‘Are you having a laugh?’: detecting humorous expressions on social media: an exploration of theory, current approaches and future work

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Abstract: The role of humorous content on social media has rarely been taken into account in prior work. Understanding its dynamics on social media provides insight that could benefit a range of applications in sentiment analysis. This paper introduces literature on humour theory, related human behaviour and a discussion of existing automated approaches to humour detection. We present and review current research on humorous language use on social media and its significance. In particular, example humorous expressions from Twitter are used to illustrate the heterogeneous types of humour on social media. Since most prior work focused on English language contexts, the analysed example uses of humour are set in the Arabic cultural context, providing a novel view. The primary contribution of this paper is the position that similar to sentiment analysis, automated humour detection in its own right has potential in understanding public reactions and should be explored in future studies.

Keywords: humour; social media; Twitter; sentiment analysis; natural language processing; data mining; automated humour detection; computational linguistics; social media analytics.

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1 Introduction

Social psychologists have been concerned with understanding human behaviour and human interactions for centuries. Since the inception of the eighteenth century stream of thought that general principles of human nature should be established in order to reduce social conflict, abolish mental illness, and create ideal social conditions (Gergen, 1973), psychologists and social scientists have been studying the behavioural patterns of individuals, groups, families, and societies. Among the behavioural patterns examined in the developmental years of social psychology is humour as a behavioural and social phenomenon in humans. Humour is a universal (Ekman, 1973) relationship builder (Kuipers, 1975) that is also a biological human instinct (Keith-Spiegel, 1972). Psychologists today are still exploring the biological effects of humour (Okafor et al., 2016), and social psychologists are still trying to understand the dynamics and consequences of humour within groups (Curseu and Fodor, 2016; Martin and Ford, 2018).

In 1928 Sigmund Freud suggested that humour was a coping mechanism that humans adopt in order to curb potential suffering. He hypothesised that a joke can bring pleasure that has been attained in the service of aggression, that a joke serves as an indication that "a person refuses to suffer" [Freud, (1959), p.127] which is possibly the reason behind the existence of humour in humans since there is clear evidence of humour having an evolutionary basis (Weisfeld, 1993).[1] Rnic et al. (2016) argue that identifying different types of humour may help identify depressed or distressed individuals. They show evidence that certain types of humour are linked with loneliness and anxiety. The possibility to detect mental health through the use of humour could be particularly beneficial to society since research has shown that there is a connection between certain mental health conditions and violence (Hiday, 1997; Candini et al., 2018). This has

further relevance to public health surveillance, as mental health conditions are largely under-diagnosed (Sigalas and Barkla, 2014). Studies using automated computational approaches have shown social media profiles may provide an efficient way for estimating prevalence of mental health conditions (Coppersmith et al., 2014), although such approaches have to-date only relied on traditional features, such as n-grams, sentiment and emotion-based variables (Chen et al., 2018), while no work to date has taken humour related variables, such as deprecating humour, into account (Sinnenberg et al., 2017). Now with the popularity of social media platforms, researchers can explore many issues, including Freud's theories regarding humour as a coping mechanism and Rnic et al.'s (2016) theories about types of humour reflecting an individual's mental state. Social media captures users' spontaneous thoughts, ideas, opinions, emotions, feelings, and experiences, enabling researchers to study the patterns produced at various times, places and in context of different social networks. Micro-blogging systems such as Twitter are seen as a source of real time information, which is why successfully detecting, interpreting, and monitoring events of interest has obvious economic, security and humanitarian importance (Osborne et al., 2014). Twitter also exhibits traces of social discourse which provides an opportunity for researchers to investigate how a social system reacts to internal and external stimuli (Lehmann et al., 2012), also allowing governmental and non-governmental institutions to monitor public reactions to events and conduct user profiling (Sykora et al., 2013). Lansdall-Welfare et al. (2012) propose that effectively monitoring social media may eventually help prevent social disasters. In her position paper, de Choudhury (2013) suggests that mental health studies would benefit from employing social media, as it provides an unbiased collection of an individual's language and behaviour, and Coppersmith et al. (2014) further highlight how social media enables large-scale analyses, which have not been previously possible with traditional methods, with significant potential applications in public health surveillance.

In this literature review position paper, we will explore the role of humour in social media-based expression. Using discourse analysis to interpret and decipher humorous tweets, we identify a number of patterns of linguistic expression, and provide some examples of humorous tweets, identifying different types of humour that emerge in various situations, with a specific focus on the Arabic Twitter sphere. Due to the predominant focus and bias towards English speaking expression in prior social media literature in this area, this paper specifically studies the above in the Arabic cultural context.

The paper is organised as follows. Section 2 introduces crucial theoretical background surrounding humorous expression and the primary motivations for automated humour detection. Section 3 presents several example events as a case study exploring associated humour, specific to a social media platform. Section 4 provides a discussion highlighting positions of the paper, which are centred on investigating the heterogeneous function of humour, cultural and multilingual considerations, and suggested future work for improving automated humour detection, followed with concluding remarks.

2 Related literature and theoretical background

2.1 Social function of humour

Humour has been playing a social role since the dawn of civilisation; there are records that show that comedy has been a popular genre since the times of the ancient Greeks. Among the earliest surviving Greek comedies is a play where at the eve of war the comic hero attempts to escape by flying to heaven on the back of a giant beetle (Konstan, 1995). This recurring comedic theme (escaping from danger using unlikely methods) in popular culture is in line with Freud's theory of humour functioning as a coping mechanism that comforts an individual at trying times of danger or conflict. Comedy in general draws the interest of audiences, since laughter can also be viewed as a form of escapism (Woods, 1976). In 1990, the top 100 rental films 'of all time' list showed that comedies were the most popular films being rented in the USA. It was also shown that comedies attracted more attendance in theatres at that time (Bryant and Zillmann, 1993). Comedy on American television was also the most popular genre with 46% of the highest rated shows being comedy shows, followed by drama (at 23%). This popularity of comedy is telling; the fact that individuals invest their time and money on laughter speaks volumes about human nature and the instinctive tendency to seek out laughter. Snyder (1974) found that many individuals tend to laugh out loud more while watching comedies when they are with others than when they are alone, which also implies that there is an additional social element to laughter and humour.

Individuals with a 'good sense of humour' are generally more socially desirable (Cann and Calhoun, 2001); this may be because they decrease social gaps while interacting with people (Graham, 1995). Research conducted by Romero and Pescosolido (2008) finds that whenever humour is used in groups, the individuals within the group experience positive affects which create efficient and effective social processes that require less energy and effort to establish a social bond. These theories provide a feasible explanation for the spreading of humour on different social media platforms in various situations. Indeed, humorous expression on social media is widespread. In a study conducted by Whiting and Williams (2013), over 60% of respondents were reported to use social media as a source of entertainment, with a particular interest in its use for humour and comic relief. Seltzer et al. (2015) reported as many as 42% of health-related topical posts on Instagram to contain humorous messages. A number of further empirical studies reviewed the significant role that humour plays in shared social media content (Guskin and Hitlin, 2012; Madden et al., 2013). Locher and Bolander (2015) in a focus group-based study found that prevalence of humour on text-based Facebook status updates was around 20%. Humorous content and content that evokes emotions has been identified in the past as a significant driver of virality (Porter and Golan, 2006; Berger, 2014; Berger and Milkman, 2012) and identifying such content automatically has important applications in social media marketing (e.g., Nikolinakou and King, 2018). Interestingly, some evidence indicates that humour on Twitter tends to be relatively widespread even during times of crises (Guskin and Hitlin, 2012; Jong and Dückers, 2016), but Jong and Dückers (2016) also point out that it can be the cause of misunderstandings and emergence of rumours. Specific humorous social media memes[2] have also been explored, for instance Zappavigna (2012) looked at the #fail Twitter meme, including work by Lin and Hsu (2014) on humorous multimedia-based memes.

Casey et al. (2018) also examined humorous memes on Instagram and found that they often encourage unhealthy behaviours.

Nevertheless, given the potentially highly significant role of humour and its effects on social networks, its nature and exploitation within social media platforms has received relatively little attention in prior work (Pang and Lee, 2008; Ravi and Ravi, 2015). Arguably quantifying humorous expression on social media posts, in addition to sentiment analysis, would provide more meaningful and holistic insights than sentiment analysis on its own. A rigorous comparison of sentiment, emotion, and subjectivity/objectivity analysis is available in other works such as Yadollahi et al. (2017), while a typology of humour is presented in Section 2.4. We consider sarcasm to be a specific function of humour (Norrick, 2003) that contains subjectivity (Voyer and Techentin, 2010).

2.2 A biological look at humour

To further motivate research focusing on measuring the prevalence of humour on social media, it is informative to consider the biological and physiological effects of humour. Some of the relevant literature outlined below illustrates this significance. Importantly, Keith-Spiegel's (1972) view is that tension-release is a basic function of humour. Her research compared the effects of traditional therapies on muscles with that of laughter; since physiotherapy and various massage techniques use muscle extension followed by muscle relaxation as a means of directly reducing tension. Vigorous laughter was found to have a similar effect as it simultaneously causes many different muscle systems to activate, creating a sequence of continuous muscle extension followed by muscle relaxation resulting in tension-relief (Keith-Spiegel, 1972). Fry and Rader (1977) and Fry (1994) claimed that laughing 100 times a day equals 10 minutes of rowing. He also examined the effects of vigorous laughter; finding that the involuntary muscle spasms also increase the oxygenation of blood, hence exercising the heart and increasing endorphin production. Zand et al. (1999) documented several physiological benefits of humour (which provokes laughter) besides the reduction of stress levels and depression. They explain that laughter has been shown to stimulate and increase defensive immune cell activity, including T-cells that fight viruses and cancer cells. Zand et al. (1999) also explain that laughter boosts the activity of antibodies that fight against harmful organisms and increases the production of interferon (a virus-fighting and cell growth-regulating hormone). The psychophysiological benefits of laughter and humour are also comparable with the benefits of aerobic exercises (Berk, 2001). The impact of humour on physiology tends to receive very little attention in computational social media research (e.g., Pang and Lee, 2008; Ravi and Ravi, 2015) although it is likely to motivate approaches and applications in future work, and hence we believe should not be ignored nor overlooked.

2.3 Types of humour

As discussed previously in this paper, humour as a field of study has scholars studying its types and functions from several perspectives in psychology, literature, film, even biology. However, our aim is to explore humour-use and its relevance to the emerging field of social media analytics, automatic sentiment analysis, and data science. Since Twitter has been described as a platform for 'conversation' (Smith et al., 2015; Garside,

2015.) and 'banter' (Mishori et al., 2014; Keib et al., 2018), we have adopted theories from the linguistic study of humour and present types of a humour that are found within spontaneous conversation. Norrick (2003) classified conversational humour into four types:

1 jokes

2 anecdotes

3 wordplay

4 irony.

According to Norrick (2003), although sarcasm and mockery do not fall under any of these four categories; as they can be found in all four. Instead, he has a different classification for the functions of humour;

1 aggression

2 rapport whereby sarcasm and mockery fall under the former.

In this paper, we will treat sarcasm and mockery as a function of humour based on Norrick's (2003) theory.

From a cultural perspective, there are normative differences in what is considered humorous (Martin and Sullivan, 2013) and how for instance some jokes are not humorous, not appropriate, or contextually irrelevant. Davies (2009) hypothesises that fear of ridicule might be more prevalent in cultures that have a hierarchical social structure. Similarly, Proyer et al. (2009) conducted a cross-cultural study and found that people from Asian countries have a bigger fear of being laughed at than people from Western countries. Interestingly, none of the studies discussed in Section 2.4 have explicitly taken cultural differences into account. We discuss some specific cultural aspects of humour use in our case study in Section 3.

2.4 Automated humour detection

Using models from computational linguistics, Mihalcea and Strapparava (2005, 2006) have illustrated that to some extent it is indeed possible to automatically differentiate certain text-based non-humorous expressions from humorous ones. This can be achieved using features-based around antonymy, adult slang and other semantic and word/sentence-level features (Mihalcea and Strapparava, 2005, 2006; Buscaldi and Rosso, 2007; Zhang et al., 2017). Interestingly Mihalcea and Pulman (2007) also found humorous expressions to contain higher proportions of negative sentiments. Skalicky et al. (2016) recently analysed longer pieces of texts (i.e., student essays) and reported that humour can be partially predicted using linguistic features in text, such as the degree of descriptiveness (i.e., more adjectives and adverb use), etc. Despite this prior computational work on humour showing much promise, there is actually very little work on detecting humorous expressions on social media. Existing computational methods, when applied to social media, face various issues due to the enforced brevity of messages, and as repeatedly highlighted by various authors (e.g., Zappavigna, 2012) textual content commonly encountered on social media, contains extensive use of slang, shorthand syntax, incorrect spelling, repeated letters, repeated words, inconsistent punctuation, odd Unicode glyphs, emoticons/emojis and overall a high proportion of out-

of-vocabulary (OOV) terms. Sentences are often also not grammatically bound nor constructed properly, for instance tweets often start with a verb where the subject is implied and hashtags (and at-mentions) can be used as part of the tweet's message, e.g., 'rushing to the station, need 2get home in time for #dinnertime & avoid the #londonriots #whatalovelyday lol!!'.

Khandelwal et al. (2018) have attempted to use computational methods to detect humorous tweets posted in English and Hindi written in Latin script. They trained their models by having human annotators pre-process the corpus of tweets, deciding whether a tweet was humorous or not, with 3,453 tweets in total, achieving an inter annotator agreement of 0.821. They attained 69.3% accuracy by combining the classifiers support vector machine (SVM) and extra tree. However, this approach of supervised learning needs vast quantities of labelled training data, which is a time-consuming process (i.e., the authors needed 60 hours to annotate the 3,453 tweets), and the authors did not address issues around cultural elements of humour. The closest stream of social media specific research that has emerged in recent years looked at automated detection of sarcasm (Riloff et al., 2013; Joshi et al., 2014; Rajadesingan et al., 2015; Khattri et al., 2015; Bamman and Smith, 2015; Parde and Nielsen, 2018). As already described in Section 2.3, sarcasm is a fairly narrow and specific function of aggressive humour Norrick (2003). Riloff et al. (2013) were the first to attempt to leverage recognising contexts that contrast a positive sentiment with a negative activity or state to detect sarcasm. Their approach assumes that sarcasm arises from the contrast between a positive sentiment referring to a negative event, where the challenge is to recognise the stereotypically negative events that may generally be considered undesirable or unenjoyable. Such events are highly context sensitive and are dependent on a person's demographics and their social network. Although Riloff et al. (2013) did not consider the aforementioned, they proposed a rule-based classifier detecting positive verb phrases followed by a negative event with a custom set of learned phrases accomplishing a respectable 0.7 precision score, with a low recall of 0.09, and an overall F measure of 0.15. Their final proposed system was an ensemble of this rule-based approach and an SVM model combined, achieving an F score of 0.51 (precision 0.62, recall 0.44). Joshi et al. (2014) have also used linguistic features to present a computational approach to detect sarcasm on Twitter, leveraging incongruity, as in Riloff et al. (2013), as a possible indication that a text might contain sarcasm. They differentiate between implicit incongruity which is more time-consuming to process, and explicit incongruity which is quicker to detect albeit less prevalent on Twitter according to the researchers' findings.

Detecting social media-based humour automatically using computational and machine learning approaches may be extremely challenging, primarily due to how highly contextual most humour tends to be, as illustrated in Section 3 in this paper. Integrating common-sense world knowledge within such automated approaches is a major challenge (Parde and Nielsen, 2018); however, a number of semantic knowledge resources that could be useful for this exist (e.g., SenticNet by Cambria et al., 2016; or ConceptNet by Speer and Havasi, 2013). An early proposal of using a formal semantic world knowledge model, an ontology, was suggested for humour detection by Taylor (2009). It has been highlighted repeatedly by various authors that this kind of knowledge would be an important element in humour detection (Taylor, 2009; Mahler et al., 2017), with some initial attempts at this on automated irony detection achieving limited success (Hee et al.,

2018). Hee et al. (2018) relied on the SenticNet semantic resource, as well as semantics from word embeddings.

Beyond that, Madden et al. (2013) point out how in their study of over 800 teenager's use of social media they found that 58% of teen social media users say they share inside jokes or cloak their messages on purpose, to help hide their true meaning to others in their social network. Hence for computational approaches to be successful they must also consider the social network and personality profile of the individual creating the message. More recently, research attempted to explore more contextual features. Rajadesingan et al. (2015) exploit behavioural traits from a user's past tweets, in addition to lexical and linguistic cues. In a similar approach Khattri et al. (2015) also apply ideas from Riloff et al. (2013) and propose a classifier centred around contrast-based identification (i.e., if there is a sentiment contrast within a target tweet) and a historical tweet-based model that identifies if the sentiment expressed towards an entity in the target tweet agrees with sentiment expressed by the author towards that entity in the past. Comparing their approach against the same datasets that Riloff et al. (2013) used, Khattri et al. (2015) achieved an F score of 0.83 (precision 0.84, recall 0.81). Their work indicates that making use of text other than just the target text; by leveraging historical text-based features within a supervised sarcasm detection framework is a promising direction of future work. Bamman and Smith (2015) explore contextual features further and consider communicative context and the context of the audience. They look at the social network of the user, since they argue that sarcasm is more likely to take place between people who are more familiar with each other, and especially the response to the particular tweet is considered, pointing out that features based on these may significantly help in accurately identifying instances of sarcasm. Bamman and Smith (2015) show how incorporating simple features based on audience reaction can improve classification accuracy by over 5%.

Nevertheless, this work, although insightful, is still distinct from identifying broader humorous expression. Undeniably highly relevant, specific methods for humorous expression detection on social media require further development. Most work in this area is still in its infancy, and this paper puts forward the position that approaches need to leverage existing theories and semantic, linguistic, social context and social network features more explicitly to improve baseline performance in automated detection of humour on social media. We also argue that humorous expression is significant in sentiment analysis and for various applications yet to be explored, which are discussed in Section 2.5.

2.5 Position: why monitor humour on social media?

Less than a decade ago O'Connor et al. (2010), Tumasjan et al. (2010) and Lansdall-Welfare et al. (2012) suggested replacing data gathering through traditional opinion-polls with gathering opinion-related data through social media platforms. For instance Lansdall-Welfare et al. (2012) collected words that express mood such as fear, joy, anger and sadness on Twitter and found that occasions such as Christmas, Valentine's Day and Halloween generate similar responses on Twitter every year, discovering that specific events or announcements made by the government about cuts to public spending generated a shift in public mood so great that signs of recovery were not visible until a long period of time had lapsed. The researchers monitored tweets around the time of the 2011 London riots and were able to conclude that public anger was

steadily increasing before the riots erupted and found that there were some indicators that could have foreseen the riots had they been analysed. Another interesting shift in public mood occurred just before the royal wedding; when sentiments seemed to mellow down. The researchers attribute this to the fact that "communications, or 'tweets', tend to be in-the-moment expressions of the user's current experiences" [Lansdall-Welfare et al., (2012), p.1222] thus highly reflective of public mood at certain times. De Choudhury (2013) points out that due to social media being an unbiased collection of an individual's language and behaviour it may even be well suited in mental health studies. Other researchers also examined flu rates – an indicator to the potentials of future work beneficial to social scientists and epidemiologists for example (Nagar et al., 2014). More generally in public health applications, space-time syndromic surveillance has been shown to be effective in the detection of disease outbreaks indicating specific areas and populations with excess risk over time (Lawson and Kleinman, 2005, Kleinman et al., 2005; Kulldorff et al., 2007). Recently, Gruebner et al. (2016) proposed systematic public health monitoring for population mental health from social media datasets, which in particular allows detailed geographical and temporal resolution, and has shown promise using automated sentiment analysis on geo-located tweets. They base their approach on the hypothesis that since early emotional reactions predict longer term mental health needs, this approach could assist in the allocation of services over time and help inform public health interventions to promote the well-being of vulnerable populations. Indeed, monitoring humour could fall under this preventative function. Since humour is often used as a buffer between individuals and stressful events (Solomon, 1996) and humour is also used to vent and express frustration (Sala, 2001), the excessive appearance of humorous tweets in a specific geographical location could be an indication that users in that area are experiencing frustration or anger.

3 Example use of humour on twitter: the Arabic context

Due to the prominent focus in literature towards analysing English speaking social media expressions, this section studies the use and role of Twitter in the Arabic cultural context. The importance of social media platforms has grown in the Arab speaking world since the Arab Spring erupted in 2011, since then the emergence of online Arabic situational humour on social media has become a common phenomenon (Moalla, 2013). According to Moalla (2013) in the wake of the removal of the Tunisian ex-president Zine El Abidine Ben Ali, social media contributed in "the creation of new social bonds and the development of national identities" (2013, p.1), and notes that the uncertain and violent days that followed the initial victory triggered an insurgence of humour on social media; with the growing violence came the growth of humorous posts. Moalla (2013) claims that there had never been such a collective insurgence of humour among Tunisian social media users. She believes that it reflected the psychological confusion that the nation was experiencing, hence conducting a study on the types of situational humour that emerged in post-revolution Tunisia. Her findings conclude that the aggressive humour targeting the ex-president was caused by the 'deep-rooted suffering' caused by the regime and that in this instance humour could be viewed as 'liberation and relief' (2013, p.3). Moalla (2013) argues that it was the many years of oppression and alienation that gave way to aggressive humour as a release of the suppressed emotions that the nation was feeling.

Her theory, similar to Keith-Spiegel's (1972), is that humour and laughter's most basic function is to release tension.

Moalla (2013) also established that humour served as a defence mechanism, distancing the joking Tunisians from the stressful situations that they encountered. The more violent the situations, the more they joked on social media – the further mentally distancing themselves. Another example of humour emerging at highly politically uncertain times is the 2011 Egyptian revolution, where 17% of tweets were humorous, the highest percentage after tweets with news updates (Choudhary et al., 2012). Helmy and Frerichs (2013) described Egyptians as having 'laughed themselves into democracy' (2013, p.1). They discuss another type of humour, 'political humour', explaining that it is a type of humour that gives a voice to people who would not normally participate in the political sphere. Shehata (1992) documents emergence of the political joke as a means of protest in Egypt in 1952 after a military coup. According to Shehata (1992) the political joke then became a means to criticise the regime, in spite of restrictions of freedom of speech implemented by future regimes.

Given these examples of the role humour has played in the events that have been unfolding in the Middle East, especially on Twitter, it could be highly beneficial for researchers to monitor social media and identify the situations which provoke collective joking. Examining the situations that lead to such collective tweeting could aid in further understanding the social and political issues that frustrate the average Arab tweeter. In the next section we explore broad humorous expression relating to several recent events to extend the above-mentioned work.

3.1 Methodology

Although this paper is primarily a literature review/position paper, some exploration of humorous tweets was conducted and is described in this section in order to help illustrate the heterogeneity of humorous expressions. This was done using discourse analysis to interpret and decipher humorous tweets. Standard open coding-based content analysis, as per (Thelwall, 2014), was employed. Although full results of coding are not provided herein due to brevity, some of the prototypical exemplar tweets, where for instance aggressive, disparaging or other alternative contexts of humorous expressions were used, are presented.

The datasets analysed in this section 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. 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 and chatter. Often the selected term or hashtag used for the data collection would also be trending, i.e., according to Twitter trends (for more details on the topics and hashtags examined, see Section 3.2).

3.2 Identifying types of humour

Humour is an interdisciplinary field of study that draws on research in linguistics, psychology as well as sociology (Zabalbeascoa, 2005). Aspects of these fields are certainly useful for deciphering meaning on social media where it can be difficult to determine what constitutes a joke due to the lack of availability of certain cues, such as

facial expressions, gestures, or voice tone and acoustic cues. Context is a fundamental indicator, especially with tweets, which are often in response to real time occurrences and current events. Using the following tweet as an example, "Everyone must be hoarse with rage!" one would think that this was a negative tweet, however within the context of the 2013 UK horsemeat scandal (a trending topic on Twitter at the time), the homophone is intended as a pun – hence to be perceived as humorous. Another example taken from the horsemeat scandal "Is horsemeat the mane ingredient of Tesco's beef burgers?", "Main" was deliberately misspelled, in an intended pun.

It was equally challenging to positively identify Arabic jokes on Twitter; nevertheless, we conducted a qualitative exploration of humour in Arabic tweets. Liberal use of emoticons by Arabic speakers on Twitter was found, which was a clear indication at times that a comment that could be perceived as violent or threatening, was, in fact, intended to be humorous. For example, an Egyptian journalist made an embarrassing blunder at the 2016 Oscars, the trending hashtag in Arabic was #أوسكارز (translation: #Oscars), and one of the tweets (translated from Arabic) "If it were here we would have sentenced the Oscars' journalist to 100 whips at the Exclusive Square" could have been perceived as violent, if it were not for the four smileys added to the end of it.

Examining tweets with hashtags related to the hijacking of the Egyptian plane in March 2016 (Guardian, 2016), a certain pattern was observed. The trending hashtag was in Arabic (#اختطاف_طايره_مصريه – translation: *hijacking an Egyptian plane*), however the tweets were both in Arabic and in English. Although there were sincere empathetic tweets, the majority of the tweets were humorous. The humour was direct and collectively self-deprecating in nature; as citizens of the same country, tweeters collectively made jokes of their countrymen and women's shortcomings and the unreliability of their national airline. Many of the tweets mocked the hijacker himself, once the reasons for his hijacking were known. The hijacker's motives stemmed from his wife's rejection of him, and his wanting to win back her love – clearly indicating that he was a mentally unstable individual, and not maliciously harmful since news reports claim that he did not have live weapons and never attempted to enter the cockpit (Guardian 2016). Kubie (1971) asserts that self-depreciating humour is a mode of 'defensive denial', the tendency to engage in this type of humour can be seen as a means of hiding underlying unfavourable emotions or as a method of escapism from problems. Research by Hogg and Abrams (1990) suggests that there is in-group bias or discrimination if an individual within the group (in this case, a fellow Egyptian) has direct implications on the group as a whole. Martineau (1972) suggested a model for the social functions of humour. His model illustrates that humour could be either esteeming or disparaging. Esteeming humour helps solidify the group and increase morale. If the humour is disparaging, its purpose is to control in-group behaviour – it could also harbour demoralisation and the social integration of the group. Martineau's (1972) model proposes that humour in outgroup situations can also be either esteeming or disparaging.

Consider the following examples of the Arabic tweets on the hijacking (the first 7 tweets were translated to English by a native speaker, the remaining tweets were written in English but had the Arabic # اختطاف_طايره_مصريه (translation: *hijacking an Egyptian Plane*), in Table 1.

Table 1 Example tweets on the Egyptian plane hijacking (the first seven tweets were translated from Arabic to English)

"Whoever knows somebody who kidnaps, give me his number. I am an Egyptian who wishes to be kidnapped on the condition of letting the plane fly me around."
"The man who hijacked the plane is sweet. He wrapped sandwiches in foil and hid them in his shirt, adding wires and a detonator and made the airport stand on one foot."
"Does one have to hijack a plane to have his demands met? Please, early retirement after 15 years of service."
"He hijacked the plane for his sweetheart, and the passengers took selfies with him!!"
"Behind every great disaster is a woman."
"Praise be God, one was traveling from Cairo to Alexandria and found himself in Cyprus.. Son of a lucky woman.. no visas no fuss.."
"Egyptians issued that a plane was hijacked and is heading to Cyprus. Why doesn't anyone kidnap us and take us to Cyprus?"
"Hijacking airplanes from Egypt is easier than taking candy from children"
"When you break up with your boyfriend & he hijacks a plane to get you back. It's the little things!" #اختطاف_طايره_مصريه
"If you really love her, hijack her heart, not planes. ;)" #EgyptAir #اختطاف_طايره_مصريه
"-#اختطاف_طايره_مصريه We Live In A World Where Hijacking A Plane Is Lot Easier Than Keeping A Relationship Together. #EgyptAir #اختطاف_طايره_مصريه"
"I think the hijacker took 'love is in the air' way too seriously" #اختطاف_طايره_مصريه
"If he's willing to hijack a plane for you, he's the one" #اختطاف_طايره_مصريه
"Roses are red 🌹 Violets are blue ✿ I've hijacked a plane ✈ To be with you 👫." #اختطاف_طايره_مصريه
"Most guys would hijack a plane to get away from their ex-wives. This guy is doing it all wrong."

Zillmann (1983) places sarcasm under 'aggressive humour' with the psychological implications of aggression and hostility; which may explain its excessive appearance on social media platforms when disruptions occur. Appreciating or using hostile or aggressive humour provides a release of anger (Van Zandt and LaFont 1985).

A prominent example of tweets (in Arabic) portraying 'aggressive humour' targeted at somebody was after the 2016 Oscars when the first Egyptian journalist covered the Oscars and asked the actor Leonardo DiCaprio a what was widely perceived to be a 'primitive' question (Shepherd, 2016). There was an element of aggressive humour, which uses teasing and ridicule aimed at the journalist. Martin et al. (2003) find that this type of humour often indicates that the person who engages in it will often also portray neuroticism, hostility, anger, and aggression. It is our consensus that since Twitter is a social media platform that enables groups to engage in dialogue with one another through hashtags, the tweeters who engaged in aggressive humour display neuroticism and hostility, anger, and aggression as a collective. Example translated tweets which we collected using the terms 'أوسكارز' (translation: *Oscars*) and 'Oscars' are shown in Table 2.

Table 2 Example tweets on the Egyptian Oscar journalist (translated to English) (see online version for colours)

"If it were here we would have sentenced the Oscars' journalist 100 whips at the exclusive square for example :) :) :) :)"
"The woman at the Oscars, yes I will not call her a journalist for sure, her dignity has been humiliated in every possible way everywhere :D"
"I wish I could understand, why would Leonardo care that you're the first Egyptian journalist covering the Oscars?"
"Please ask Leonardo 'what about the first Egyptian journalist from there'"
"Every time I remember the Egyptian that jumped at Leonardo at the Oscars I collapse from laughter 😂😂😂"
"My God, I can still see the interview that the Egyptian journalist had with Leonardo at the Oscars, I can't finish the video because of the extent of the disgrace 😂😂😂😂"
"The newspaper "the Independent" says that Leonardo deserves a second Oscar for the well behaved way he answered the stupid question"
"Did you have to say that you're Egyptian? You could have just asked the question and ended it."
"Did she have to say Egyptian? Egypt doesn't need this, I swear 😭"
"Leonardo, not all Egyptians are garbage like this, I swear"
"Turns out Shayma Oscars, the journalist of the seventh day, is the daughter of a colonel. Leonardo DiCaprio might be thrown in the department [of corrections] and might find himself in a drug trial"
"Leonardo's reaction when she asked him her great question is priceless. She made him forget that he won the Oscar"
"The sentence 'the first Egyptian journalist covering the Oscars' is full of all the psychological problems that control us"

Users with Arabic names also tweeted about it aggressively in English;

> "THAT FUCKING EGYPTIAN JOURNALIST OR WHATEVER THAT WENT TO THE OSCARS WHYWHYWHYWHYWHY KILL ME PLEASE"
>
> "U r the first and last Egyptian journalist that covers the Oscars ! 😒"
>
> "Reason 646383 I hate being Egyptian That journalist that was at the Oscars Fuck you"
>
> "What do you expect after 30 yrs of Mubarak?"

These tweets display mockery targeting the journalist harshly, some of them clearly displaying a sense of superiority – a phenomenon discussed as early as the seventeenth century by British philosopher Thomas Hobbes who found that humour can be extracted from a feeling of superiority over others. The majority of tweets in the English language by Arab tweeters, however, identified as being represented by the journalist and took her public mistake in the West as a negative representation of their Egyptian identity.

4 Discussion, conclusion and future work

The primary position of this paper is that further work on humour analysis as an application in its own right, as well as in conjunction with existing sentiment analysis approaches is necessary due to the significant impact humorous expression have on our lives. The bullet points below summarise the presented positions in more detail.

4.1 Considering the function of humour

- The preventative function of humour provides motivation for automated humour detection. Since humour is often used as a buffer between individuals and stressful events and to vent and express frustration (Solomon, 1996; Sala, 2001), being able to detect humorous expression in relation to various events or geographic locations at large scale accurately, would have a number of heterogeneous applications.
- As discussed in Section 2.1 and suggested by Jong and Dückers (2016), humour can be a source of misunderstandings and rumours. Hence the analysis of humorous expressions in heterogeneous contexts may have its uses in detecting mis/disinformation. The emergence of rumours on social media, especially during crises has been documented to be a widespread issue (e.g., Procter et al., 2011). Applications of humour detection may also have a place in political disinformation, this is especially relevant with the recent dominance of 'fake news' in the public sphere, and the rate at which such content emerges on social media (Tucker et al., 2018).
- There is already some empirical evidence of humorous expressions to contain higher proportions of negative sentiments (Mihalcea and Pulman, 2007); however, this has not yet been studied in the context of social media data and the full emotional range from advanced sentiment analysis (e.g., fine-grained basic emotions in systems such as Sykora et al., 2013) deserve further exploration. Humour analysis in conjunction with sentiment analysis will add an additional dimension, and a more holistic view to sentiment analysis approaches will be possible. For instance, the prevalence of highly charged humorous expressions in messages expressing disgust would arguably have a different meaning overall to messages only expressing the emotion of disgust on its own. These types of studies on social media user-generated content are currently non-existent and lacking, yet given the rich data available, social media provides for a unique opportunity for ecological momentary assessment as described in Shaughnessy et al. (2018), where social media can provide high levels of ecological validity, avoiding certain biases.

4.2 Cultural and multilingual considerations

- Research opportunities may also arise in pragmatics and corpus linguistics (Partington, 2006), where large quantities of readily available social media data could provide significant contextual information at large scale and facilitate studies that explore linguistic differences in humorous expressions across cultures, gender and various other demographics (e.g., Crawford, 2003; Davies, 2003).

- It is quite clear that English specific opinion mining research has received considerably more attention within academia than other languages. Hence, further research is needed to help understand the use of humour, subjective and sentiment rich language in non-English online and particularly social media texts. For instance, recently Wenas et al. (2016) used an approach motivated by Dodds et al. (2011) to measure happiness (i.e., via valence and arousal) within Indonesian Twitter conversations. They found that Indonesian word-use on Twitter has a tendency towards positive emotions, which underlines the potentially insightful and important analyses that will be required across heterogeneous cultural and linguistic contexts. The majority of sentiment analysis and humour detection related work from social media datasets has not paid much attention to non-English language and cultural contexts (Pang and Lee, 2008; Ravi and Ravi, 2015). Nevertheless, researchers have already built numerous language-specific sentiment analysis systems, and there were attempts at approaches capable of independently handling multilingual datasets. Most attempts at multilingual sentiment analysis make use of statistical machine translation (SMT), which has the advantage of not needing language-specific corpora or resources and potentially allows deploying one system across a number of languages once, using widely available SMT systems such as the MOSES framework (Koehn et al., 2007), Google Translate, Bing Translate or Yandex Translator. Generally, most of these systems tend to perform poorly with non-Latin languages, especially with Arabic and its numerous different dialects and social media slang. A qualitative validation of this approach on work by Glass and Colbauch (2012) who used Google Translate to analyse Arabic sentiment during the Egyptian revolution, found these translations to be inaccurate, often to the extent of cancelling-out the overall sentiment polarity, thus effectively posing a major challenge to SMT approaches for sentiment analysis. Although specific pairs of languages that are closely related tend to achieve better translation accuracy. Due to the sensitive nuanced nature of language and culture specific differences in humour use, automated language translation may prove to be a significant barrier and language-specific analyses are likely needed.

4.3 Improving automated humour detection

As was already suggested in Section 2.4, this paper puts forward the position that approaches for detecting social media-based humour need to leverage existing theories and semantic, linguistic, social context and social network features more explicitly to improve baseline performance in automated detection of humour on social media. Performing an error analysis of misclassifications from an automated sarcasm detection system, Parde and Nielsen (2018) highlight three particular areas for future work

1 introducing models of world or common-sense knowledge to help detect

2 better approaches to normalising text, such as splitting up compound hashtags into individual words

3 improved performance of sentiment detection approaches, especially around evolving language and slang on social media.

The most significant challenge, and likely to provide the most effective improvements in performance is for future work to focus on 1. However, to add to this, we propose a scheme within which existing sentiment analysis approaches can be leveraged to establish features from the social network of users and audience reactions to the posts under analysis. The core idea here is based on the premise that a particular social media post can be thought of as humorous if the reactions to it imply that it is funny. In other words, a humorous message is effectively judged to be humorous by its audience and, in some respect, this can be reframed as 'crowdsourcing' the perception of 'funniness'. Particularly certain states, such as feeling amused or feeling entertained which can be linked with reactions to humorous expressions (Partington, 2006) are relevant.

Sentiment analysis traditionally looks for positive or negative sentiments (Ravi and Ravi, 2015); however sentiment analysis approaches that are based on Russel's circumplex model (Russell et al., 1989) can capture expressions that are more closely related to humour – where valence (i.e., pleasure) and arousal (i.e., activation) are represented on a plane within an emotional circumplex of affect. Various lexical resources exist, which readily map onto the two-dimensional valence and arousal circumplex model, such as the ANEW dictionary (Bradley and Lang, 1999; Finn, 2011) or work by Choudhury and Counts (2012) who used the circumplex model by extending various vocabularies, including the ANEW lexicon. Hence particularly states related to reactions to humour, such as amusement or feelings linked with being entertained can be detected using the circumplex model-based sentiment analysis, and features derived from these likely hold some promise in future work.

4.4 Concluding remarks

In this position paper the authors propose that certain computational and automated approaches to humour detection may have worthwhile and broad applications that deserve further research and exploration by the relevant research communities. From the reviewed literature it is evident that techniques and algorithms required for accurate and effective humour detection may be motivated and adapted from existing sentiment analysis and opinion mining approaches. Much work in applying computational approaches to social media datasets and especially research on sentiment analysis exists; however, this paper underlines and puts forward the case for expanding these approaches to account for humorous expressions. The significance of humour from extant theory is reviewed and highlighted, and although humour detection in social media user-generated datasets is clearly a nascent area it is hoped that this paper will aid in establishing further research activities in this exciting and interesting field, helping to lead this new stream of research.

References

Bamman, D. and Smith, N.A. (2015) 'Contextualized sarcasm detection on Twitter', *Proceedings of the 9th International Conference on Web and Social Media*, Oxford, UK.

Berger, J. (2014) 'Word of mouth and interpersonal communication: a review and directions for future research', *Journal of Consumer Psychology*, Vol. 24, No. 4, pp.586–607.

Berger, J. and Milkman, K.L. (2012) 'What makes online content viral?', *Journal of Marketing Research*, Vol. 49, No. 2, pp.192–205.

Berk, L.S., Felten, D.L., Tan, S.A., Bittman, B.B. and Westengard, J. (2001) 'Modulation of neuroimmune parameters during the eustress of humor-associated mirthful laughter', *Alternative Therapies in Health and Medicine*, Vol. 7, No. 2, pp.62–76 [online] http://www.laughteryogachicago.com/13.pdf (accessed 25 October 2017).

Bradley, M.M. and Lang, P.J. (1999) *Affective Norms for English Words (ANEW): Instruction Manual and Affective Ratings*, Technical Report, Center for the Study of Psychophysiology – Emotion and Attention, University of Florida.

Bryant, J. and Zillmann, D. (2013) *Responding to the Screen: Reception and Reaction Processes*, New York, Routledge.

Buscaldi, D. and Rosso, P. (2007) 'Some experiments in humour recognition using the Italian wikiquote collection', *International Workshop on Fuzzy Logic and Applications*, July, Springer, Berlin, Heidelberg, pp.464–468.

Cambria, E., Poria, S., Bajpai, R. and Schuller, B. (2016) 'SenticNet 4: a semantic resource for sentiment analysis based on conceptual primitives', *Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics*, Technical Papers, pp.2666–2677.

Candini, V., Ghisi, M., Bottesi, G., Ferrari, C., Bulgari, V., Iozzino, L., Boero, M.E., De Francesco, A., Maggi, P., Segalini, B. and Zuccalli, V. (2018) 'Personality, schizophrenia, and violence: a longitudinal study', *Journal of Personality Disorders*, Vol. 32, No. 4, pp.465–481.

Cann, A. and Calhoun, L.G. (2001) 'Perceived personality associations with differences in sense of humor: stereotypes of hypothetical others with high or low senses of humor', *Humor – International Journal of Humor Research*, Vol. 14, No. 2, pp.117–130.

Casey, A., Sykora, M., Elayan, S., Jackson, T. and Cale L. (2018) 'MEMEotive: analysing the effects of internet memes on young teenagers', *Health and Health Behaviours*, Evidence (SMH0167) submitted to UK Science and Technology Parliamentary Committee [online] http://data.parliament.uk/writtenevidence/committeeevidence.svc/evidencedocument/science-and-technology-committee/impact-of-social-media-and-screenuse-on-young-peoples-health/written/87284.pdf (accessed 26 October 2018).

Chen, X., Sykora, M., Elayan, S. and Jackson, T.W. (2018) 'What about mood swings? Identifying depression on Twitter with temporal measures of emotions', *WWW 2018 Conference - The Sixth International Workshop on Natural Language Processing for Social Media at SocialNLP-2018*.

Choudhary, A., Hendrix, W., Lee, K., Palsetia, D. and Liao, W.K. (2012) 'Social media evolution of the Egyptian revolution', *Communications of the ACM*, Vol. 55, No. 5, pp.74–80.

Choudhury, M. and Counts, S. (2012) *The Nature of Emotional Expression in Social Media: Measurement, Inference and Utility*, Technical Report: Microsoft.

Coppersmith, G., Harman, C., and Dredze, M. (2014) 'Measuring post traumatic stress disorder in Twitter', in *Proceedings of the 8th International AAAI Conference on Weblogs and Social Media*, Ann Arbor, USA.

Crawford, M. (2003) 'Gender and humor in social context', *Journal of Pragmatics*, Vol. 35 No. 9, pp.1413–1430.

Curseu, P.L. and Fodor, O.C. (2016). 'Humor and group atmosphere: development of a short scale for evaluating affiliative and aggressive humor in groups', *Team Performance Management: An International Journal*, Vol. 22, Nos. 7/8, pp.370–382.

Davies, C.E, (2009) 'Humor theory and the fear of being laughed at', *Humor-International Journal of Humor Research*, Vol. 22, Nos. 1–2, pp.49–62.

Davies, C.E. (2003) 'How English-learners joke with native speakers: an interactional sociolinguistic perspective on humor as collaborative discourse across cultures', *Journal of Pragmatics*, Vol. 35, No. 9, pp.1361–1385.

de Choudhury, M. (2013) 'Role of social media in tackling challenges in mental health', in *Proceedings of the 2nd International Workshop on Socially-aware Multimedia*, pp.49–52, New York, USA.

Dodds P.S., Harris K.D., Kloumann I.M., Bliss C.A. and Danforth C.M. (2011) 'Temporal patterns of happiness and information in a global social network: hedonometrics and Twitter', *PloS One*, Vol. 6, No. 12, p.e26752.

Ekman, P. (1973) *Cross-Cultural Studies of Facial Expression. Darwin and Facial Expression: A Century of Research in Review*, Malor Books, San Francisco.

Finn Å.N. (2011) 'A new ANEW: evaluation of a word list for sentiment analysis in microblogs', *Proceedings of the ESWC-2011 Workshop on Making Sense of Microposts: Big Things Come in Small Packages*, Vol. 718 in CEUR Workshop Proceedings, pp.93–98, Heraklion, Crete.

Freud, S. (1928) 'On humor', *The Psychoanalytic Review*, Vol.15, No. 85, pp.1913–1957.

Freud, S. (1959) 'Humor', in *Collected Papers*, Vol. 5, Basic Books, New York.

Fry, W.F. (1994) 'The biology of humor', *Humor: International Journal of Humor Research*, Vol. 7, No. 2, pp.111–126.

Fry, W.F. and Rader, C. (1977) 'The respiratory components of mirthful laughter', *Journal of Biological Psychology*, Vol. 19, pp.39–50.

Garside, J. (2015) 'Twitter puts trillions of tweets up for sale to data miners', *The Guardian.com. Guardian News and Media*, Vol. 18.

Gergen, K.J. (1973) 'Social psychology as history', *Journal of Personality and Social Psychology*, Vol. 26, No. 2, pp.309–320.

Glass, K. and Colbaugh, R. (2012) 'Estimating the sentiment of social media content for security informatics applications', *Security Informatics*, Vol. 1, No. 1, pp.1–16.

Graham, E.E. (1995) 'The involvement of sense of humor in the development of social relationships', *Communication Reports*, Vol. 8, No. 2, pp.158–169.

Gruebner, O., Sykora, M., Lowe, S., Shankardass, K., Trinquart, L., Jackson, T., Subramanian, S.V. and Galea, S. (2016) 'Spatial temporal surveillance of post disaster mental health', *13th International Conference on Urban Health*, San Francisco, USA.

Guardian (2016) *EgyptAir Hijacker's 'Suicide Belt' a Fake, Say Cyprus Officials – As it Happened* [online] http://www.theguardian.com/world/live/2016/mar/29/egyptair-hijack-plane-from-alexandria-to-cairo-lands-in-cyprus-live (accessed 1 April 2016).

Guskin E. and Hitlin P. (2012) 'Hurricane Sandy and Twitter: PEJ new media index', *Pew Research Centre* [online] http://www.journalism.org/2012/11/06/hurricane-sandy-and-twitter/ (accessed 19 October 2016).

Hee, V-C., Lefever, E. and Hoste, V. (2018) 'We usually don't like going to the dentist. Using common sense to detect irony on Twitter', *Computational Linguistics*, Vol. 44, No. 4, pp.1–63.

Helmy, M.M. and Frerichs, S. (2013) 'Stripping the boss: the powerful role of humor in the Egyptian revolution 2011'. *Integrative Psychological and Behavioral Science*, Vol. 47, No 4, pp.450–481.

Hiday, V.A. (1997) 'Understanding the connection between mental illness and violence', *International Journal of Law and Psychiatry*, Vol. 20, No. 4, pp.399–417.

Hogg, M.A. and Abrams, D. (1990) 'Social motivation, self-esteem and social identity', *Social Identity Theory: Constructive and Critical Advances*, Vol. 28, p.47.

Jong, W. and Dückers, M.L.A (2016) 'Self-correcting mechanisms and echo-effects in social media: an analysis of the 'gunman in the newsroom' crisis', *Computers in Human Behavior*, Vol. 59 No. 2, pp.334–341.

Joshi, A., Mishra, A., Senthamilselvan, N. and Bhattacharyya, P. (2014) 'Measuring sentiment annotation complexity of text', *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics*, June, Vol. 2, pp.36–41.

Keib, K., Himelboim, I. and Han, J.Y. (2018) 'Important tweets matter: predicting retweets in the #BlackLivesMatter talk on twitter', *Computers in Human Behavior*, Vol. 85, No. 1, pp.106–115.

Keith-Spiegel, P. (1972) 'Early conceptions of humor: varieties and issues', in Goldstein, J.H. and McGhee, P.E. (Eds.): *The Psychology of Humor: Theoretical Perspectives and Empirical Issues*, pp.4–39, Academic Press, New York.

Khandelwal, A., Swami, S., Akhtar, S.S. and Shrivastava, M. (2018) *Humor Detection in English-Hindi Code-Mixed Social Media Content: Corpus and Baseline System*, arXiv preprint arXiv:1806.05513.

Khattri A., Joshi A., Bhattacharyya P. and Carman M.J. (2015) 'Your sentiment precedes you: using an author's historical tweets to predict Sarcasm', *Proceedings of 6th Workshop on Computational Approaches to Subjectivity, Sentiment & Social Media Analysis*, Lisbon, Portugal.

Kleinman K., Abrams A.M., Kulldorff M. and Platt R. (2005) 'A model-adjusted space-time scan statistic with an application to syndromic surveillance', *Epidemiology and Infection*, Vol. 133, No. 1, pp.409–419.

Koehn, P., Hoang, H., Birch, A., Callison-Burch, C., Federico, M., Bertoldi, N., … and Dyer, C. (2007) 'Moses: open source toolkit for statistical machine translation', in *Proceedings of the 45th Annual Meeting of the ACL on Interactive Poster and Demonstration Sessions*, pp.177–180.

Konstan, D. (1995) *Greek Comedy and Ideology*, Oxford University Press, England.

Kubie, L.S. (1971) 'The destructive potential of humor in psychotherapy', *American Journal of Psychiatry*, Vol. 127, No. 7, pp.861–866.

Kuipers, G. (2015) *Good Humor, Bad Taste*: *A Sociology of the Joke*, Walter de Gruyter, Berlin.

Kulldorff , M., Mostashari, F., Duczmal, L., Yih, W.K., Kleinman, K. and Platt, R. (2007) 'Multivariate scan statistics for disease surveillance', *Statistics in Medicine*, Vol. 26, No. 8, pp.1824–1833.

Lansdall-Welfare, T., Lampos, V. and Cristianini, N. (2012) 'Effects of the recession on public mood in the UK', in *Proceedings of the 21st International Conference on World Wide Web*, pp.1221–1226, Lyon, France.

Lawson, A.B. and Kleinman, K. (2005) *Spatial and Syndromic Surveillance for Public Health*, John Wiley & Sons, UK.

Lehmann, J., Gonçalves, B., Ramasco, J.J. and Cattuto, C. (2012) 'Dynamical classes of collective attention in twitter', in *Proceedings of the 21st International Conference on World Wide Web*, Lyon, France. pp.251–260.

Lin, C. and Hsu, J.Y. (2014) 'Crowdsourced explanations for humorous internet memes', in *Proceedings of the Twenty-Eighth AAAI Conference on Artificial Intelligence*, Pittsburgh, USA.

Locher, M.A. and Bolander, B. (2015) 'Humour in microblogging: exploiting linguistic humour strategies for identity construction in two Facebook focus groups', in Dynel, M. and Chovanec, J. (Eds.): *Participation in Public and Social Media Interactions*, pp.135–155, John Benjamins Publishing, Amsterdam, Netherlands.

Madden M., Lenhart, A., Cortesi, S., Gasser, U., Duggan, M., Smith, A. and Beaton, M. (2013) *Teens, Social Media, and Privacy*, Pew Research Center [online] http://www.lateledipenelope.it/public/52dff2e35b812.pdf (accessed 10 October 2016).

Mahler, T., Cheung, W., Elsner, M., King, D., de Marneffe, M.C., Shain, C., Stevens-Guille, S. and White, M. (2017) 'Breaking NLP: using morphosyntax, semantics, pragmatics and world knowledge to fool sentiment analysis systems', in *Proceedings of the First Workshop on Building Linguistically Generalizable NLP Systems*, pp.33–39.

Martin R.A., Puhlik-Doris P., Larsen G., Gray J. and Weir K. (2003) 'Individual differences in uses of humor and their relation to psychological well-being: development of the humor styles questionnaire', *Journal of Research in Personality*, Vol. 37, No. 1, pp.48–75.

Martin, G.N. and Sullivan, E. (2013) 'Sense of humor across cultures: a comparison of British, Australian and American respondents', *North American Journal of Psychology*, Vol. 15, No. 2, pp.375–384.

Martin, R.A. and Ford, T. (2018) *The Psychology of Humor: An Integrative Approach*, Academic Press, London.

Martineau, W.H. (1972) 'A model of the social functions of humor', in Goldstein, J.H. and McGhee P.E. (Eds.): *The Psychology of Humor: Theoretical Perspectives and Empirical Issues*, pp.101–125, Academic Press, New York.

Mihalcea, R. and Pulman, S. (2007) 'Characterizing humour: an exploration of features in humorous texts', *International Conference on Intelligent Text Processing and Computational Linguistics*, Springer, Berlin, Heidelberg, February, pp.337–347.

Mihalcea, R. and Strapparava, C. (2005) 'Making computers laugh: Investigations in automatic humor recognition', *Proceedings of the Conference on Human Language Technology and Empirical Methods in Natural Language Processing*, October, pp.531–538, Association for Computational Linguistics.

Mihalcea, R. and Strapparava, C. (2006) 'Learning to laugh (automatically): computational models for humor recognition', *Computational Intelligence*, Vol. 22, No. 2, pp.126–142.

Mishori, R., Levy, B. and Donvan, B. (2014) 'Twitter use at a family medicine conference', *Family Medicine*, Vol. 46, No. 8, pp.608–14.

Moalla, A. (2013) 'Tunisia in the Aftermath of the Revolution: insights into the use of humor on Facebook to create social bonds and develop relational identity', *SAGE Open*, Vol. 3, No. 3, pp.1–7.

McGhee, P.E. (1979) *Humor, Its Origin and Development*, WH Freemanm, San Francisco.

Nagar R., Yuan Q., Freifeld C.C., Santillana M., Nojima A., Chunara R. and Brownstein J.S. (2014) 'A case study of the New York city 2012–2013 influenza season with daily geocoded Twitter data from temporal and spatiotemporal perspectives', *Journal of Medical Internet Research*, Vol. 16, No. 10, p.e236 [online] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4259880/ (accessed 27 October 2017].

Nikolinakou, A. and King, K.W. (2018) 'Viral video ads: Emotional triggers and social media virality', *Psychology & Marketing*, Vol. 35, No. 10, pp.715–726.

Norrick N.R. (2003) 'Issues in conversational joking', *Journal of Pragmatics*, Vol. 35, No. 9, pp.1333–1359.

O'Connor B., Balasubramanyan R., Routledge B. and Smith N. (2010) 'From tweets to polls: linking text sentiment to public opinion time series', *Fourth International AAAI Conference on Weblogs and Social Media*, Washington DC, USA.

Okafor, E., Lucier-Greer, M. and Mancini, J.A. (2016) 'Social stressors, coping behaviors, and depressive symptoms: a latent profile analysis of adolescents in military families', *Journal of Adolescence*, Vol. 51, No. 1, pp.133–143.

Osborne, M., Moran, S., Mccreadie, R., Von Lunen, A., Sykora, M., Cano, E., Ireson, N., Macdonald, C., Ounis, I., He, Y., Jackson, T., Ciravegna, F. and O'Brien, A. (2014) 'Real-time detection, tracking, and monitoring of automatically discovered events in social media', in *52nd Annual Meeting of the Association for Computational Linguistics: System Demonstrations*, Baltimore, MD, USA, 23–24 June, pp.37–42.

Pang B. and Lee L. (2008) 'Opinion mining and sentiment analysis', *Foundations and Trends in Information Retrieval*, Vol. 2, Nos. 1–2, pp.1–135.

Parde, N. and Nielsen, R. (2018) 'Detecting sarcasm is extremely easy;-)', in *Proceedings of the Workshop on Computational Semantics beyond Events and Roles*, pp.21–26.

Partington, A. (2006) *The Linguistics of Laughter: A Corpus-Assisted Study of Laughter-Talk*, Routledge, New York, US.

Porter, L. and Golan, G.J. (2006) 'From subservient chickens to brawny men: a comparison of viral advertising to television advertising', *Journal of Interactive Advertising*, Vol. 6, No. 2, pp.30–38.

Procter, R., Vis, F., Voss, A., Cantijoch, M., Manykhina, Y., Thelwall, M. and Gray S. (2011) 'Riot rumours: how misinformation spread on Twitter during a time of crisis', *The Guardian* [online] https://www.theguardian.com/uk/interactive/2011/dec/07/london-riots-twitter (accessed 6 March 2017).

Proyer, R.T., Ruch, W., Ali, N.S., Al-Olimat, H.S., Amemiya, T., Adal, T.A., Ansari, S.A., Arhar, Š., Asem, G., Baudin, N. and Bawab, S. (2009) 'Breaking ground in cross-cultural research on the fear of being laughed at (gelotophobia): a multi-national study involving 73 countries', *Humor-International Journal of Humor Research*, Vol. 22, Nos. 1–2, pp.253–279.

Rajadesingan A., Zafarani R. and Liu H. (2015) 'Sarcasm detection on Twitter: a behavioral modelling approach', *Proceedings of the 8th ACM International Conference on Web Search and Data Mining – WSDM*, Shanghai, China.

Ravi, K. and Ravi, V. (2015) 'A survey on opinion mining and sentiment analysis: tasks, approaches and applications', *Knowledge-Based Systems*, Vol. 89, No. 1, pp.14–46.

Riloff E., Qadir A., Surve P., De Silva L., Gilbert N. and Huang, R. (2013) 'Sarcasm as contrast between a positive sentiment and negative situation', *Proceedings of Empirical Methods in Natural Language Processing EMNLP Conference*, Seattle, Washington.

Rnic, K., Dozois, D.J. and Martin, R.A. (2016) 'Cognitive distortions, humor styles, and depression', *Europe's Journal of Psychology*, Vol. 12, No. 3, p.348.

Romero, E. and Pescosolido, A. (2008) 'Humor and group effectiveness', *Human Relations*, Vol. 61, No. 3, pp.395–418.

Russell, J.A., Lewicka, M. and Niit, T. (1989) 'A cross-cultural study of a circumplex model of affect', *Journal of Personality and Social Psychology*, Vol. 57, No. 5, pp.848–856.

Sala, F. (2001) *Relationship between Executives' Spontaneous Use of Humor and Effective Leadership*.

Seltzer E.K., Jean N.S., Kramer-Golinkoff E., Asch D.A. and Merchant R.M. (2015) 'The content of social media's shared images about ebola: a retrospective study', *Public Health*, Vol. 129 No. 9, pp.1273–1277.

Shaughnessy, K., Robertson, C., Sykora, M., Shankardass, K. and Feick, R. (2018) 'Using geo-located social media for ecological momentary assessments of emotion: innovative opportunities in psychology science and practice', *APA Canadian Psychology*, Vol. 59, No. 1, pp.47–53.

Shehata, S.S. (1992). 'The politics of laughter: Nasser, Sadat, and Mubarek in Egyptian political jokes', *Folklore*, Vol. 103, No. 1, pp.75–91.

Shepherd, J. (2016) *Egyptian Reporter who Asked Leonardo DiCaprio Awkward Question at the Oscars has Apologised* [online] http://www.independent.co.uk/arts-entertainment/films/news/egyptian-reporter-who-asked-leonardo-dicaprio-awkward-question-at-the-oscars-has-apologised-a6917426.html (accessed 2 January 2017).

Sigalas, P.D. and Barkla, X. (2014) 'Underdiagnosis of depression in young people', *British Medical Journal*, Vol. 348, No. 1, p.g170.

Sinnenberg, L., Buttenheim, A.M., Padrez, K., Mancheno, C., Ungar, L. and Merchant, R.M. (2017) 'Twitter as a tool for health research: a systematic review', *American Journal of Public Health*, Vol. 107, No. 1, pp.e1–e8.

Skalicky, S., Berger, C.M., Crossley, S.A. and McNamara, D.S. (2016) 'Linguistic features of humor in academic writing', *Advances in Language and Literary Studies*, Vol. 7, No. 3, pp.pp–248-259.

Smith, M.A., Himelboim, I., Rainie, L. and Shneiderman, B. (2015) 'The structures of Twitter crowds and conversations', in *Transparency in Social Media*, pp.67–108, Springer, Cham.

Snyder, M. (1974) 'Self-monitoring of expressive behavior', *Journal of Personality and Social Psychology*, Vol. 30, No. 4, pp.526–537.

Solomon, J.C. (1996) 'Humor and aging well', *The American Behavioral Scientist*, Vol. 39, No. 3, pp 249–271.

Speer, R. and Havasi, C. (2013) 'Conceptnet 5: a large semantic network for relational knowledge', in Gurevych, I. and Kim, J. (Ed.): *The People's Web Meets NLP*, pp.161–176, Springer, Switzerland.

Sykora, M. D., Jackson, T., O'Brien, A. and Elayan, S. (2013) 'Emotive ontology: extracting fine-grained emotions from terse, informal messages', *Proceedings of the IADIS International Conference Intelligent Systems and Agents 2013, ISA* Prague, pp.19–26.

Taylor, J.M., (2009) 'Computational detection of humor: a dream or a nightmare? the ontological semantics approach, web intelligence and intelligent agent technologies', *IEEE/WIC/ACM International Joint Conferences on WI-IAT'09'*, Vol. 3, pp.429–432.

Thelwall, M. (2014) *Big Data and Social Web Research Methods*, University of Wolverhampton, UK

Tucker, J., Guess, A., Barberá, P., Vaccari, C., Siegel, A., Sanovich, S., … and Nyhan, B. (2018*). Social Media, Political Polarization, and Political Disinformation: A Review of the Scientific Literature*, A Technical Report, published 19 March 2018, SSRN [online] https://ssrn.com/abstract=3144139 or http://dx.doi.org/10.2139/ssrn.3144139 (accessed 28 October 2018).

Tumasjan A., Sprenger T.O. and Welpe I.M. (2010) 'Predicting elections with Twitter: what 140 characters reveal about political sentiment', *Fourth International AAAI Conference on Weblogs and Social Media*, Washington DC, USA.

Van Zandt, S. and LaFont, C. (1985) 'Can a laugh a day keep the doctor away?', *The Journal of Practical Nursing*, Vol. 35, No. 3, pp.32–35.

Voyer, D. and Techentin, C. (2010) 'Subjective auditory features of sarcasm', *Metaphor and Symbol*, Vol. 25, No. 4, pp.227–242.

Weisfeld, G.E. (1993) 'The adaptive value of humor and laughter', *Ethology and Sociobiology*, Vol. 14, No. 2, pp.141–169.

Wenas, A., Sjahputri, S., Takwin, B., Primaldhi, A. and Muhamad, R. (2016) 'Measuring happiness in large population', *IOP Conference Series: Earth and Environmental Science*, January, Vol. 31, No. 1, p.012023, IOP Publishing Ltd.

Whiting, A. and Williams, D. (2013) 'Why people use social media: a uses and gratifications approach', *Qualitative Market Research: An International Journal*, Vol. 16, No. 4, pp.362–369.

Woods, P. (1976) 'Having a laugh: an antidote to schooling', in M. Hammersley and P. Woods (Eds.): *The Process of Schooling*, pp.178–187, London, Routledge.

Yadollahi, A., Shahraki, A.G. and Zaiane, O.R. (2017) 'Current state of text sentiment analysis from opinion to emotion mining', *ACM Computing Surveys (CSUR)*, Vol. 50, No. 2, pp.25–33.

Zabalbeascoa, P. (2005) 'Humor and translation – an interdiscipline', *International Journal of Humor Research*, Vol. 18, No. 2, pp.185–208.

Zand J., Spreen A.N. and LaValle J.B. (1999*) Smart Medicine for Healthier Living*, Penguin Press, Garden City Park, New York.

Zappavigna M. (2012) *Discourse on Twitter and Social Media: Howe We Use Language to Create Affiliation on the Web*, A&C Black, London, UK.

Zhang, D., Song, W., Liu, L., Du, C. and Zhao, X. (2017) 'Investigations in automatic humor recognition', *10th International Symposium on Computational Intelligence and Design (ISCID)*, Vol. 1, pp.272–275.

Zillmann, D. (1983) 'Transfer of excitation in emotional behavior, social psychophysiology', in J.T. Cacioppo and R.E. Petty (Eds.): *Social Psychophysiology: A Sourcebook*, pp.215–240, Guilford Press, New York.

Notes

1 Research that has been carried out by other scientists support Weisfeld's (1993) theory; experiments conducted on signing primates in the 1970s showed signs of playfulness and displayed evidence of behaviour that can be viewed as humorous, which also suggests that early humans could have been playful and/or humorous (McGhee, 1979).

2 Memes are concepts, catchphrase or pieces of media which spreads, often as mimicry.