 8). We can see that some sources like (government, non-government, Traditional media and journalist) were high in the informativeness categories, while other sources were high in the not informative category like (politician, digerati and ordinary). A source like (business) has the same ratio in the both categories.

Credibility

The results of the credibility annotations of the tweets were 44.13% (4236 tweets) “Definitely credible”, 54.5% (5229 tweets) “Seems incredible”, only 1.34% (129 tweets) “Definitely incredible” and <1% (6 tweets) “I can’t decide”. Next, since “seems incredible and definitely incredible” belong to incredible category, we combined them in one class called “incredible”, same to (Castillo et al., 2011). The “I can’t decide” tweets were discarded, so we end up with two credibility classes “credible and incredible”. There is impact of location on content credibility, 41% of local tweets were credible comparing to 48% remotely. On the other hand, 59% of local tweets were incredible, while it was 52% remotely. We can see that the content of the remote sources are more credible than the local ones.

Feature	Example
Function	it, to, no, very
Affect	happy, cried
Social	mate, talk, they
Cognitive (cogproc)	cause, know, ought
Perceptual (percept)	look, heard, feeling
Biological (bio)	eat, blood, pain
Drives	ally, win, superior
Relativity (relativ)	area, bend, exit
Informal language (informal)	damn, btw, umm
Authentic, Word count(WC), Qmark, Exclam, Hashtags and URL	count each category in a tweet

TABLE 3: The LIWC categories used to perform analyses on tweet content.

Linguistic Feature Analysis

Having studied the distribution of the sources and credibility between event, location, and topic, we next analyze the features of the tweet content. There are many types of features in Twitter, generally classified into content-based, social-based, and network-based features (Castillo et al., 2013; O’Donovan et al., 2012; Kang, O’Donovan, and Höllerer, 2012). Although credibility research in social media has grown rapidly, investigations into the linguistics features around credibility are few.

We used a tweet’s language as the indicator of credibility for many reasons. (1) The linguistic features of tweets have been found to be important predictor for credibility in social media events (Mitra et al., 2017b; Kwon et al., 2013), (2) The language of the tweets is influenced by user’s location (Cheng et al., 2010; Han et al., 2014) and that allows us to study impact language and location on credibility. (3) The text is available in all tweets whereas other features might be absent.

We used a sentiment analysis tool called Linguistic Inquiry and Word Count (LIWC), which is an application analyzing text by counting words of different psychological categories (Tausczik and Pennebaker, 2010). Its dictionary of categories include almost 6,400 words and word stems. Use of LIWC is common in social media data analyses (Nguyen, Gravel, Trieschnigg, and Meder, 2013; Golbeck, 2016), and for credibility research in specific areas such as (Gupta and Kumaraguru, 2012; Kwon et al., 2013; Zeng et al., 2016; Rosso and Cagnina, 2017; Mitra et al., 2017b). The categories we used are listed in Table.3 and have been used in the previous research. All of these categories except the last one in the table have subcategories, for example, affect feature is the main category, which includes two subcategories: positive and negative emotions. The negative emotion includes three subsub categories anxiety, anger, and sad. So in our analyses, we include general categories; the full list of both general and sub-categories are available at [5], the results were normalized[0-1]. We investigated whether any of the categories dominantly appear in such source, credibility level, location and topic.

Source and Linguistic Features Distribution

In this section we present the features across different sources and the source interaction with location and topic. For each factor and factorial interaction we showed the The Pillai’s trace result, which shows how all of these outcomes variables together differs between group such as source, credibility, location and topic. Then we follow that by investigating the individual Anova for each linguistics outcome.

Source: Since we have eleven different sources, we investigate how they differ from each other. In our analysis we include nine different sources. (W did not include eyewitness and researcher as there were not enough samples, 8 and 78, respectively). The Pillai’s trace was significant (p<0.001). The separate ANOVA showed significants effects with all features, (p<0.001), except percept and drives (p<0.05). This significant effect means that different sources have different styles of writing and the features distribution are different in their content.

5. http://liwc.wpengine.com

	Source vs Location		Source vs Topic		Source vs Location vs Topic	
	F	P_{value}	F	P_{value}	F	P_{value}
Function	0.927	0.493	4.864	0.000**	1.903	0.016*
Affect	0.164	0.995	2.749	0.000**	1.956	0.012*
Social	1.359	0.209	7.105	0.000**	2.633	0.000**
Cogproc	1.033	0.409	3.093	0.000**	1.016	0.436
Percept	0.369	0.937	5.676	0.000**	0.928	0.535
Bio	0.224	0.987	0.610	0.879	0.860	0.616
Drives	2.386	0.014*	2.796	0.000**	2.905	0.000**
Relativ	0.822	0.583	8.779	0.000**	2.193	0.004*
Informal	0.377	0.934	9.015	0.000**	2.952	0.000**
Authentic	0.462	0.883	6.083	0.000**	1.385	0.138
WC	0.672	0.717	4.866	0.000**	3.041	0.000**
Pronoun	1.026	0.413	4.135	0.000**	0.864	0.612
QMark	0.974	0.454	4.930	0.000**	1.363	0.150
Exclam	1.088	0.368	0.640	0.854	0.996	0.457
Hashtags	0.823	0.582	6.298	0.000**	1.494	0.092
URL	0.874	0.538	12.803	0.000**	2.837	0.000**

TABLE 4: ANOVA result for source interaction with other factors, * p<0.05, ** p<0.001.

Source *vs* Location: After we found there were significant differences in all features between sources, we studied the impact of location on a source's feature distribution. The Pillai's trace showed no significant interaction between source and location. Only the separate ANOVA showed "derive" had a significant interaction, see Table.4. This means that the same source type has a similar feature distribution regardless of the source's location.

Source *vs* Topic: The Topic factor influences the feature distribution across different topics. We studied how features distribution differs for the same source in different topics. Pillai's trace shows a significant result, p<0.001, there are significant interactions with all features (p<0.001), except in the bio and exclam categories where there were no significant interactions, refer to Table.4.

Source *vs* Location *vs* Topic: The impact of location on feature distribution of source was weak shown in the interaction between source and location. Here we include the third factor "Topic". In considering the interaction between source and location. The feature distribution differs considerably between topics: the three-way interaction shows a significant results in Pillai's trace, (V=0.09, F(256,9460)=1.691, p<0.001). Many features have significant interactions as in Table.4 shows. This result indicates that the feature distribution of source tweets across locations change according to different topics.

Credibility and Linguistic Features Distribution

In this section, we study how the used language different between the the credibility levels.

Credibility: We analyzed the distribution of features between the two credibility classes, credible and incredible.

	Credibility vs Location		Credibility vs Topic		Credibility vs Location vs Topic	
	F	P_{value}	F	P_{value}	F	P_{value}
Function	0.207	0.649	7.070	0.001*	13.602	0.000**
Affect	1.221	0.269	4.578	0.010*	11.765	0.000**
Social	4.216	0.040*	135.564	0.000**	0.842	0431
Cogproc	0.737	0.391	12.615	0.000**	5.331	0.005*
Percept	2.470	0.116	20.508	0.000**	0.514	0.598
Bio	0.573	0.449	4.879	0.008*	3.822	0.022*
Drives	7.927	0.005*	23.746	0.000**	9.494	0.000**
Relativ	2.763	0.097	105.807	0.000**	7.862	0.000**
Informal	3.429	0.064	34.155	0.000**	8.056	0.000**
Authentic	4.166	0.041*	52.025	0.000**	3.669	0.026*
WC	7.169	0.007*	23.504	0.000**	9.492	0.000**
Pronoun	5.834	0.016*	66.657	0.000**	6.798	0.001*
QMark	0.288	0.591	46.399	0.000**	0.683	0.505
Exclam	6.871	0.009*	2.521	0.008*	1.414	0.243
Hashtags	0.647	0.421	8.981	0.000**	2.375	0.093
URL	7.090	0.008*	28.862	0.000**	13.034	0.000**

TABLE 5: ANOVA result for credibility interaction with other factors, * p<0.05, ** p<0.001.

The Pillai's trace's result shows a significant effect of the credibility levels on the linguistics features distribution, (V = 0.184, F(16,9573) = 134.773, p<0.001). The two credibility levels are different in many features as shown by the ANOVA results, we found significant differences with all features (p<0.001) except "drives and authentic" were not significant. Moreover, occurrences of some features in the incredible class are higher than those in the credible class (Function, Affect, Social, Cogproc, Bio, Informal, Pronoun, Qmark, Exclam, Hashtag, (p<0.001). This indicates that credible content is not necessary connected with more features' presence, this confirm the finding made by (O'Donovan et al., 2012). On the other hand, only a few features (Percept, Relative, WC, URL, p<0.001) occurred in the credible class more than incredible class.

Credibility *vs* Location: In this section, we study the interaction between credibility and location. For example, the tweets of the same credibility class but from different location will share similar features distribution, or the location factor will effect on the features distributions.

	Credible			Incredible		
	Local	**Remote**	**P** two locations	**Local**	**Remote**	**P** two locations
Social	0.136	0.132	0.212	0.164	0.150	0.000**
Drives	0.100	0.089	0.000**	0.0.92	0.0.92	0.909
Authentic	0.186	0.174	0.193	0.175	0.192	0.041*
WC	0.548	0.561	0.004*	0.479	0.476	0.394
Pronoun	0.082	0.079	0.437	0.157	0.141	0.000**
Exclam	0.008	0.008	0.893	0.018	0.013	0.000**
URL	0.166	0.194	0.000**	0.125	0.136	0.016*

TABLE 6: Credibility vs Location, * p<0.05, ** p<0.001

The interaction between credibility and location is significant as Pillai's trace has shown (p<0.001). Individual univariate ANOVAs on the outcome variables revealed significant interactions on "social, drives, authentic, WC, pronoun, exclam and url", (p<0.05). Table.6 presents where is significant happened between credibility and location for the features found to be affected by the interaction. A bonferroni correction was applied to mitigate the multiple comparison effect.

The credible class has three features were impacted by location, "drive" was significantly higher in local location than remote, while "WC and URL" were higher in remote than the local location. On the other hand, location effect on five features in the incredible class, two of them "social and URL" were higher locally and the rest "authentic, pronoun and exclam" were the opposit. In both classes, Url was higher at a remote location than in local one. This indicates the remote authors share more Urls, regardless of their credibility.

	Entertainment			Politics			Crisis		
	Credible	**Incredible**	**P** two levels	**Credible**	**Incredible**	**P** two credibility	**Credible**	**Incredible**	**P** two levels
Function	0.275	0.339	0.000**	0.365	0.398	0.000**	0.323	0.354	0.000**
Affect	0.074	0.090	0.000**	0.090	0.102	0.007*	0.076	0.103	0.000**
Social	0.100	0.137	0.000**	0.187	0.156	0.000**	0.116	0.179	0.000**
Cogproc	0.063	0.109	0.000**	0.139	0.151	0.021*	0.083	0.128	0.000**
Percept	0.053	0.054	0.795	0.044	0.046	0.664	0.052	0.029	0.000**
Bio	0.017	0.029	0.000**	0.020	0.022	0.450	0.024	0.035	0.000**
Drives	0.098	0.078	0.000**	0.097	0.101	0.337	0.087	0.099	0.001*
Relativ	0.194	0.131	0.000**	0.136	0.139	0.582	0.230	0.140	0.000**
Informal	0.153	0.166	0.000**	0151	0.137	0.001*	0.142	0.172	0.000**
Authentic	0.126	0.181	0.000**	0.145	0.181	0.002*	0.269	0.193	0.000**
WC	0.551	0.446	0.000**	0.542	0.494	0.000**	0.570	0.493	0.000**
Pronoun	0.050	0.130	0.000**	0.138	0.161	0.000**	0.053	0.155	0.000**
QMark	0.009	0.048	0.000**	0.018	0.028	0.022*	0.006	0.065	0.000**
Exclam	0.010	0.021	0.000**	0.010	0.017	0.000**	0.002	0.008	0.000**
Hashtags	0.123	0.119	0.149	0.118	0.133	0.000**	0.104	0.114	0.001*
URL	0.224	0.140	0.000**	0.129	0.096	0.000**	0.186	0.154	0.000**

TABLE 7: Interaction between credibility classes and topics with different features, * p<0.05, ** p<0.001.

Credibility *vs* Topic: The Pillai's trace result show a significant interaction between credibility and topic with the features, (p<0.001). The separate univariate ANOVAs show that all features have significant interaction with credibility and topic. Table.7 shows that the features found to be important via the ANOVA test are different between credibility classes in different topics. "Crisis" was the most affected topic, then entertainment and politics. There are some features such as "WC and URL" are highly significant at credible class for all topics. Some features such as "Function, Affect, Cogproc, Pronoun, Qmark and Exclam" are high in the incredible class in all topics. Moreover, some features such as "Informal, Social" are high in incredible class in entertainment and crisis, while the opposite applied in the politics topic as it was high in the credible class. On the other hand, some features are different between the two credibility classes in some topics, such as "Bio" is high in incredible class for entertainment and crisis, and "percept" is high at credible class in crisis while no impact in politics.

Credibility *vs* Location *vs* Topic: In this section we study the three-way interaction between credibility, location and topic. Topic has been found to be important factor that can affect the features distribution in social media (Imran and Castillo, 2015; Boididou et al., 2014).

The Pillai's trace results present a significant interaction of the three factors' interaction, (V = 0.014, F(32,9575) = 4.115, p<0.001). This result shows that the features of different topics differ significantly when interacting with credibility and location. Separate univariate ANOVAs on the outcome variables show significant interactions on eleven features (Function, Affect, Drive, Relative, Informal, WC and Url, p<0.001.) and (Cogproc, Bio, and Authentic, p<0.05).

	Credible								
	Entertainment			Politics			Crisis		
	Local	**Remote**	**P** two locations	**Local**	**Remote**	**P** two Locations	**Local**	**Remote**	**P** two Locations
Function	0.278	0.272	0.633	0.366	0.363	0.848	0.349	0.297	0.000**
Affect	0.070	0.078	0.163	0.087	0.093	0.266	0.085	0.066	0.000*
Cogproc	0.060	0.067	0.378	0.137	0.140	0.671	0.095	0.71	0.000*
Bio	0.014	0.021	0.047*	0.022	0.019	0.414	0.023	0.024	0.848
Drives	0.105	0.090	0.007*	0.097	0.098	0.868	0.097	0.077	0.000*
Relativ	0.139	0.158	0.008*	0.136	0.135	0.967	0.239	0.220	0.004*
Informal	0.152	0.155	0.528	0.150	0.152	0.830	0.136	0.148	0.018*
Authentic	0.121	0.131	0535	0.141	0.148	0.657	0.295	0.243	0.000*
WC	0.531	0.571	0.000*	0.546	0.539	0.452	0.567	0.574	0.320
Pronoun	0.045	0.055	0.165	0.136	0.141	0.507	0.066	0.041	0.000*
URL	0.220	0.227	0.439	0.118	0.141	0.008*	0.159	0.213	0.000*

TABLE 8: Credible vs Location vs Topic, * p<0.05, ** p<0.001.

Table.8 shows the mean differences between the features in the credible class in different locations and topics. From the three topics, crisis was the most affected topic by location classes: it had nine out eleven features with significant differences between the two locations. seven of these features were high locally, and only two features were high remotely: "Informal and URL".

In the credible class, entertainment and politics were the least sensitive compared to crisis. "Bio, Relative and WC" at entertainment, "URL" at politics and "Cogproc, Informal and URL" at Crisis were significantly higher at remote than local locations. Interestingly, for politics and crisis, URL was significantly high at a remote location. This finding shows that "foreign" tweets (i.e from out-side the country of event) always include third party information.

Table.9 presents the mean differences of different features in the incredible class for different topics and locations. In this table, we want to see how tweets from different locations classified as incredible share the same or different linguistics features distribution.

Five features have significant differences between local and remote classes in politics comparing to four for entertainment and crisis. All features with significant difference in politics were locally higher than remotely; while the opposite at entertainment significant features except "Function was higher locally". In crisis the "Informal and Pronoun" were locally higher than remotely and the opposite with the other two features "Relative and WC".

In comparison between Table.8 and .9, we can realize the impact of location on the linguistic features distribution between the two credibility levels for the same topic. For example, there was almost no impact of location on politics at the credible class while in incredible class we found a big influence of location. The same finding in crisis with an opposite way, it was highly impacted by location in the credible class and we found less impact in the incredible class. The influence of location on entertainment is same in both credibility level with almost different features.

DISCUSSION

Around the world, many events occur daily, and social media has become an important platform where people read and share information about these events (Kwak et al., 2010). These events are combined from many different topics, regardless of event type or the users who contribute in these events, who can be close to or far from the location of the event. Information manipulated during the event varies in credibility and can include inaccurate and false information such as rumors.

In reviewing the literature, no data were found regarding the association between credibility and other factors such as location, topics, and linguistic features. Olteanu et al. (2015) found that sources and information type differ in different events, and location is found to affect user behavior in terms of language use when a tweet author broadcasts from the affected region at the time of the event (Morstatter et al., 2014; Poblete et al., 2011). The content features of tweets is found to be different for different credibility levels (Mitra et al., 2017b; O'Donovan et al.,

	Incredible								
	Entertainment			Politics			Crisis		
	Local	**Remote**	**P** two locations	**Local**	**Remote**	**P** two locations	**Local**	**Remote**	**P** two locations
Function	0.354	0.324	0.000**	0.412	0.384	0.015*	0.350	0.359	0.320
Affect	0.094	0.086	0.101	0.110	0.093	0.006*	0.100	0.106	0.233
Cogproc	0.107	0.112	0.430	0.156	0.146	0.209	0.124	0.131	0.322
Bio	0.031	0.026	0.054	0.021	0.024	0.496	0.035	0.036	0.696
Drives	0.073	0.082	0.028*	0.108	0.094	0.011*	0.096	0.102	0.170
Relativ	0.125	0.136	0.050	0.140	0.137	0.732	0.130	0.150	0.001*
Informal	0.158	0.174	0.000**	0.142	0.133	0.125	0.179	0.165	0.002*
Authentic	0.173	0.188	0.222	0.178	0.185	0.654	0.185	0.202	0.200
WC	0.441	0.451	0.114	0.519	0.469	0.000**	0.479	0.507	0.000**
Pronoun	0.130	0.130	0.918	0.179	0.144	0.000**	0.162	0.148	0.017*
URL	0.123	0.158	0.000**	0.103	0.090	0.128	0.149	0.160	0.130

TABLE 9: Incredible vs Location vs Topic, * $p<0.05$, ** $p<0.001$.

2012). However, no previous research has investigated how the distribution of information sources differ within and outside the country of event, and how the author location can impact on linguistic features distribution among credibility level.

Our study found that the location of an author influences the distribution of sources that contribute at the time of an event, and this influence also impacts on the credibility distribution over two different locations. As we see in Table.2 the distribution of many source types differ across locations. This finding can impact on the users' classification models (De Choudhury et al., 2012) where they do not consider the source based on location. For example, during a crisis, it is necessary to define the type of users along with information categories, as in (Imran and Castillo, 2015).

Table 2 shows the source distribution locally and remotely, and Figure 1 presents the informativeness status of different sources. These type of results can provide an expectation of what type of sources and informative status that will contribute in time of event from different locations which can be beneficial to many people. For example, the stakeholders like the decision making people always turn to Twitter when they need to take a decision (Olteanu et al., 2015). Also, it is a common practice for journalists to deal with huge amount of data manually in order to make a news story (Dailey and Starbird, 2014; Heravi and McGinnis, 2015), it is important for them to know the information types that Twitter might provide in different events.

We believe that our research presents the importance of the textual features to identify the credibility in social media, and also shows the influence of author's location on the way of writing. So, these findings can inform wide range of systems, for example, in news reporting systems which try to reach to a credible source in time of event like a journalist or eyewitness (Diakopoulos et al., 2012), or the system for fact checking which differentiate between high and low credible content (Popat et al., 2017). While we don't claim that a stand alone system with only textual features can be set out for rumor detection, but they can be used as extra credibility signals.

Most of the current works that attempt to classify credibility in social media like Twitter uses features beyond the content of the tweets, usually use the social based and network-based approaches (Castillo et al., 2013), temporal approaches (Mitra, Wright, and Gilbert, 2017a), or popularity of tweets (Mendoza et al., 2010). As all of them are useful, all of the previous features need sometimes after posting the content to be collected (Zhao, Resnick, and Mei, 2015). Using the linguistic features as a marker is a key factor for identifying incredible content, preventing a possible damage that can occur (Bovet and Makse, 2018).

Additionally, the current credibility prediction models face difficulty when they are applied to different events (Boididou et al., 2014; Aker et al., 2017), as the performance accuracy is overestimated. Our results found that there are significant differences of content of the same credibility level and topic when generated from different locations. For example, Table 8 shows many differences of the linguistics features of the same topic but with different location. This finding shows the impact of location on features distribution, which might indicates some ambiguity behind the credibility classifiers variance across topics.

When we look at features proportions of the tweet, we can see some commonalities regardless of credibility. For example, the URL features highly in a remote location in credible and incredible level. This suggests that remote users always share third party information as an external source in their tweets: using URL as an indicator of credibility at the time of an event might not be very accurate because that might relate to the place of the author more than to credibility. However, (Popat et al., 2016) shows the impact of the web source reliability hosting such article on increasing the performance of the credibility model prediction, the same approach can be used in the URLs within social media.

The impact of location on the used language for the tweets of the same credibility level. For example, Table.9

shows that incredible tweets don't always have the same features when generated from from different locations. This is a bit different to (Kwon et al., 2013), as they found that rumors always share the same linguistic features in different topics. On the other side, there are many significant differences between the two location in credible level in topic like crisis, while there was less impact of location on incredible tweets for the same topic. This is an interesting finding, which mean the credible tweets have different characteristics when generated close from the affected region. This is might have an impact on the eyewitness identification research (Morstatter et al., 2014).

As we found that incredible information shares the same linguistic features in social media, they share the same behavior in different contexts like financial fraud and web pages. Humpherys, Moffitt, Burns, Burgoon, and Felix (2011) investigated the text of hundreds of financial disclosures and found that fraudulent disclosures use some linguistic features more than non-fraudulent ones such as number of words. The researchers were able to achieve high classification accuracy using linguistic features. On the other hand, in judging web site credibility, Wawer, Nielek, and Wierzbicki (2014) used linguistic features to predict the credibility of web pages. They found that trusted words are associated with government web pages for example. The researchers' classification models achieved accurate results.

Findings have shown how textual features have the power to assess credibility, comparing to other features like visual ones, which can lead sometimes to wrong judgments by users (Zubiaga and Ji, 2014). So, implementing a credibility model which can handle the text of different contexts will be beneficial.

In this research we mainly focus on the source and credibility of the content, regardless of information type. The information may be credible but not highly informative, so future research could consider the content informative as (Kumar et al., 2013) and credibility, and study the credibility with time as in some cases like crisis time is very important factor. If we know that a very few users generate most of the social media content, for example, 2% of Twitter users generate fifty percent of the tweets (Baeza-Yates and Sáez-Trumper, 2015). That adds further more challenge to find informative and credible source at the same time because of scarcity of rare in the information sources.

Conclusion

In this work for a diverse set of events, we have particularly consider the impact of location on information source and credibility level in social media. By developing a hypothesis driven by previous research that location of users affect their behavior, we included the location of both event and author in our study to clarify their impact on credibility status. The research questions that we investigated in this paper were:

- What are the types of sources expected in different events from both in- and outside the country of events?
- How linguistic features differ among sources of different type, credibility level, and location?

We found that distribution of some sources differ between locations significantly. For the second research question, we found the tweets of the same credibility level have different linguistic features based on their distance from an event and the topic of an event. In future we will include other features in way to have a complete list of common and different behaviors between sources across locations. Moreover, information type with users location can influence content credibility and this is part of our proposed future research.

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APPENDIX

Description of the task

Informativeness

Please read the following tweet, and check the link inside it if needed, and select the most appreciate category:

- The tweet is related to the event and informative, if it includes information about the event that useful and helps you understand what happened.
  - @CNN: The Oscars werent afraid to get political https://t.co/pE5zvwe6me https://t.co/XK2FdGvTF8
- The tweet is related to event, but it is not informative, if it mentions to the event but it isn't help you understand what happened.
  - Did Antoine Fuqua just direct a Walmart short film or am I crazy? Oscars2017
- The tweet is not related to the event.
  - Thanks so much i love you Oscars2017 ??
- The tweet is not applicable, has some problems like the tweet is not readable, or other issues.

Source

Please read the tweet posted at the time of the Cyclone Debbie 2017 in Australia, check the link inside the tweet if needed, and select the most appreciate source of information as:

- A government: information published by the official, such as, police, hospitals,etc.
  - @BOM_Qld: Radar loop from the #Mackay radar shows the eyewall and eye of #CycloneDebbie as it tracks towards the coast.
- A non-profit organization: information published by administration of non- governmental and not for profit organizations such as Red Cross, UNICEF, etc.
  - @RACQOfficial: Don't risk your safety, stay off the roads. #FloodedForgetIt #BigWet #bnetraffic https://t.co/jccsBrBrpb
- A business: information published by profit-related business and enterprise.
  - @AEMO_Media: We are working with @PowerlinkQLD to prepare for TC Debbie and keeping a close eye on the situation. #CycloneDebbie
- Traditional and/or Internet media: information that published by sources news organizations, web blogs, such as TV, radio.
  - @ABCemergency: All #Brisbane schools to close today as former #CycloneDebbie heads south #bigwet
- Eyewitness: information reported by an eyewitness to the event, or from his family, friends, etc.
  - So our fence has come down. Tried to save it but it's too windy too strong. https://t.co/fp69EZB2QK #Mackay #bowen #CycloneDebbie
- A journalist: associated with an organization or a freelance journalist.
  - #CycloneDebbie blew the feathers off a cockatoo. https://t.co/hmELUDw65S
- Academic, researcher or specialist: an individual who is working in a university or think-tank.
  - @climatrisk: Stay safe FNQ a real frightnener. Hope everything is battened down #CycloneDebbie https://t.co/Ea9z5ASZMl
- Politician: an individual who is working in government.
  - @AnnastaciaMP: #CycloneDebbie is now crossing the coast between #Bowen and #AirlieBeach. Stay safe everyone. https://t.co/9u2mY2zguY
- Digerati: an individual who is popular in area of social media and technology.
  - Absolutely APPALLED at @Avis car hire charging us $158 to extend our car rental as #CycloneDebbie is stopping us from reach
- Celebrity: individual who is famous for any reason, singer, actor, media presenter, etc (not in technology).
  - The team at SDBHQ, and the entire #BlakeArmy is thinking of everyone in North Qld. Stay safe Queenslanders, SDBHQ xo
- Ordinary individual: users on Twitter posting updates on their daily life, or non-identified sources.
  - Good luck North Queensland. Batten down the hatches. Don't drive in flood waters. Look after each other! STAY SAFE! #cyclonedebbie

All the included sources in this studied like organizations (non-profit, business, etc) have included their profile locations. The same source type can be local and remote of such event at the same time. For example, "the Red Cross" was engaged from both locations in "Cyclone Debbie Australia":

- Australian Red Cross (local) (@RedCrossAU: Affected by #CycloneDebbie? Let your family know you are ok. Register at https://t.co/NruW5WjXtO https://t.co/EGChoXeh9X).
- Papua New Guinea Red Cross (remote) (@PNGRedCross: High tide in 5 hrs. #RedCross running evac centres. The latest from #TVNZ KimberleeDowns #CycloneDebbie #TCDebbie https://t.co/BvLXnOL7kN).

The same thing for other organizations like government, a government account sometime engage in an international event, for example:

- This tweet about 'Rio2016" from "Road authority" of Uganda government located at (Kampala Uganda): (@UNRA_UG: Wishing #TeamUganda at the #OlympicGames all the entire best! We're your fans and you have our support! Cheers #UGA #RIO2016).
- This tweet about "Cyclone Debbie Australia" from "Met Office Storms" of Uk government located at (Exeter, UK): @metofficestorms: Rainfall radar image of #CycloneDebbie which is slow moving off the coast of #Queensland. Peak wind gust 117 mph at Hamilton Island.
- This tweet about "Italy earth quack" from "Italy UN" of Italy government located at (New York): @ItalyUN_NY: At least 241 dead & 2.5k displaced so far after #ItalyEarthquake. We are very grateful for the solidarity in #NYC
- This tweet about "Rio2016" from "Dept of Sport" of Indian ministry of youth located at (India):@IndiaSports: Indian players / teams event schedule, fixtures for #RioOlympics on Day 4. #Rio2016 #Olympics https://t.co/AvwhX9haVe

The same apply for traditional media, all the included traditional media sources have included their profile's location, for example:

- This tweet from "BBC" at "Rio2016" and their profile location is (London, UK): @BBCWorld: If Michael Phelps was a country https://t.co/wTxvBP8CL5 #Rio2016.
- This tweet authored by "The New Your Times" about "oscar2017" and their profile location (New York City): @nytimes: The #Oscars audience wonders: Who is Gary from Chicago? https://t.co/HDbLOGzn6z.

Credibility

Please read the tweet posted at the time of "the event name", check the link inside the tweet if needed, and determine the credibility level of the tweet as:

- The tweets is definitely Credible.
- The tweet seems Incredible.
- The tweet is definitely Incredible.
- I can't decide.