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Twitter based Analysis of Public, Fine-Grained Emotional Reactions to Significant Events

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Due to the real-time nature and the value of social media content for monitoring entities and events of significance, automated sentiment analysis and semantic enrichment techniques for social media streams have received considerable attention in the literature. These techniques are central to monitoring social-media content, which is now becoming a significant business with commercial, institutional, governmental and law enforcement interest into its applications. Prior work in sentiment analysis especially has focused mostly on negative-positive sentiment classification tasks. Although numerous approaches employ highly elaborate and effective techniques with some success, the sentiment or emotion granularity is generally limiting and arguably not always most appropriate for real-world problems. In this paper a newly developed ontology based system is employed, to semantically enrich Tweets with fine-grained emotional states, in order to analyse the subjective public reactions to a wide selection of recent events. The approach detects a range of eight high-level emotions and their perceived strength (also known as activation level), specifically; anger, confusion, disgust, fear, happiness, sadness, shame and surprise. A set of emotional profiles for different events is obtained and an in-depth analysis of the emotional responses is presented. Recent events, such as the 2013 horsemeat scandal, Nelson Mandela's death, September 11th remembrance anniversary, recent tube strikes in London are analysed and discussed. The feasibility and potential benefits of automated fine-grained emotional event response analysis from social-media is illustrated and further, future work suggested.

Keywords: Social Media, Twitter, Sentiment Analysis, Basic Emotions, Natural Language Processing, Ontology

1. Introduction

Automated sentiment analysis and semantic enrichment (e.g. geo-location inference, named entity recognition, topic classification, etc.) of social media text streams, such as Tweets and Facebook status updates is receiving considerable attention in the literature. This is largely motivated by the insights and value that such datasets were shown to provide (Chew and Eysenbach, 2010; O'Connor et al., 2010; Tumasjan et al., 2010; Lansdall-Welfare et al., 2012; Abel et al., 2012). It has also been evidenced that during times of natural crises and terrorist incidents Twitter is often the first medium through which the news breaks and through which individuals express their initial impressions and emotions relating to the events (Beaumont, 2008; Cashmore, 2009; Sakaki et al., 2010; Cheong and Lee, 2011; Glass and Colbaugh, 2012). Social-media streams, in general, allow for observing large numbers of spontaneous, real-time interactions and varied expression of opinion, which are often fleeting and private (Miller, 2011). Miller (2011) further points out that some social scientists now see an unprecedented opportunity to study human communication, which has been an obstacle up until recently. O'Connor et al. (2010) demonstrated how large-scale trends can be captured from Twitter messages, based on simple sentiment word frequency measures. The researchers evaluated and correlated their Twitter samples against several consumer confidence and political opinion surveys in order to validate the approach, and have pointed out the potential of social-media as a rudimentary yet powerful polling and survey methodology. Motivated by such work, this paper will specifically focus on automated fine-grained emotion analysis (also known as advanced sentiment analysis) over a number of recent events, ranging from the European horsemeat scandal, to the recent tube strikes in London. As far as the authors are aware this study is novel in the range of heterogeneous events

analysed and the range of emotions detected. Most literature in sentiment analysis field has looked at polarity sentiment (i.e. negative – positive sentiment) classification only, with a few exceptions (Bollen et al., 2011; Lansdall-Welfare et al., 2012; Choudhury and Counts, 2012). In this paper a recent technique, called EMOTIVE, developed by Sykora et al. (2013) which identifies eight basic fine-grained emotions from sparse text, namely; anger, disgust, fear, happiness, sadness, surprise (also known as Ekman's basic emotions – Ekman and Richard, 1994), and confusion and shame, is employed. Novel insights towards a fine-grained emotional composition of reactions to events discussed over Twitter are provided in this paper.

The remainder of the paper is organised as follows. Section 2 introduces some background and prior work in the sentiment analysis field, and gives brief method details. Event characteristics based on Twitter features and detected emotions are presented in section 3. Section 4 analyses and discusses the events further. The paper is concluded in section 5.

2. Background and Methodology

A recent, in-depth overview of prior academic work in the sentiment analysis field is provided in Thelwall et al. (2012). The approach used in this paper (Sykora et al., 2013) broadly falls under the lexicon / linguistic analysis approach, from the three approaches presented in Thelwall et al. (2012) – except that we draw on emotion terms from within an ontology with a richer semantic representation than commonly used emotion term-lexicons. Although numerous approaches employ highly elaborate and effective techniques with some success, the sentiment or emotion granularity is generally limiting. Specifically, there are three main problems with existing approaches. 1-Notions of affect and sentiment have been rather simplified in current state-of-the-art, often confined to their assumed overall polarity (i.e. positive / negative), Thelwall et al. (2012). 2-Another problem with polarity-centric sentiment classifiers is that they generally encompass a vague notion of polarity that bundles together emotion, states and opinion (Bollen et al., 2011). 3-There is no common agreement about which features are the most relevant in the definition of an emotion and which are the relevant emotions and their names, (Grassi, 2009). In the emotion analysis employed in this paper, sentiment is fine-grained, based on the widely accepted Ekman's emotions (Ekman and Richard, 1994) from social psychology, while other work on emotions was also considered (Plutchik 1980; Drummond, 2004; Izard, 2009) and is further discussed in Sykora et al. (2013). Only explicit expressions of emotions are extracted, and ambiguous emotional expressions, such as certain moods and states that are not expressing emotions are ignored on purpose, as opposed to Bollen et al., (2011), Lansdall-Welfare et al. (2012), and Choudhury and Counts (2012). The EMOTIVE ontology employed in this paper was designed to detect a wider range of well recognised human emotions, such as 'surprise', 'disgust', or 'confusion', but at the same time differentiate emotions by strength (e.g. 'uneasy', 'fearful', 'petrified'). In addition to the basic emotions, the ontology also covers and handles negations, intensifiers, conjunctions, interjections, and contains information on the perceived strength (also known as activation level) of individual emotions, whether individual terms and phrases are slang or used in standard English and their associated POS (Parts-of-Speech) tags, where this aids to resolve ambiguity. In Sykora et al. (2013) our technique was evaluated and compared to Choudhury and Counts (2012) and Thelwall et al. (2012) – SentiStrength 2 – in terms of emotion detection and emotion strength scoring, respectively. Good results, comparable with state-of-the-art were achieved and a high f-measure for emotion extraction on an initial test dataset was reported (see sub-section 2.2).

2.1 Data Collection

The datasets analysed within this paper were continuously retrieved from Twitter, using the standard REST Twitter Search API. The retrieval occurred during the related time-period of an event and a search-term or hashtag, known to be extensively used by the Twitter community for that event was chosen by a microblogging expert. For most events of interest data collection would occur during the days / time-period of the event, or the days immediately following the event in order to collect the related reactions, chatter and emotions. Often the selected term or hashtag used for the data

collection would also be trending, i.e. according to Twitter trends. The maximum possible number of tweets, given the API limitations and compatible with Twitter's terms of service, was automatically retrieved using custom developed scripts. In total 1,570,303 tweets were collected and analysed (see sections 3 and 4).

2.2 Fine-Grained Emotion Extraction

Due to enforced brevity of messages (e.g. 140 characters or less on Twitter), textual content commonly encountered on social media is often not grammatically bound nor constructed properly and contains extensive use of slang, short-hand syntax, incorrect spelling, repeated letters, repeated words, inconsistent punctuation, odd Unicode glyphs, emoticons and overall a high proportion of OOV (Out-Of-Vocabulary) terms. Hence it has been suggested that a retrained NLP pipeline for sparse, informal text is necessary to effectively process such language (Ritter et al. 2011). The approach used to extract the fine-grained emotions from tweets is described in some detail within Sykora et al. (2013). Essentially the approach has two parts and is based on (1) a custom Natural Language Processing (NLP) pipeline, which parses tweets and classifies parts-of-speech tags, and (2) an ontology, in which emotions, related phrases and terms (including a wide set of intensifiers, conjunctions, negators, interjections), and linguistic analysis rules are represented and matched against. An initial evaluation of the system achieves excellent results, with an f-measure of .962, precision of .927 and recall of 1. The recall is likely to be lower on larger test datasets containing higher proportion of OOV slang, yet the high recall on the test dataset is strongly indicative of good coverage of expressions. A comparison with Choudhury and Counts (2012) and Thelwall et al. (2012) performed in Sykora et al. (2013) showed that the emotion detection performs better, and in the latter case in line with state-of-the-art approaches.

3. Emotions and Event Characteristics

This section presents the analysis of emotional expression for 28 separate datasets relating to 25 distinct events, over a total collection of 1,570,303 tweets. Table 1 summarises the datasets and presents details on how many tweets were collected for each specific hashtag / search terms (i.e. 'Dataset' column in table), what percentage of those contained emotions, over what time-period the data retrieval took place and basic background information on the related event (please visit <http://emotive.lboro.ac.uk/resources/ECSM2014> for a full list of links to specific event related articles). As can be observed from table 1, the five most emotional datasets relate to #jacinthasaldanha (37.91%), #ChineseNewYear (36.13%), #royalprank (23.17%), 'Daniel Pelka' (21.54%) and #2DayFM (20.43%). The hashtags #jacinthasaldanha, #royalprank and #2DayFM all refer to the same event, in which a nurse (Jacintha Saldanha) committed suicide after being the victim of a public (2Day FM radio station) prank (#royalprank). The emotional outpour on Twitter over her needless and tragic death was enormous. The torture and death of the four-year-old boy, Daniel Pelka, was also met with outrage and significant outpour of highly emotionally charged tweets. #ChineseNewYear (31st Jan 2014) was naturally filled with mostly positive emotions and New Year wishes. However, quite often tweets carry relatively low emotional content, which seems to be due to the nature of the event / topic discussed in tweets. On average 12% of tweets contain explicit emotions (standard deviation being 9%).

Table 1: Overview of the collected and analysed datasets and their relationship to events

Dataset	Total (N)	Emotional Tweets (%)	Event	Event Type	Time Period
helicopter crash	25,387	13.99%	Helicopter crashes into crane in central London (16th Jan)	accident	16 Jan-17th Jan 2013
#september11	88,739	9.62%	September 11th 2013 anniversary	anniversary	11th Sep-12th Sep 2013
#twintowers	28,168	16.32%	September 11th 2013 anniversary	anniversary	11th Sep-12th Sep 2013
#ChineseNewYear	22,466	36.13%	Chinese New Year, 31st Jan 2014	cultural event	31st Jan-1st Feb 2014
#bankholiday	7,862	11.71%	Bankholiday - public holiday in the UK	daily life	24th May 2013
#sleep	36,139	3.65%	An eight day long period	daily life	23rd Oct-31st Oct 2013
#tired	79,253	4.49%	An eight day long period	daily life	23rd Oct-31st Oct 2013
#JamesGandolfini	11,975	18.92%	Death of actor James Gandolfini	death	20th Jun-23rd Jun 2013
Ariel Sharon	90,603	8.18%	Death of the ex-prime minister of Israel	death	11th Jan-15th Jan 2014
Nelson Mandela	108,794	12.51%	Death of Nelson Mandela	death	5th Dec-9th Dec 2013
'Daniel Pelka'	11,708	21.54%	Sentencing of the killers in the brutal murder of school boy Daniel Pelka	death / murder	1st Aug-5th Aug 2013
#RoyalMail	4,309	6.75%	Privatisation of the British Royal Mail, 12th Sep announcement	economic / controversial	12th Sep 2013
#tubestrike	41,176	8.47%	London February tube strike by RMT and TSSA unions	economic / controversial	5th Feb-7th Feb 2014
#LFW	43,509	4.27%	London Fashion Week	fashion event	17th Feb-18th Feb 2014
Anjem Choudary	1,047	5.44%	Controversial comments from a radical cleric on BBC	hate speech incident	24th May 2013
#2DayFM	10,898	20.43%	Royal prank by Australian 2DayFM - suicide of Nurse Jacintha Saldanha	incident / death	7th Dec-14th Dec 2012
#jacinthasaldanha	1,216	37.91%	Royal prank by Australian 2DayFM - suicide of Nurse Jacintha Saldanha	incident / death	7th Dec-14th Dec 2012
#royalprank	10,459	23.17%	Royal prank by Australian 2DayFM - suicide of Nurse Jacintha Saldanha	incident / death	7th Dec-14th Dec 2012
g8 summit	32,676	4.24%	39th G8 Summit in UK on 17th-18th June	political / controversial	16th Jun-20th Jun 2013
#iPhone5C	8,824	3.90%	Announcement of new iPhone on 10th Sep	product release	11th Sep-12th Sep 2013
#iPhone5S	14,638	5.70%	Announcement of new iPhone on 10th Sep	product release	11th Sep-12th Sep 2013
gta5	130,748	4.22%	Release of computer game GTA 5 on 17th Sep	product release	17th Sep-18th Sep 2013
#NSA	381,402	5.08%	National Security Agency PRISM surveillance program (initially leaked early Jun)	Scandal	13th Jun-15th Jul 2013
#prism	106,432	4.96%	National Security Agency PRISM surveillance program (initially leaked early Jun)	Scandal	13th Jun-15th Jul 2013
Horsemeat	56,970	7.47%	Horsemeat mislabeled as beef (issue came to light on 15th Jan)	Scandal	16th Jan-18th Jan 2013
#ClosingCeremony	87,943	11.55%	London 2012 Olympics - Closing ceremony	sport event	12th Aug-17th Aug 2012
#paralympics	27,993	13.97%	London 2012 Olympics - Paralympic games (29th Aug - 9th Sep)	sport event	4th Sep-6th Sep 2012
#woolwich	98,969	12.63%	Recent attack and murder of Drummer Lee Rigby in Woolwich, by extremists	terror incident / murder	23rd May-24th May 2013

Despite some datasets containing relatively low proportion of emotional tweets, no dataset has less than 291 emotional tweets (avg. being 4,670), with the exception of Anjem Choudary. Only 57 tweets with explicit emotions were available for Anjem Choudary (i.e. 5% out of 1,047 tweets). Figure 1 illustrates how a useful emotional 'footprint' can nevertheless be generated, despite the low count of emotional tweets. Specifically, figure 1 presents the distribution of the proportion of emotions among eight basic, fine-grained emotions for #woolwich (incident in which a UK soldier was murdered in broad daylight in London) and Anjem Choudary (a religious radical who was given air-time on BBC after the event, and was accused of hate speech and declined to condemn the attack on the soldier).

The distribution of emotions is intuitive and can be interpreted in a straight forward manner in relation to #woolwich.

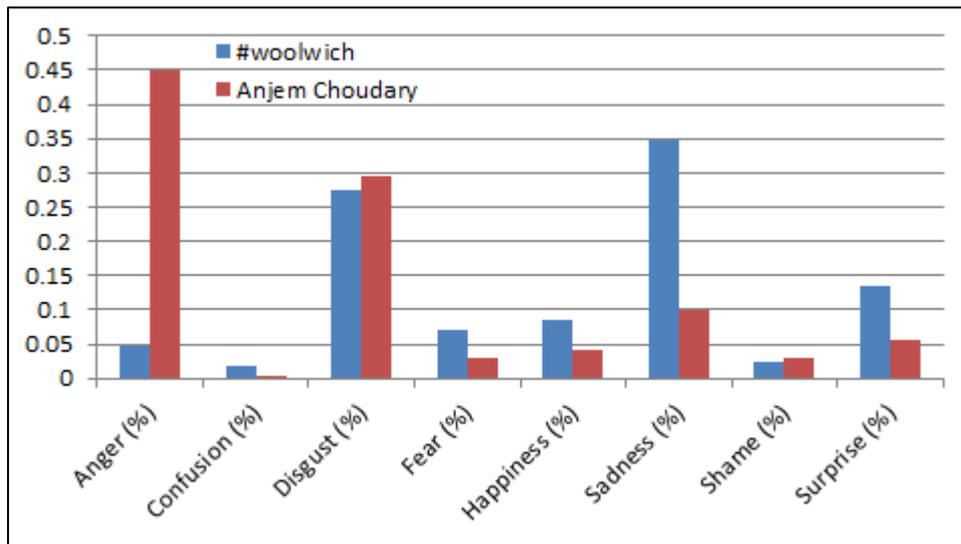


Figure 1: Basic emotions detected for #woolwich (blue) and Anjem Choudary (red)

Anjem Choudary was most often mentioned with extreme emotions of anger and disgust. Intuitively, the proportion of anger is much higher for Choudary than for #woolwich, whereas both contain similar levels of disgust, but sadness dominated #woolwich. Several exemplar tweets illustrate the outpour, below (basic emotions are highlighted in the square brackets).

- I'm quite angry that Anjem Choudary is on Newsnight tonight - I can only imagine how furious Muslims he falsely claims to speak for must be [anger]
- And I'm angry that Anjem Choudary is aloud to preach hate in our towns and city's It's the government we should be angry with not a religion [anger]
- Anjem Choudary, gfy. Ruining the 'Choudhary' name for all of us, you complete bastard, it's sickening #woolwich [disgust]
- @EDLTrobinson so sad, and so wrong that ANJEM CHOUDARY can get air time saying muslims around the world will call them heroes what a twat. [sadness]

3.1 Overview of Event Detected Emotions

This subsection focuses on several specific example events and their emotional profiles, in order to further illustrate the use and highlight several nuances of our Twitter emotion detection system.

The 2013 September 11th terror attack anniversary related tweets (represented by #september11 and #twintowers) mostly contain sadness and a similar emotional distribution overall. Nevertheless, although subtle yet noticeable, it is interesting that happiness is much lower for the #twintowers than #september11 tweets. A detailed inspection of the tweets showed that #september11 was used more widely and somewhat surprisingly by people with radical and offensive opinions, who actually expressed happiness about the terror attacks of 2001, see bullet list below for some example tweets.

- Glad to say I'm from Canada #september11 [happiness]
- Yes We Are Terrorist And We Are Proud!When It Comes To Scaring Pigs #september11 (*attributed to the account @albatar_moahed, other such as @laskegah have retweeted it*) [happiness]
- We will never forget that HAPPY day #september11 really we love u "Osama" #Remember_11_September enjoy your eyes <http://t.co/c8bSkSZOY4> [happiness]
- I will never forget where I was on #september11 Keep your thoughts w/ the families who lost their loved ones. I am Proud to be an American! [happiness]
- Remembering 9/11& feeling blessed for the safety of my friends & family and the freedoms we all still enjoy. God bless us all. #september11 [happiness]

- I still remember like it was yesterday, watching the #twintowers tumble down on TV, hands tied, in complete state of shock and anguish. [surprise]
- This day 12 years ago, I was sitting on my coffee table in shock, 16 miles away from Ground Zero. #remember #nyc #newyork #911 #twintowers [surprise]
- I'm flying today....is that my bad luck kicking it....9-11 brings back more fear when you're flyin on it #twintowers #Remember_11_September [fear]
- I was scared shitless for my mother, the then ignorant me didnt know that Atlanta was miles away from #twintowers #sept911th [fear]
- The fact that Miley Cyrus is trending over #september11 and #twintowers is actually disgusting. [disgust]

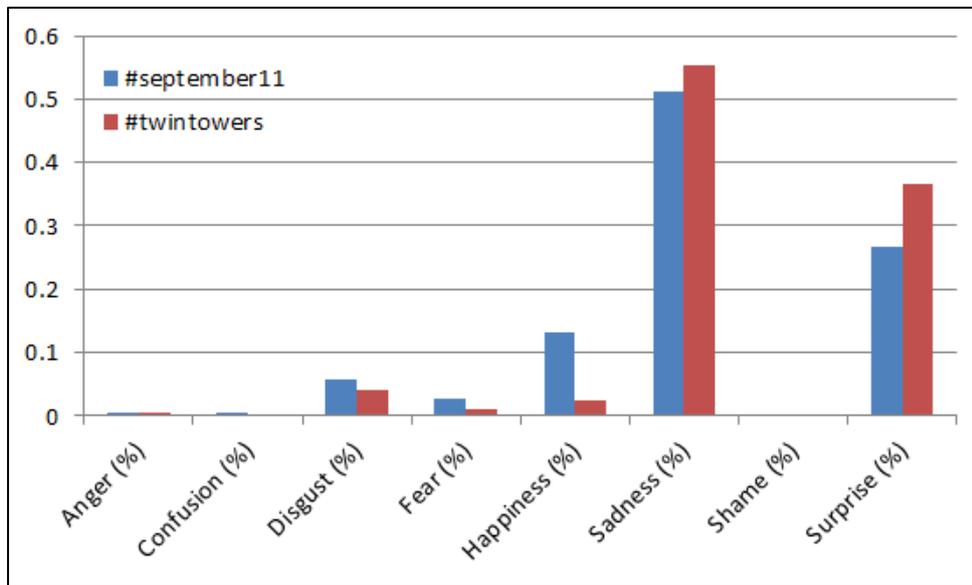


Figure 2: Basic emotions detected for #september11 and #twintowers

As evidenced by our dataset, it seems that generally speaking deaths of (well known) people tend to be accompanied with relatively high level of emotional outpour. Figure 3 highlights that sadness, as expected, tends to be a well represented emotion in such events, as well as higher levels of surprise.

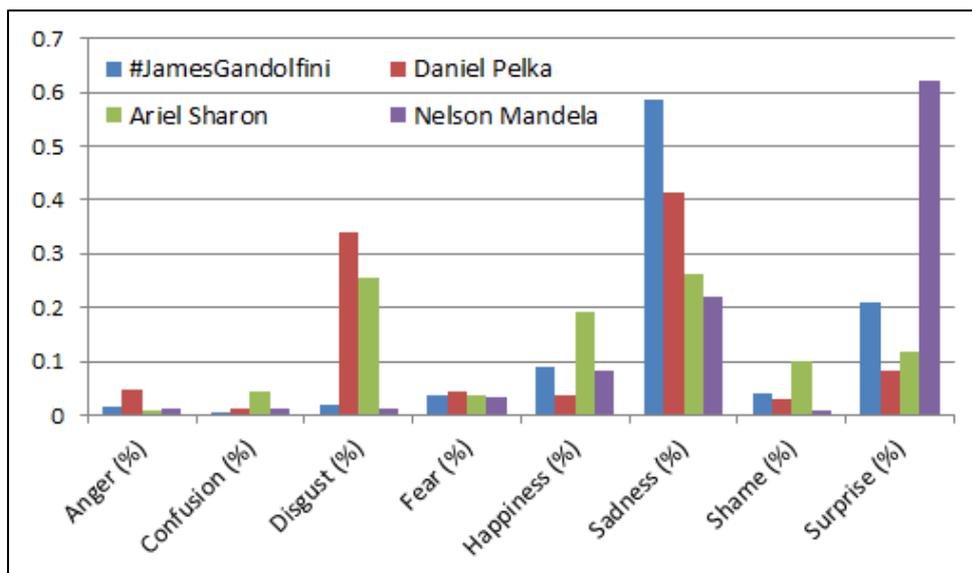


Figure 3: Emotions detected for #JamesGandolfini, Daniel Pelka, Ariel Sharon and Nelson Mandela

The figure further illustrates that in the case of the controversial former prime minister of Israel, people expressed disgust, shame and even happiness, which is significantly higher, although a proportion of

it is in his remembrance by his supporters. The actor James Gandolfini died unexpectedly from a heart attack aged 51, hence the associated higher level of surprise. Interestingly very high proportion of tweets containing surprise were detected for Nelson Mandela, which were mostly expressions of disbelief that such a legendary leader has passed away, although he has been in frail health for a prolonged time.

Finally, tweets employing the hashtags and relating to the individual #JacinthaSaldanha, #2DayFM, the radio station responsible for the so-called #royalprank, which resulted in the nurses' suicide, highlight an interesting aspect about our emotion detection system.

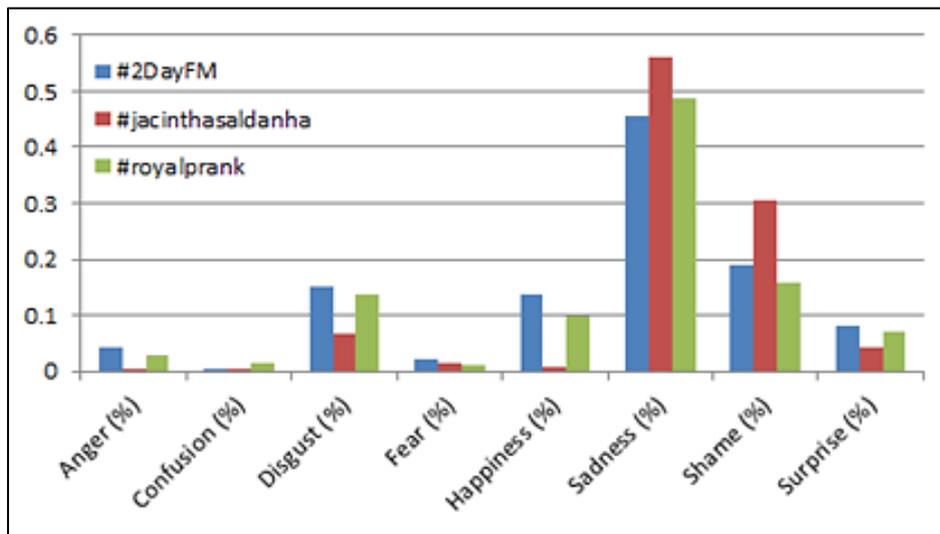


Figure 4: Emotions detected for #2DayFM, #jacinthasaldanha and #royalprank

From figure 4 it is apparent that sadness, followed by shame, dominated the emotional reaction in the immediate days following the event. Also the higher levels of sadness and shame for #JacinthaSaldanha relative to the two other hashtags point out that these reactions were marginally more prevalent in relation to the nurse. Expressions of disgust, happiness, surprise and anger on the other hand were more prevalent for #2DayFM and #royalprank relative to #JacinthaSaldanha, which indicates that these emotions were targeted not at the victim but the radio station and tweets relating to the prank. This relative difference is especially noticeable for 'happiness', where a manual inspection of individual tweets reveals a proportion of sarcasm and irony, but at the same time people did not react with 'happiness' (including sarcasm) to the victim of the prank.

3.2 Correlations

An initial evaluation of correlations between emotions and basic twitter usage features (e.g. tweet @replies and tweet @mentions), was performed. Kendall's Tau β , which is generally more conservative than Spearman's rank correlation was employed on ratio summaries of the 28 topical datasets. All the significant correlations, at p (two-tailed) $< .001$, were between; happiness–sadness (-.614), anger–confusion (.444), anger–disgust (.370), disgust–happiness (-.360), anger–mentions in tweets (-.524), anger–replies (-.386), fear–mentions in tweets (-.402) and fear–replies (-.349). The strongest association exists between happiness and sadness for the different datasets, as well as increased levels of anger which tends to coincide with increased levels of confusion and disgust. Tweet mentions (i.e. not replies, but rather mentions of other @user_accounts in a tweet) and tweet replies are also both negatively correlated with increased levels of anger and fear. Although with much lower significance levels, some other interesting correlations were found, such as a negative correlation between proportion of geo-located tweets and increased fear. These correlations are; however, unreliable due to the small dataset (28 measurements) and hence in future work we intend to extensively increase the size of analysed events and employ a thorough regression analysis.

4. Further Analysis and Discussion

In order to measure similarities, purely based on emotional scores for the eight basic emotions, between the events, hierarchical clustering was employed. The clustering method used was Agglomerative between groups linkage clustering with squared Euclidean distance (values were normalised to z-scores) to generate the Dendrogram in figure 5.

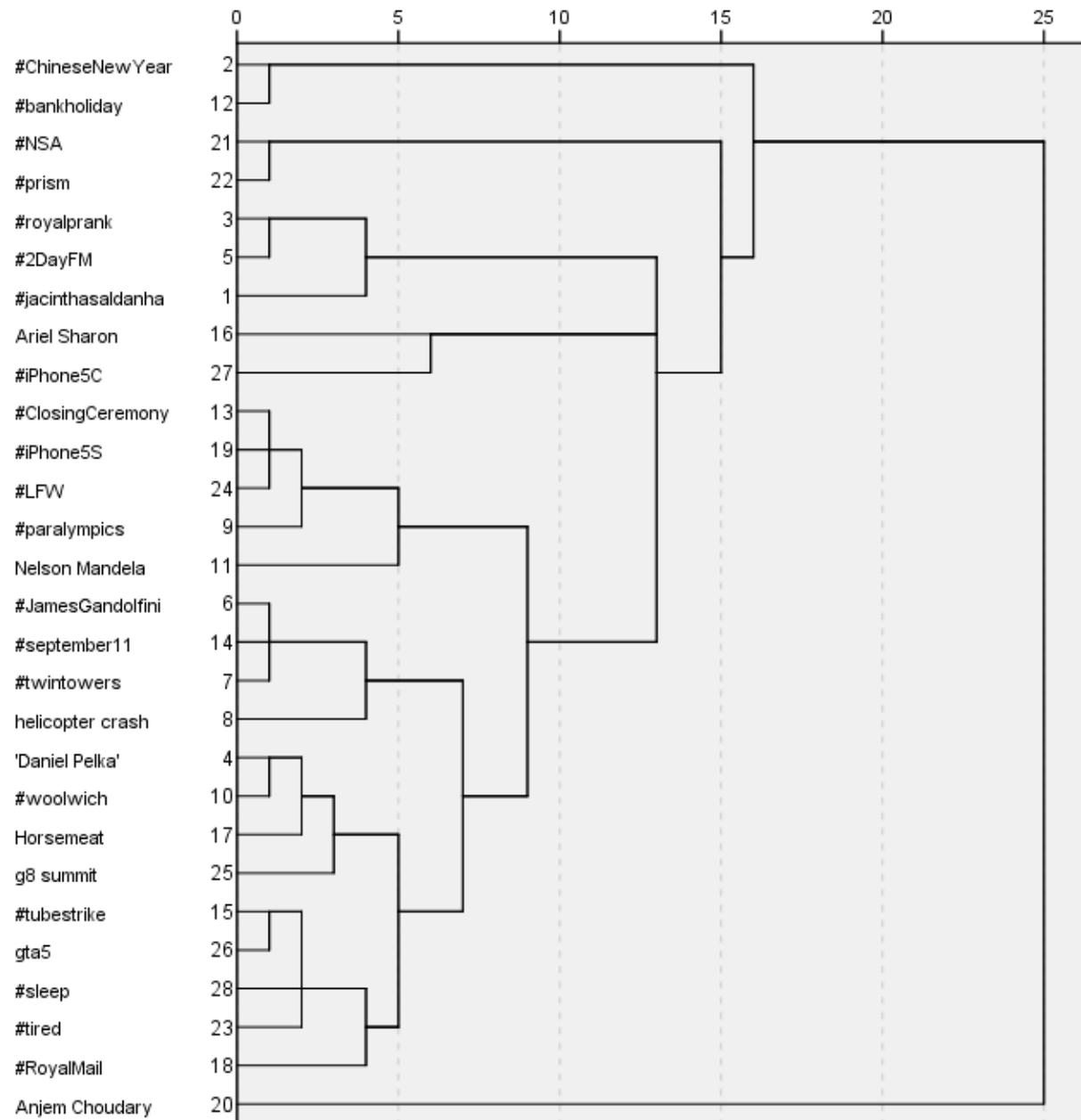


Figure 5: Dendrogram – Agglomerative between groups linkage clustering (based on emotion scores)

Reading the Dendrogram horizontally from left to right, some spontaneous clusters of related events become apparent. It can be observed that #ChineseNewYear and #bankholiday are grouped in the same cluster, which is also quite distinct from other clusters. This is due to the emotional profile for both events predominantly containing happiness (96% and 85% respectively), and other emotions virtually not being present. Other events contain more widely distributed emotional profiles which are still closely related, for instance; #royalprank, #2DayFM and #jacinthasaldanha all cluster together. #ClosingCeremony and #LFW are both events which had a similar distribution of emotions as

generally positive emotions with some level of surprise. iPhone5S, which was received better than the iPhone5C model, and Paralympics cluster together. Some unexpected and sad events, such as #JamesGandolini, #september11, #twintowers and helicopter crash all cluster together as well, and not surprisingly the more controversial and very sad events, such as tweets relating to Daniel Pelka, Woolwich attack, Horsemeat scandal and the G8 summit all fall into a cluster, which is also related to a similarly sized cluster with events 15, 26, 28, 23 and 18 (consult figure 5). Some events could not be placed into very meaningful clusters, such as Ariel Sharon and iPhone5C which have some similarity, as iPhone5C was disappointing and had more specific negative emotions, similar to the profile of emotions for Ariel Sharon, yet still related to the clusters containing the other deaths (1, 11, 6 and 4). Anjem Choudary had a sufficiently different emotional profile and did not compare closely with the other clusters.

4.1 Limitations and Future Work

There are several limitations to the work presented in this paper. Spam on social-media streams is a major issue (Yardi et al. 2010), as it is not uncommon for hashtags to be misused, often by rogue accounts, to piggyback on a popular twitter topic and feed spam into the social-media stream. In this paper's analysis tweets were indirectly filtered to only the ones that contained explicit expressions of emotion, as detected by EMOTIVE, which seems to be relatively effective in filtering out obvious spam and hijacked hashtag tweets, since these often don't contain subjective content, such as emotions. However, effective recognition of dubious accounts and their profiling may improve future analysis. Linked to this, is the issue of profiling individual Twitter accounts to better understand demographic variables of the analysed sample, such as detecting the likely age, gender, or income level of specific user accounts. Currently available techniques unfortunately leave much to be desired, in terms of inference accuracy; however, there is ongoing research in this area (Bates et al. 2012). In this paper we did not distinguish between RTs (re-tweets) and original tweets, as there is some evidence that RTs are useful because they amplify and validate a message or opinion (Starbird and Palen 2012). Hence there is an argument to be made for their inclusion in analysis. To address the issue of a relatively small sample size (see sub-section 3.2), we intend, in the future, to generate fine-grained emotional footprints for much larger event samples. We also see significant potential in investigating how emotions in long-lived events evolve over time, and how they differ between events.

5. Conclusion

This paper presents some novel results of emotionally annotated Twitter events, with respect to the range of heterogeneous events analysed and the range of fine-grained emotions detected. Analysis of emotions was performed on over 1.5 million tweets, relating to 25 distinct events. The employed technique is a newly developed advanced-sentiment analysis technique, which automatically detects fine-grained, basic emotions (as identified in psychology literature) with an already established accuracy. Several examples of emotional profiles were given and the emotionality within tweets for different datasets discussed. Hierarchical clustering was employed to help organise the events based on emotions in tweets, in which it was found that events that generate similar emotional reactions on Twitter tend to also be similar in type, and can hence be organised based solely on specific fine-grained emotional information. Future work includes a larger study and analysis of emotions over time.

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