Impact of Rumor Messages in Social Media

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Abstract. As social media continues to grow, the connectivity between individ- ualsandorganisationsbecomestighter,andtheavailabilityofdatabecomesmore immediate, constant and abundant. Aside from conversational chat, social media platforms are being used to share relevant information and to report news. As information credibility becomes an increasing concern, there rises an important question regarding the impact of a rumour. We address this challenge, focusing on rumour impact on social media. In this paper, we measure the impact of a given rumour, impact that will be calculated by a formula we suggest, represent- ing social media user engagement measures. Our results indicate that rumoursdo differ in terms of impact, with some rumours representing higher impact. Analy- sis is then conducted in an attempt to understand why some rumours are more impactful thanothers.

Keywords: Rumours, Fake News, Rumour Detection, SocialMedia, Twitter, Rumour Impact

1 Introduction

The explosion of social media has characterised Internet growth in recent years. Some originalsocialnetworksincludedAOL,chatroomsandLiveJournal.Whilemanyhave come and gone, some more notable than others, social networking is no passing trend, with market leaders, such as Facebook, Twitter and WhatsApp, boasting billions of users. Social networks provide an online voice to just about anyone. Users can publish their thoughts, opinions and ideas, through online communities. Today's Internet is flooded with such user-generated content, and opinionated material in particular[1].

Rumoursareprevalentinoursociety.Fromthehometotheonce,theyinfluenceour beliefsandbehaviourstowardothersandgenerallyaffectthewayweseetheworld[2]. There is a myriad of research around rumours in a variety of fields, primarily from a psychological perspective [3-5]. However, the advent of the Internet and social media, offers opportunities to transform the way we communicate, giving rise to new ways of communicating rumours to a broad community of users [6]. Moreover, information spreadonsocialmediahasahighpotentialforimpact,duetothereal-timenatureof

these media. As a result, news organisations are losing their audiences to lies and un- verified stories, costing them both money and reputation. Misinformation can also en- danger life if adopted by individuals during times of crisis.
There is an increasing need to interpret and act upon rumours spreading quickly through social media, especially in circumstances where their veracity is hard to estab- lish [7]. Analysing the potential impact of rumours is often as important as checking theirtruthfulness.Rumourimpactanalysisusuallyfocusesonimpactonrealworldsit- uations such as in crisis situations [8-10] and the impact rumours have on individuals [11-13].However,thereisaninherentgapintheStateoftheArtrelatedtothestudyof rumourimpactonsocialmediaitself.Therefore,thereexistsanopportunitytoformally measure the impact of rumours on social media, and we endeavor to address this chal- lenge. An impactful rumour is one that has potential to ferociously penetrate its social network, through high volumes of shares and user uptake or belief. We consider user engagements as a means for measuring impact and determine impact as an accumula- tive score of such engagements, e.g. favourites and retweets in the case ofTwitter. In our study, we consider an important property of rumours, the temporal character- isticthatexists,relatedtotherumour'slifetime.Duringthislifetime,therumourspreads andisreceivedbyindividualsthatcomeacrossit.Manystudieshavebeendonefocus- ing on the long term spreading of rumours, and the speed of spread [14-16]. Some ru- mours penetrate their network quickly. They appear in a moment and are quickly re- ceived and known to many. This immediate potential, characteristic to a rumour, moti- vates our study. We collect a snapshot representation of rumorous messages, a given set at one moment in time. Analysis is conducted immediately, and at this immediate time only, rather than at later intervals, or within a longer time frame. This lends to automatic and real-time impact assessment of rumours in socialmedia.

2 RelatedWork

Weareinterestedinunderstandingaspeci_ctopicrelatedtothebehaviourofrumours. Psych logical research has been cyclical for many years, while technological research is of very recent interest, following the birth and success of the Internet and social me- dia,givingrisetonewwaysofcommunicatingrumourstolargeaudiences.Theability to understand and control the type of information that propagates social networks has become ever more important [17], and has resulted in plentiful research conducted re- lated to rumourbehaviour.

Historical Rumour Behaviour Research

Rumour research is a topic of historical interest, as it is a problem central to human psychology. [18] mentions the burst of interest that arose during World War II, which saw seminal work completed in [3]. The next decade witnessed some developmental research[19,20].The1960sand1970ssawanothercycleofinterest,withmanyfamous publications[21,22].Morerecently,therehasbeenanotherroundofrumourbehavior

research[23,24].Worksmentionedareofapsychologicalandsociologicalbackground, and the intent in mentioning them is to elucidate the importance of rumour study his- torically.

Temporal Patterns in Rumour Frequencies

The problem of modelling frequency profiles of rumours in social media was intro- duced in [25]. Through their methods, the authors were able to recognise and predict commonly occurring temporal patterns. Text data from social media posts also added important information, a motivation and aid for much rumour related research, includ- ing our study. Another study concerned with the temporal nature of social media in- volvedmodellinghashtagfrequencytime-seriesinTwitterviaaGaussian-process[26]. Both studies discussed, aim to help with identifying those rumours, which, if not de- bunked early, will likely spread very fast. This is a common concern of much research in rumour dynamics, and is a motivating factor for our specificresearch.

Rumour Impact

Studieswithinrumourimpacthavelargelyfocusedonthewaysinwhichrumoursaffect people, their beliefs, and various aspects within their lives. In [11], the impact of iden- tification and disidentification on rumour belief is examined, with results indicating that a variation in identification, influences the impact of a rumour on an individual's beliefs.Inanorganisationalorpoliticalcontext,rumourscanbeespeciallyproblematic for a company's, party's, or candidate's reputation if they contain negative information about the object of focus [11]. During organisational change, rumours of layoffs, clo- sures,ormergersmaycreatemistrustandlowermorale[12].PostingURLsindisaster-relatedtweetsincreasedrumour-spreadingbehaviour[27].Rumoursinrelationtostock markets,suchascorporateacquisitionannouncements,earningexpectations,underval- ued stocks, can result in significant share price changes[28-30].

3 Rumour Gathering & FeatureRetrieval

Weadopttheapproachasimplementedby[31],involvingrumourdetectionbysearch- ing for a handcrafted regular expression relating to a known rumour, a rumour deemed as such by complying to our formal definition. Known rumours that comply with our rumour definition can be used in rumour search. Choosing keywords, the words asso-ciatedwiththecontroversialaspectsofarumour,aregularexpressioncanbegenerated and submitted to the message source (e.g. the Twitter public stream), for the retrieval of messages associated with the rumour. Forexample:

Rumour: "The movie 'The Notebook 2' has started filming."

Keywords: 'Notebook 2', 'Notebook sequel'

Regular Expression: Notebook & (2 j sequel)

In this example, messages related to the rumour, "The movie 'The Notebook 2' has started filming.", are expected to be collected. To collect messages related to another

rumour, the same process is followed - choosing keywords and crafting a regular ex- pression. This creates unique groups of rumorous tweets relating to specific rumours. We favour this detection approach, over others such as [32] and [33], due to our re- quirement of individual sets of rumours, with which impact will be measured and ana- lysed. Such an approach provides us with natural separation of rumour sets, each com- plying to our rumour definition.

4 RumourDetection

Rumours are detected and gathered from the Twitter API, necessary filtering is per- formed, and metadata related to these tweets is parsed.

Gathering

The *Gathering* process submits query strings to Twitter's Search API, queries that re-flectregularexpressions,constructedofkeywordsspecifictothedesiredrumour.There are pre-processing requirements that are met prior to rumour search. Firstly, the tool must be capable of handling many different search requests, and keeping rumour sets organised, i.e. separated in their applicable sets. Retweets are excluded to allow for a diverse set of tweets relating to the rumour in question. Finally, we avoid searching in the same time range more than once, i.e. searching only for tweets older than the last setreceived,toavoidreceivingthesamesettimeandtimeagain,andtogatherthemost advantageous snapshot, avoidingduplicates.

Rumourswerechosenandcollectedatonepointintimebetween FebruaryandApril 2016, by the detection approach discussed in the previous section (IV). Each query represents a known rumour, fitting to our rumour definition, introduced in section II. We are interested in rumours of the day, rumours that were circulating stories at the timeofsearch.Toavoidrumoursandbuildasnapshot,circulatingrumourstoriesfitting our rumour definition were found using online resources, similar to the approach adopted in previous work [31], sources such as, Snopes.com[1], starcasm[2] and CELEBUZZ[3].

We selected Rumour Targets based on present regular expression queries used for detection and the number of tweet collected in each rumour set. Each set corresponds to a rumorous story chosen from an online source. For example, 'germany pork' relates to the rumour, "Germany bans pork under Sharia law"[4]. The size of the rumour sets varies greatly. This has added complexity to the research, where the temporal charac- teristicsofrumours,andthedecisiontocollectinasnapshotmethoddisallowingalarge

[1]http://www.snopes.com/
[2]http://starcasm.net/
[3]http://www.celebuzz.com/
[4] http://www.snopes.com/germany-bans-pork-under- sharia-law/

dataset built over time, has affected set sizes. The mean size of rumour sets is noted below,alongwiththestandarddeviation.Thelargestandarddeviationreflectsthewide spread of set populationsizes.
Themeansizeoftherumoursetsis139,andthestandarddeviationinthesizeofthe rumour sets is156.
The next step is to collect the metadata required, properties used for impact meas- urement,andothermetadatapropertiesthatareinvestigatedasbeinginfluentialtosuch measurements.

Feature Retrieval

The *Feature Retrieval* process takes each Tweet object received from the Search API, funnelled through the Gathering process, and parses the metadata required for impact scoring, namely retweet count and favourite count, as required by our formula, (1), section II, page 2. It also obtains those features required for subsequent impact investi- gation,thelistofotherfeaturesforanalysisaspotentialinfluencerstoourimpactmeas- urement. After preparation of impact measurement properties and impact analysis fea- tures, the data are organised together, along with the associated tweet ID andtext.
Table I details the user engagements by which impact is formalised and de_ned. Table II details Message-Based Features and table III details Account-Based Features
– count or averages where applicable. While features were gathered for each rumour set listed in table I, the data presented in these tables (I, II, III) only represents half of the sets gathered, the 13 that are larger insize.

Impact Measurement Variables

To measure impact, we implemented formula (1), section II, requiring the following variables:

- RT: Accumulative#Retweets
- F: Accumulative#Favorits

Table 1. Table captions should be placed above thetables.

Rumour	Size	Retweets	Favourites
evans_arrested	*287*	272	513
ford_trump	*124*	104	105
germany_pork	*596*	605	493
gilt_shot	*131*	45	80
khloe_parentage	*100*	165	319
kim_divorce	*98*	64	70
kim_doppelganger	*101*	7	30
kylie_jenner_lips	*334*	64	248
obama_pay_incr	*217*	501	416
rob_blac	*184*	54	103
soros_ferguson	*183*	389	281
spaceballs_sequel	*142*	18	99
splenda_unsafe	*594*	370	420

Table 2. Table captions should be placed above thetables.

Rumour	Size	HT	M	URL	UM	R	AC	?	!	Q	Av.L
e_a	*287*	83	102	280	12	0	0	87	0	1	105
f_t	*124*	18	12	110	71	0	0	24	0	8	97
g_p	*596*	156	79	569	115	0	0	100	0	17	107
g_s	*131*	27	10	116	26	0	0	0	0	6	114
k_p	*100*	51	51	90	2	0	0	0	0	0	107
k_d	*98*	27	38	96	8	5	0	0	0	2	122
k_do	*101*	12	30	92	5	0	0	0	0	6	123
k_j_l	*334*	114	50	289	17	0	0	199	0	5	109
o_p_i	*217*	24	13	128	80	0	0	100	0	10	117
r_b	*184*	43	50	179	26	0	0	0	0	0	127
s_f	*183*	31	13	169	32	0	0	0	0	2	107
s_s	*142*	3	0	114	6	0	0	0	0	0	100
s_u	*594*	173	73	550	114	0	0	197	0	11	98

Message-Based Features

These features are collated, parsing properties of the tweet itself, and are used to deter- mine if composition features inuence the impact of a rumour on social media.

- **HT:** #tweets in the set containingHashtags
- **M:** #tweets in the set containingMedia
- **URL:** #tweets in the set containingURLs
- **UM:** #tweets in the set containing UserMentions
- **R:** #tweets in the set containing the word'retweet'
- **AC:** #tweets in the set entirely AllCaps
- **?:** #tweets in the set containing a QuestionMark
- **!:** #tweets in the set containing an Exclamation Mark
- **Q:** #tweets in the set containing aQuote
- **Av .L:** Average Length of the tweets in theset

Account-Based Features

These features correspond to account properties of the tweet's

composing author, and are used to determine if characteristics of the author and their account, influence the impact of a rumour on social media.

- **Y:** Average Creation Year of the accounts associated with theset
- **FO:** Accumulative#Followers
- **FR:** Accumulative#Friends
- **S:** Accumulative#Statuses
- **DP:** Accumulative #DefaultPro_les
- **DA:** Accumulative #DefaultAvatars
- **V:** #Veri_ed accounts associated with theset

Table 3. Table captions should be placed above the tables.

Rumour	Size	Y	FO	FR	S	DP	DA	V
e_a	*287*	2013	3011983	715931	16447580	159	3	9
f_t	*124*	2011	767542	361021	3485078	41	6	2
g_p	*596*	2012	2226140	1066305	31710003	248	23	2
g_s	*131*	2011	634807	302507	3604420	37	4	7
k_p	*100*	2013	140413	60857	6490747	74	7	0
k_d	*98*	2014	315434	250111	4427747	57	0	0
k_do	*101*	2013	969098	205493	6480350	46	0	5
k_j_l	*334*	2013	14089288	411349	28255599	186	32	13
o_p_i	*217*	2012	501664	376337	3963232	113	10	2
r_b	*184*	2013	7778250	756902	15792014	74	2	7
s_f	*183*	2011	501124	394641	11184692	61	11	1
s_s	*142*	2014	322135	83652	2528130	15	5	0
s_u	*594*	2012	11174880	1033550	40865809	250	17	10

5 Impact Measure RumourDetection

The rumour sets gathered through the Gathering process, section V(A), have allowed the detection and collection of rumorous tweets, supplying a rumorous corpus. The Feature Retrieval process, section V(B), carried out the task of building the data re- quired for impact measurement, and obtained a selection of tweet property data which would allow for further analysis.

It is worth noting the observations that are apparent from this raw data. The largest rumour set collected is germany pork, the set related to the rumour, "Germany bans pork under Sharia law". This set has obtained the highest impact score of 1098. How- ever,themeanimpactoftherumourtweetswithinthesetisonly1.84,whichisnotone of the highest mean impact scores obtained. Therefore, it can be argued that this high impact score is largely depending of the set size, with more tweets lending to a higher accumulative score. Thus, we cannot simply analyse impact scores on their own. The meanimpactscoresareimportant,astheysupplyanindicationoftherespectiveimpact ofeachrumourtweetwithineachset.Themeanscoresallowusdatathatiscomparable.

As the snapshot method was followed in rumour gathering, all tweets related to a rumourwerecollectedatonetimeonly,i.e.wedidnotconductnumeroussearchesover anumberofdays,forexample.Adirectresultofthisisthatthetimingofarumourhas had a great effect on the amount of tweets that were available for retrieval. To put this in simple terms, if rumour A became topical only today, and rumour B became topical 3 days ago, it is very likely that there will be a lot more rumour tweets to collect for rumour B, if we perform our search today. Interestingly, khloe_parentage is one of the smallest sets of rumours collected, but represents the highest mean impact score, re- flective of the high impact of the rumour tweets within theset.

Statistical Significance inImpact

A t-test is a statistical hypothesis test that can be used to determine if the variances of two sets of data are significantly different from each other. Rumour sets that are statis- tically different from each other can be taken as statistically significant, rejecting the null hypothesis[5]. Therefore, the means of the rumour populations are not equal, with one representing high impact, in contrast to the other set.

T-tests were conducted on impact scores (Table IV). A random sample, of size 40, was chosen for all tests. The decision regarding 40 as the size of the random sample wasmadeinanattempttodetectthemostmeaningfuldifferenceaspossible,withcon- sideration of the varying set (total population)sizes.

By performing t-test analyses, we endeavored to and statistical significance in the data, allowing us to ag rumours that were higher in impact compared to others. There- fore, the null and alternative hypotheses were as follows:

H0: There is no significant difference between specific populations, or no difference among rumour sets, regarding their impact.

H1: There is significant difference between specific populations. The rumour sets are different in terms of impact.

As is to be expected, with data as flimsy as that associated with rumours, and under the limits of our snapshot method, statistical significance was not found in a large pro- portionofcases.However,thestudywassuccessfulinobtainingstatisticalsignificance in some cases, by t-test analyses, highlighting those rumours that were statistically dif- ferent in term of impact, granting us the ability to perform furtheranalysis.

Once again related to the changeable nature of rumours, we were cautious in imme- diately accepting results obtained through t-test analyses. The t-test calculation is re- flective of the sample populations it is presented with. Being aware of how flimsy ru- mourdatais,andhowvaryingindividualimpactscorescanbe,manyt-testsonpairsof

samples were performed, which at first appeared to be statistically different, but for which assurance was needed.

Asthevariancesdiffered,H0wasrejectedforcertainrumours,thosedetailedintable IV,afterreceivingsimilart-valueresultswithmanyt-testcalculations,withinthesame rumour populations, selecting different random sample sets. Table IV presents exam- ples of those rumours where statistical signifcance was found, with a t-value and p- value, representative of one of the t-test calculations associated with the pair. Rumour A is of higher impact than RumourB.

Degrees of Freedom:
*(sample size * 2) - 2 = (40 * 2) - 2 = 78*

SignificanceLevelα:
0.05, the most widely used significance level.

Table 4. Cases for which the null hypothesis can be rejected, where P _ 0.05.

Experiment	Rumour A	Rumour B	T	P
A	*kim_divorce*	*rob_blac*	2.36	0.02
B	*kim_divorce*	*spaceballs_sequel*	2.24	0.03
C	*obama_pay_incr*	*rob_blac*	2.34	0.02
D	*obama_pay_incr*	*spaceballs_sequel*	3.6	0
E	*soros_ferguson*	*rob_blac*	2.02	0.047
F	*soros_ferguson*	*spaceballs_sequel*	2.27	0.03
G	*evans_arrested*	*kim_doppelganger*	2.39	0.02

Given a t-value and the degrees of freedom, a p-value is obtained. The p-value is comparedtoα.Asmallp-value(0.05)indicatesstrongevidenceagainstthenullhy- pothesis, so it is rejected. Following our comprehensive study, and with the data we have presented, we conclude that there exists statistical difference between the impact of respective rumours. We must now make attempts to understand why this difference exists,highlightingpotentialfactors,whichsupply/inuencethisdifference.

Features Influential to Rumour Impact on SocialMedia

Recall in section V(B), we gathered Message-Based Features and Account-Based Fea- tures, through the feature retrieval process. After observing the raw data collected, it was decided to reduce the number of features that would be taken any further through the process of impact analysis. The key objective to the following analyses is to those features that are influential to rumour impact on social media, i.e. contributing to a higherimpactscore,obtainedthroughtheformulawesuggest,formula(1).Thefeatures that will not be considered are asfollows:

Message-Based Features
Word 'retweet', All caps, Question mark, Exclamation mark, Quote - Eliminated due to minimal existence in the dataset.

Account-Based Features
Year, Default Proble, Default Avatar - Eliminated due to minimal / insuficient existence in the dataset.

Theapproachtakeninfeatureanalysisistotakeeachfeaturethatwillbeinvestigated individually.Wepresentthoserumoursonceagain,thoseincurringstatisticaldifference related to impact, and compare each feature's existence in the higher impact rumour compared to that of lower impact. Those features that are more substantial in higher impact rumours can then be concluded as contributing / in toimpact.

Features Influential to Rumour Impact on SocialMedia

We investigate whether account properties of the composing author influence rumour impact on social media. The features that are analysed are followers, friends, and sta- tuses, representing how popular and active the authors are. The inuence of verified ac- counts is also investigated, those accounts belonging to key individuals that Twitter have signified by placement of the verified badge. These accounts, belonging to politi- cians, celebrities, journalists tend to have many followers, and attract significant user attention.

Table 5. Account-Based Features, Higher Impact (HI) vs Lower Impact (LI) (Higher count between HI & LI in bold)

	P		Rumour	FO	FR	S	V
A	0.02	HI	*kim_divorce*	**365**	**926**	**16310**	0
		LI	*rob_blac*	222	19	12068	0
B	0.03	HI	*kim_divorce*	**752**	**1761**	**1764**	0
		LI	*spaceballs_sequel*	113	242	1366	0
C	0.02	HI	*obama_pay_incr*	**132**	**327**	**2050**	0
		LI	*rob_blac*	68	202	579	**1**
D	0	HI	*obama_pay_incr*	**7233**	**4048**	**4372**	**1**
		LI	*spaceballs_sequel*	82	307	1454	0
E	0.047	HI	*soros_ferguson*	292	178	**99898**	0
		LI	*rob_blac*	**5148**	**4659**	3537	**1**
F	0.03	HI	*soros_ferguson*	**965**	**881**	**16697**	0
		LI	*spaceballs_sequel*	95	264	1674	0
G	0.02	HI	*evans_arrested*	**793**	**916**	**85613**	1
		LI	*kim_doppelganger*	260	231	4097	1

Table V presents results, detailing feature counts in those rumours deemed higher impact versus those deemed lower impact, related to the seven experiments (table V) for, which statistical difference was found between rumours in terms of impact score. Thefollowingsectionsinvestigateeachfeatureindividually,furtherdescribingthefea- ture data presented in tableVI.

Followers

Weinvestigatewhetherthenumberoffollowersassociatedwiththecomposingauthors involved in a rumour, has an effect on the impact of the rumour. Followers are those people who have connected with a Twitter account. Someone who thinks you're inter- esting can follow you. Following is not mutual, you don't have to followback.

Out of the seven experiments where statistical difference was found, highlighting the higher impact of one rumour compared to another, six cases have higher follower counts in the higher impact rumour than for the lower impact rumour, see table V, col- umn 'FO'. Experiment E is the one exception where the lower impact rumour has more followers in the set than the higher impact rumour. Six cases out of seven represents 86%.Underthespecificconditionsofourexperiments,itcanbeconcludedthatfollow- ers in the impact of arumour.

Friends

We investigate whether the number of friends (followees) associated with the compos-ingauthorsinvolvedinarumour,hasaneffectontheimpactoftherumour.Friendsare those people you have connected with, the people you follow, who do not necessarily follow you back. A result similar to Followers was obtained. Six cases out of seven, 86%,havehigherfriendscountsinthehigherimpactrumourthanforthelowerimpact rumour,withExperimentE.Underthespecificconditionsofourexperiments,itcanbe concluded that friends influence the impact of arumour.

Statuses

Weinvestigatewhetherthetotalnumberofstatuses(messages/tweets)thattheauthors have composed in the lifetime of their accounts, has an effect on the impact of the rumour. In all seven experiments where statistical difference was found, highlighting the higher impact of one rumour compared to another, total statuses counts associated with the authors are higher in the higher impact rumour compared to the lower impact rumour.Thisresultrepresents100%.Underthespecificconditionsofourexperiments, it can be concluded that the total number of statuses associated with author accounts influences the impact of arumour.

Findings of our comprehensive study suggest:

- The number of followers has a significant in on the impact of arumour.
- The number of friends has a significant influence on the impact of arumour.
- The total statuses related to the author, has a significant influence on the im- pact of arumour.
- Verified accounts do not significantly influence the impact of arumour.
- hashtags do not significantly influence the impact of arumour.
- media is likely to be influential to rumourimpact.
- user mentions are likely to be influential to rumourimpact.
- URLs do not significantly influence the impact of arumour.
- length 120-130 chars does not significantly in the impact of arumour.

Impactful Rumours compared toNon-Rumours

The final stage of impact evaluation is inspired by a question of the specific nature of rumours, compared to all other messages. Following our investigation and findings re-gardinginfluentialfeatureslendingtotheimpactofrumours,analysesisnowextended as we ask if there is a measurable difference between rumours and non-rumours - not related to the text but related to impact andfeatures.

Forchoosingnon-rumours,newsstoriesfromthecrediblesource-BBCNews6were selected.Thesestorieswerechosenonthe26thApril2016,andinvolvefactualevents, i.e. no question regarding veracity. Table VII, presents non-rumour sets collected - set names,associatednewsstories,andthenumberoftweetscollectedineachnon-rumour set.

The steps taken for these analyses is as follows:

- T-test analysis between sample size (40) messages of impactful rumour and sample size (40) messages ofnon-rumour.

- Where statistical difference is not found, i.e. the rumour and non-rumour represent the same impact, the presence of features investigated previously iscompared.

By performing this investigation, we are ultimately asking, "are rumours and non- rumours essentially the same or is there something that can be measured that makes them different".

Asummaryoffindingsrelatedtorumoursvsnon-rumoursispresentedinthecoming discussions. The rumours compared to the five non-rumours listed in table VII, are kim_divorce and obama pay increase, the three higher impact rumours of the data, noted in table VI. This gives a total of fifteen experiments: (3 rumours) * (5 non-ru- mours).

The five features are presented individually, the five deemed to be influential and likely influential. In each case, we assess whether the feature is more prominent in the rumoursetscomparedtothenon-rumoursets.Afeaturemoreprominentintherumour sets allows something that can be measured specific to rumours and theirimpact.

Followers

Followingfeatureanalysis,ourstudysuggestedthatfollowersareinfluentialtorumour impact. By comparing the numbers of followers associated with impactful rumours against non-rumours, we now determine whether there are more followers associated with rumours compared with non-rumours. Out of fifteen experiments, ten cases had morefollowersintherumoursetcomparedtothenon-rumourset.Thisresultrepresents 67%, see table V, column 'FO'. This result is not quite conclusive but we believe that with more data and more analyses, this percentage is likely to increase, and become moreconclusive.

Under the specific conditions of the experiments of our study, it can be concluded thatthenumberoffollowersislikelytobeanacceptablemeasureforrumourimpact,a measure unique to messages deemed rumorous, highlighting the different nature of ru- mours compared to othermessages.

Friends

Friends were suggested as being inuential to rumour impact by our study, and we now determinewhethertherearemorefriendsassociatedwithrumourscomparedwithnon- rumours. Out of fifteen experiments, 12 cases had more friends in the rumour set com- pared to the non-rumour set. This result represents 80%, see table V, column 'FR'. Un- derthespecificconditionsoftheexperimentsofourstudy,itcanbeconcludedthatthe number of friends is an acceptable measure for rumour impact, a measure unique to messages deemed rumorous, highlighting the different nature of rumours compared to other messages.

Statuses

Our feature study suggested that the total number of statuses associated with the ac- countsoftherumourauthors,i.e.totalnumberofmessagescomposedinthelifetimeof the accounts, is influential to rumour impact. We now ask whether there are more sta- tusesassociatedwiththeauthorsofrumourscomparedwithnon-rumours.Outoffifteen experiments,onlythreecaseshadmoretotalstatusesassociatedwiththeauthorsinthe rumour set compared to the non-rumour set. This result represents 20%, see table V, column 'S'. In other words, the authors posting non-rumours, related to credible news, tend to post more often in general, compared to those who post rumorous messages. Under the specific conditions of the experiments of our study, it can be concluded that the total number of statuses associated with the author accounts is a likely measure for the impact of all types of messages and is not unique torumours.

Media

The inclusion of media items (images) is likely to be iential to rumour impact, accord- ing to our feature study. We now investigate whether there are more tweets containing media items associated with rumours compared with non-rumours. Out of _fteen ex- periments, ten cases had more tweets containing media items in the rumour set com- pared to the non-rumour set. This result represents 67%, see table V, column 'M' This result is not quite conclusive but it is believed that with more data and more analyses, this percentage is likely to increase, and become more conclusive. Under the specific conditions of the experiments of this study, it can be concluded that the inclusion of mediaitemsislikelytobeanacceptablemeasureforrumourimpact,ameasureunique to messages deemed rumorous, highlighting the different nature of rumours compared to othermessages.

User Mentions

Our feature study suggested that the inclusion of user mentions (tagging another user, @user) is likely to be intential to rumour impact. User mentions are the last feature we analyseinconsiderationofnon-rumours.Weinvestigatewhethertherearemoretweets

containingusermentionsassociatedwithrumourscomparedwithnon-rumours.Outof fifteen experiments, eight cases had more tweets containing user mentions in the ru- mour set compared to the non-rumour set. This result represents 53%, see table VI, column 'UM'. In other words, the authors posting non-rumours, related to credible news, tend to include user mentions as commonly (slightly more) as authors posting rumorous messages.

Under the specific conditions of the experiments of this study, it can be concluded that the inclusion of user mentions is a likely measure for the impact of all types of messages and is not unique torumours.

6 Conclusion

We have collected a dataset of rumour messages, associated with known rumours sourced online. This dataset represents a rumorous corpus su_cient for experimental analyses within rumour behaviour, such as those associated with rumour impact. Fea- ture data associated with every rumour message in the dataset has been collected and storedwiththerumoroustext,enrichingtheresultantdatasetofrumours.Aformulahas been suggested for calculating the impact of rumours on social media itself. The for- mula presented by the work appears Twitter specific in its variables; retweets and fa- vourites. However, this may be customized / altered / extended, to reflect user engage- ments or other application specific properties on other social media.

The significant findings of our study are, a) statistical significance has been high- lightedinourrumourdata,wherebywehavefoundstatisticaldifferencebetweensome rumours, in terms of social media impact, b) important findings related to rumour au-thorfeaturesandrumourcompositionfeaturesthatwesuggestareinuential(andnotin to the impact of rumours on social media, c) behavioural differences in rumours com-paredtoallothermessages,propertiesimpactfultorumoursspecifcally,suggestingthat rumours act differently to other messages, and that there exists measurable differences in terms of influential features unique to rumourimpact.

In the context of the greater research area, the work bridges the void that exists in the State of the Art, and provi des study, measurement, and analyses of rumour impact onsocialmediaitself,agapcreatedasrumoursandnewenvironmentstothrive,result-ingfromthesuccessandgrowthofsocialmedia.Ourstudyactsasanencouragingstep towards building a customisable model for measuring impact, that can be applied over the various social media platforms that exist. This work introduces an exciting oppor- tunity for extensive research in rumour impact on social media itself, where research should be continued, possibly according to some of the suggestions tofollow.

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