Towards Understanding how Emojis Express Solidarity In Crisis Events

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Abstract. We study how emojis are used to express solidarity on social media in the context of three major crisis events - a natural disaster, Hurricane Irma in 2017; terrorist attacks that occurred in November 2015 in Paris; and the Charlottesville protests in August 2017. Using annotated corpora, we first train a recurrent neural network model to classify expressions of solidarity in text. Next, we use these expressions of solidarity to characterize human behavior in online social networks, through the temporal and geospatial diffusion of emojis, their co-occurrence patterns and sentiment scores. Our analysis reveals that emojis are powerful indicators of sociolinguistic behaviors (solidarity) that are exhibited on social media as the crisis events unfold.

Keywords: solidarity · social movements · emoji · social diffusion

1 Introduction and Related Work

Research has shown that emoticons and emojis are more likely to be used in socio-emotional contexts [5] and that they may serve to clarify message structure or reinforce message content [14, 6]. Riordan [18] found that emojis, especially non-face emojis, can alter a reader's perceived affect of messages. Wood et al. [22] found emoji to be far more extensively used as compared to hashtags, and noted that emoji present a faithful representation of a user's emotional state. While research has investigated the use of emojis over communities and cultures [1, 12] as well as how emoji use mediates close personal relationships [11], the systematic study of emojis as indicators of human behaviors in social movements has not been undertaken. Our work seeks to fill this gap.

The collective enactment of certain online behaviors, including pro-social behaviors such as solidarity, has been known to directly affect political mobilization and social movements [20, 7]. Social media, due to its increasingly pervasive nature, permits a sense of immediacy [8] - a notion that produces a high degree of identification among politicized citizens of the web, especially in response to crisis events [7]. Social movements with a strong sense of online solidarity have had tangible offline (real-world) consequences, exemplified by movements related to *#BlackLivesMatter*, *#MeToo* and *#NeverAgain* [4, 3]. Herrera et al. found that individuals were more outspoken on social media after a tragic event [9].

They studied solidarity in tweets spanning geographical areas and several languages relating to a terrorist attack, and found that hashtags evolved over time correlating with a need of individuals to speak out about the event. However, these prior approaches do not consider the use of emoji in their analysis.

We thus seek to understand how emojis are used when people express behaviors online on a global scale and what insights can be gleaned through the use of emojis during crisis events. We make the following salient contributions:

1. Advance the understanding of the pragmatic function of emoji and how they contribute to enrich expression of sentiment.
2. Demonstrate how emojis are used to express pro-social behaviors such as solidarity in the online context, through the study of temporal and geospatial diffusion, as well as co-occurrence patterns in online social networks.
3. Three large-scale corpora (made available to the research community upon publication), annotated for expressions of solidarity using multiple annotators and containing a large number of emojis, surrounding three distinct crisis events that vary in time-scales and type of crisis event.

2 Data

In this section, we briefly describe the three crisis events we analyze and the annotation procedures used for labeling our social media text data.

Hurricane Irma corpus: Irma was a catastrophic Category 5 hurricane and was one of the strongest hurricanes that ever formed in the Atlantic. The storm caused massive destruction over the Caribbean islands and Cuba before turning north towards the United States. People expressed their thoughts on social media along with tracking the progress of the storm. To create our Irma corpus, we used Twitter streaming API to collect tweets with mentions of the keyword "irma" starting from the time Irma became an intense storm (September 6^{th}, 2017) and until the storm weakened over Mississippi on September 12^{th}, 2017.

Paris Corpus: Attackers carried out suicide bombings and multiple shootings near cafes and the Bataclan theatre in Paris on November 13^{th}, 2015. More than 400 people were injured and over a 100 people died. People all over the world took to social media to express their reactions. To create our Paris corpus, we collected tweets from 13^{th} November, 2015 to 17^{th} November, 2015 containing the word "paris" using the Twitter GNIP service.

Charlottesville Corpus: The Charlottesville Protest, also called the Unite the Right rally. On August 12^{th}, a protester rammed his car into a crowd of counter-protesters, killing Heather Heyer and injuring 19 others. During the next 2 days, marches and observations of solidarity were held throughout the US in remembrance of Heyer and against white nationalism. We collected tweets between February 2017 to October 2017 using the Twitter GNIP service with a carefully curated set of keywords including *cville*, *antifa*, *Nazi* and *neo-Nazi*.

Annotation Procedure: We performed distance labeling [15] by asking two trained annotators to assign the most frequent hashtags in each corpora with one of three labels ("Solidarity" (e.g. *#solidaritywithparis, #westandwithparis,*

#prayersforpuertorico), "Not Solidarity" (e.g. *#breakingnews, #facebook*) and "Unrelated/Cannot Determine" (e.g. *#rebootliberty, #syrianrefugees*). Using the hashtags that both annotators agreed upon ($\kappa > 0.65$, an acceptable agreement level) [19], we filtered tweets that were annotated with conflicting hashtags from both corpora, as well as retweets and duplicate tweets. Table 1 provides the total of the original (not retweets), non-duplicate tweets, that were annotated as expressing solidarity and not solidarity based on their hashtags.

# of Tweets	**Solidarity**	**Not Solidarity**	**Total**
Irma	12000 (13%)	81697 (87%)	93697
Paris	20465 (41%)	29874 (59%)	50339
Charlottesville	25240 (30%)	59588 (70%)	84828

Table 1. Descriptive statistics for crisis event corpora

3 Understanding the Emojis of Solidarity

We outline our analyses in the form of research questions (RQs) and present our findings in the sections below.

3.1 RQ1: How useful are emojis as features in classifying expressions of solidarity?

After performing manual annotation of the three corpora, we trained classifiers for detecting solidarity in text from all three corpora described in the Data section. We applied standard NLP pre-processing techniques of tokenization, removing stopwords and lowercasing the tweets. We also removed hashtags that were annotated from the tweets. Class balancing was used in all models to address the issue of majority class imbalance.

Hyper-parameter	**Value**
Batch Size	25
Learning Rate	0.001
Epochs	20
Dropout	0.5

Table 2. RNN+LSTM model hyperparameters

Accuracy	**Irma**	**Paris**	**Cville**
RNN+LSTM (w emojis)	**93.5%**	**86.7%**	**69.3%**
RNN+LSTM (wo emojis)	89.8%	86.1%	68.9%
TF-IDF	85.71%	75.72%	68.56%
TF-IDF + Bigrams	82.62%	76.98%	59.16%
Bigrams only	79.86%	75.24%	63.12%

Table 3. Performance of baseline SVM models and LSTM models in classifying messages of solidarity

Baseline Models: We used Support Vector Machine (SVM) with a linear kernel and 10 fold cross validation to classify tweets containing solidarity expressions. For the baseline models, we experimented with three variants of features including (a) word bigrams, (b) TF-IDF [13], (c) TF-IDF+Bigrams.

RNN+LSTM Model: We built a Recurrent Neural Network (RNN) model with Long Short-Term Memory (LSTM) [10] to classify social media posts into Solidarity and Not Solidarity categories. The embedding layer of the RNN is initialized with pre-trained GloVe embeddings [17] and the network consists of a single LSTM layer. All inputs to the network are padded to uniform length of 100. Table 2 shows the hyperparameters of the RNN model.

Table 3 shows the accuracy of the baseline and RNN+LSTM models in classifying expressions of solidarity from text, where the RNN+LSTM model with emojis outperforms the Linear SVM models in both Irma and Paris corpora. However, the performance of the RNN+LSTM model for the Charlottesville (Cville in table) corpus does not show significant improvement over the baseline, likely due to overlap of terms in tweets in the two categories.

Finding 1: For all three corpora, we find that the addition of emojis as a feature improves the performance of the RNN+LSTM model in classifying solidarity messages.

3.2 RQ2: What sentiments are conveyed by emojis in solidarity expressions during crisis events?

We created emoji sentiment maps for our three crisis events: Irma, Paris and Charlottesville. We extracted sentiment and neutrality scores following the method described by Novak et al. [16] from the emoji sentiment website.[1] We used the `ggplot` package[2] in R to create the emoji sentiment maps in Figure 1. The x-axis represents sentiment scores from most negative (-1.0) on the left side towards most positive (+1.0) on the right. As described by Novak et al. [16], the position of an emoji is determined by its sentiment score $\overline{S}$ and its neutrality p_0 (shown on y-axis, representing probability distribution of the neutral class).

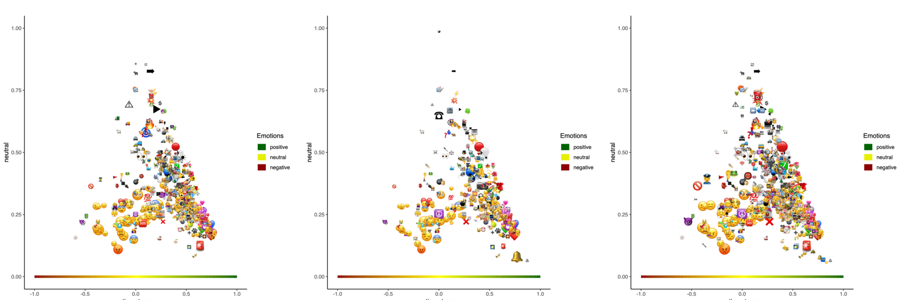

Fig. 1. Emoji sentiment maps (left: Irma, middle: Paris, right:Charlottesville)

The maps provide an overall view of the sentiments conveyed by the emojis to express solidarity across the three different crisis events. We observe that

[1] http://kt.ijs.si/data/Emoji_sentiment_ranking/emojimap.html
[2] https://tinyurl.com/y9ekcutf

negative emojis (left side of each of the three charts in Figure 1) are much more frequently used across all the events than positive sentiment emojis. The prevalence of negative emojis indicate the sadness, worry and negative emotion that are common across all the three crisis events. We observe that 🔴 is consistent across all three events, symbolizing danger. 😡 is consistently present across all the three events and most frequent in Charlottesville, expressing the sorrow and concern towards the people affected by these events. In addition, 💔 is present in all three events expressing sorrow, concern and anger or frustration. Another emoji that is consistent across the events is ❤️, expressing the concern and love. On the other hand, 🌹 is present across all three events but is more frequent in Charlottesville and Paris, and less frequent in Irma. Similarly, 🚨 is present in Irma and Charlottesville but is very infrequent in Paris.

Finding 2: We observe that while the positive sentiment emojis are less frequent (as seen in the relative size compared to negative emoji), they have more variety. Put another way, there are many more *different* positive emojis present in each of the three corpora, while negative emojis are more frequent.

3.3 RQ3: Which emojis co-occur in tweets that are posted within areas directly affected by crisis events as compared to those tweets that are posted from other areas?

This RQ is driven by the hypothesis that solidarity would be expressed differently by people that are directly affected by the crisis than those who are not [2]. To address this RQ, we first geotagged tweets using `geopy` Python geocoding library[3] to map the users' locations to their corresponding country. We then built co-occurrence networks of emojis in all three corpora using the R `ggnetwork` package[4] with the force-directed layout to compare these emoji co-occurrence networks in solidarity tweets that were posted within areas directly affected by the crisis and the areas that were not. Our goal was to determine how emojis co-occur to reinforce not only the accompanying text but also *each other*.

Figure 2 **(left)** represents the co-occurrence network of emojis within the regions affected by Hurricane Irma (United States, Antigua and Barbuda, Saint Martin, Saint Barthelemy, Anguilla, Saint Kitts and Nevis. Birgin Islands, Dominican Republic, Puerto Rico, Haiti, Turks and Caicos and Cuba)[5]. We find the pair 🙏 – ❤️ occurs most frequently in solidarity tweets collected within Irma affected regions. The other top co-occurring pairs following the sequence include 💙 – 🐷, 🙏 – 🇺🇸, 🌊 – 🌪 and 🌪 – 😳; these pairs might convey the concerns expressed in the tweets that originate within affected areas. 💥 appears at the centre of the network denoting the impact of the Irma event. The 👇 – 🌧, ✨ – 💪, 👍 – 🐯 are the emoji pairs that appear in isolation from the network. The 💪 and 🐯 emojis can serve as indicators to stay strong during this hurricane calamity. Figure 2 **(right)** represents the co-occurrence network of emojis

[3] https://github.com/geopy/geopy
[4] https://tinyurl.com/y7xnw9lr
[5] http://www.bbc.com/news/world-us-canada-41175312

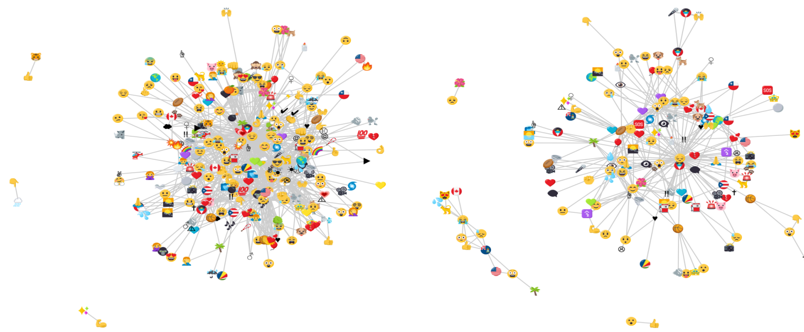

Fig. 2. Co-occurrence network for emojis expressing solidarity from regions affected(left) and **not** affected(right) by Hurricane Irma

in tweets posted outside the regions affected by Irma. We find that the pair 💙 – 🐷 tops the co-occurrence list. Next, we have other co-occuring pairs like 🌊 – 🌬 and 🌬 – 😳 following the top most frequent pair in sequence. We see the three disjoint networks apart from the main co-occurrence network. The 😔 emoji appears at the centre of the network expressing sorrow and the concern of the people during the event. The disjoint networks also contain flags and other emojis that express sadness and sorrow.

Fig. 3. Co-occurrence network for emojis expressing solidarity from regions affected(left) and **not** affected(right) by November 2015 terrorist attacks in France

Figure 3 **(left)** shows the co-occurrence network of emojis for November terrorist attacks in France. Within France, the pair 🇫🇷 – ❤️ tops all the co-occurrence pairs. Co-occurrence pairs like 🙏 – 🇫🇷 and 🙏 – ❤️ follow the top co-occurring sequence, strongly conveying the solidarity of people who tweeted during November terrorist attacks. We also have co-occurring pairs containing flags of other countries following the top-tweeted list that shows uniform feeling among the people by trying to express their sorrow and prayers. The 🔴 emoji appears in the centre of the large network as an expression of danger during terrorist attacks. We can also see that the network contains many flags that indicates the concern and worries of people from many different countries. There are five disjoint networks that again contain emojis that express the sorrow, prayers and discontent. Figure 3 **(right)** represents the co-occurrence network of emojis for November terrorist attacks in Paris outside France. We find that the pair 🇫🇷 – ❤️ tops the co-occurrence list as within France, which is followed by the co-occurring pairs 🙏 – 🇫🇷 and 🙏 – ❤️. We can infer that the people within or outside France shared common emotions that includes a mixture of prayers, support and concern towards Paris and its people. We find the 🇫🇷, 💗 and 💓 appear at the centre of the network to convey solidarity. The 💥 emoji also appears at the center, similar to Figure 2 (left). One important feature is that the 💥 emoji appears at the network center Irma affected regions whereas it appears at the network center for *unaffected* regions in Paris event.

Finding 3: We find the co-occurrence patterns of emojis differ in each of the three crisis events, signifying that the emojis are used with each other in unique ways to reinforce the accompanying message as well as each other. We exclude the Charlottesville corpus from the analysis of RQ3 due to lack of sample size (number of co-occurring emoji pairs within Virginia).

3.4 RQ4: How can emojis be used to understand the diffusion of solidarity expressions over time?

For addressing this RQ, we plot the diffusion of emojis across time. For the Hurricane Irma solidarity corpus, we filtered emojis that occur <50 times, and for the Paris solidarity corpus, we filtered emojis that occurred <25 times per day. Since the Charlottesville solidarity corpus had a smaller sample size (total 4982 emojis (c.f. Table 1)), we did not filter emojis from this corpus based on frequency. In all three figures (Figure 4), the emojis are arranged on y-axis based on their sentiment score based on the publicly available work done by Novak et al. [16]. The frequency of occurrence of emoji is represented by intensity of color in these figures (color intensity legend shown on right of the figures).

In the Irma corpus, the temporal diffusion of emojis is quite interesting (Figure 4 middle). Hurricane Irma grabbed attention of the world on September 6th when it turned into a massive storm and the reaction on social media expressing solidarity for Puerto Rico was through ❤️ and 🙏. During the following days, the United States was in the path of the storm, and there was an increased presence of 🇺🇸 and the presence of other countries flags. As the storm lashed out on the islands on September 7th, people expressed their feelings through ❤️ and 🙏, and also warned people about caring for the pets. As the storm moved through the Atlantic, more prayers with ❤️ and 😔 emerged on social media for people affected and on the path of the storm. The storm struck Cuba and part of Bahamas on September 9th before heading towards the Florida coast. As the storm moved towards the US on September 10th, people express their thoughts through 🌊, 🌪 and 🌬 causing tornadoes. When images of massive flooding emerged on

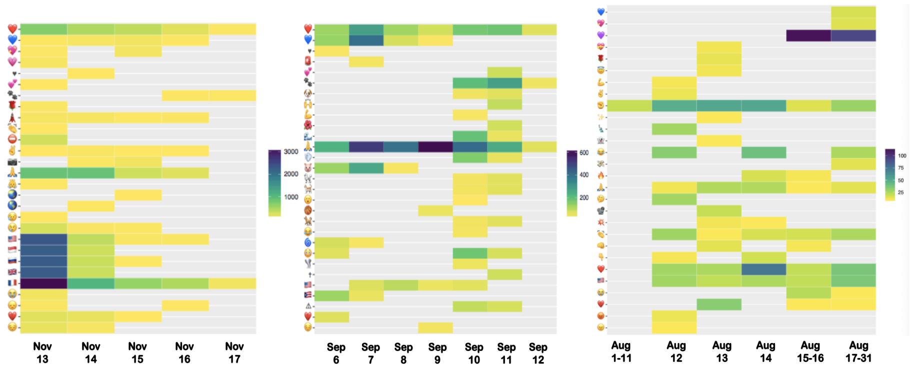

Fig. 4. Diffusion of emojis across time (left: Paris; middle: Irma; right: Charlottesville).

social media, people responded with pet emojis like 🐷, 🐶, 🐈 and 🐕 to save them. The 🐷 emoji may also serve as an indicator of high-pitched crying [21].

In the Paris attacks, the first 24 hours from 13th night to 14th were the days on which most number of emojis were used (Figure 4 left). When news of this horrible attack spread on social media, the immediate reaction of the people was to express solidarity through hashtags attached with 🇫🇷. As a result, 🇫🇷 was the most frequently used emoji across all days. Emojis of other country flags such as 🇺🇸, 🇬🇧 emerged to indicate solidarity with France from people of these countries. Even after the end of the attack on Nov 13th, people expressed prayers for the people of France through 🙏. Images and videos of the attacks emerged on social media on Nov 14th leading to the use of the 📷. The ❤️ occurred across all days for the Paris event in solidarity messages.

Figure 4 (right) represents the diffusion of emojis across the month of August during the Charlottesville protest. For ease of presentation, we grouped the emojis into 5 buckets, namely Aug 1-11 which would show emojis before the main protest, Aug 12th representing the day of the protest, Aug 13th,14th, 15-16 representing the immediate aftermath of the protests and the last bucket represents the rest of the month of August. ✊ that represents solidarity is prominent across the entire month. Its usage increases during the day of the protest and couple of days following the protest. On the day of the protest, there was an outcry of emotions with multiple emojis like ✊, 👊, 🙏, 🇺🇸, 💪, demonstrating the messages of solidarity. Another prominent emoji was the 👏 which shows support in favor of the people who stood up against these protesters. There was also widespread anger on social media towards this incident with usage of 😠 and 😡 but these emojis are not prominent as time passes. On August 13th, the day after the protest, there is the presence of 🌹 and 💔 showing solidarity towards Heather Heyer, who was killed during the protests. After the protests there is increase in the usage of 🙏, that was also used in conjunction with the Heather Heyer incident and as a mark of respect for her.A few days on from the protest, the negatively valenced emojis are not as prominent, with emojis such as 💜, 💖, 💙, ✊ and 👊 being more present, expressing solidarity towards Charlottesville.

Finding 4: Across all three events, we observe a steady presence over all days of positively valenced emojis in the tweets expressing solidarity (the top parts of the diffusion graphs), while negatively valenced emojis are less prevalent over time (e.g. 💔 appears in the first two and three days in the Irma and Paris events resp.). During the Charlottesville event, the ✊ is characteristic to the protest, along with the heart emojis in positively valenced messages.

4 Conclusion and Discussion

We described our data and methods to analyze corpora related to three major crisis events, specifically investigating how emojis are used to express solidarity on social media. Using manual annotation based on hashtags [15], we categorized tweets into those that express solidarity and tweets that do not. We then analyzed how these tweets and the emojis within them diffused in social media over time and geographical locations. We make the following overall observations:

- Emojis are a reliable feature to use in classification algorithms to recognize expressions of solidarity.
- From the emoji maps, we discovered the solidarity messages demonstrated negatively valenced emojis with more frequency, while positively valenced emojis demonstrated less frequency but more variety.
- Through the co-occurrence networks, we observe that the emoji pairs in tweets that express solidarity include anthropomorphic emojis (🙏, 😔, ❤️) with other categories of emojis such as 💨 and 🇫🇷.
- By analyzing the temporal diffusion of emojis in solidarity tweets, we observe a steady presence over all days of positively valenced emojis, while negatively valenced emojis become less prevalent over time.

Future Work: While this paper addressed several research questions, we recognize a few limitations. First, our corpora contain emojis that number in the few thousand, which is relatively small when compared to extant research in emoji usage [12]. However, we aim to reproduce our findings on larger scale corpora in the future. Second, we analyzed solidarity during crisis events including a terrorist attack, a protest and a hurricane, whereas solidarity can be triggered without an overt shocking event (ex. the *#MeToo* movement). In future work, there is great potential for further investigation of emoji diffusion across cultures.

References

1. Barbieri, F., Kruszewski, G., Ronzano, F., Saggion, H.: How cosmopolitan are emojis? exploring emojis usage and meaning over different languages with distributional semantics. In: Proceedings of the 24th ACM international conference on Multimedia. pp. 531–535 (2016)
2. Buechler, S.M.: Understanding social movements: Theories from the classical era to the present. Routledge (2016)
3. Bureau, I.U.: #neveragain walkouts spark half a million social media posts in 24 hours (Mar 2018), http://usa.inquirer.net/10900/neveragain-walkouts-spark-half-million-social-media-posts-24-hours

4. De Choudhury, M., Jhaver, S., Sugar, B., Weber, I.: Social media participation in an activist movement for racial equality. In: Tenth International AAAI Conference on Web and Social Media (2016)
5. Derks, D., Bos, A.E., Von Grumbkow, J.: Emoticons and social interaction on the internet: the importance of social context. Computers in human behavior **23**(1), 842–849 (2007)
6. Donato, G., Paggio, P.: Investigating redundancy in emoji use: Study on a twitter based corpus. In: Proceedings of the 8th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis. pp. 118–126 (2017)
7. Fenton, N.: Mediating solidarity. Global media and Communication **4**(1), 37–57 (2008)
8. Giddens, A.: The consequences of modernity. John Wiley & Sons (2013)
9. Herrera-Viedma, E., Bernabe-Moreno, J., Gallego, C.P., Sanchez, M.d.l.A.M.: Solidarity in social media: when users abandon their comfort zone-the charlie hebdo case. ICONO 14, Revista de comunicación y tecnologías emergentes **13**(2), 6–22 (2015)
10. Hochreiter, S., Schmidhuber, J.: Long short-term memory. Neural computation **9**(8), 1735–1780 (1997)
11. Kelly, R., Watts, L.: Characterising the inventive appropriation of emoji as relationally meaningful in mediated close personal relationships. Experiences of technology appropriation: unanticipated users, usage, circumstances, and design **20** (2015)
12. Ljubešić, N., Fišer, D.: A global analysis of emoji usage. In: Proceedings of the 10th Web as Corpus Workshop. pp. 82–89 (2016)
13. Manning, C.D., Raghavan, P., Schütze, H.: Introduction to information retrieval. Cambridge university press (2008)
14. Markman, K.M., Oshima, S.: Pragmatic play? some possible functions of english emoticons and japanese kaomoji in computer-mediated discourse. In: Association of Internet Researchers annual conference. vol. 8 (2007)
15. Mintz, M., Bills, S., Snow, R., Jurafsky, D.: Distant supervision for relation extraction without labeled data. In: Proceedings of the Joint Conference of the 47th Annual Meeting of the ACL and the 4th International Joint Conference on Natural Language Processing of the AFNLP: Volume 2-Volume 2. pp. 1003–1011. Association for Computational Linguistics (2009)
16. Novak, P.K., Smailović, J., Sluban, B., Mozetič, I.: Sentiment of emojis. PloS one **10**(12), e0144296 (2015)
17. Pennington, J., Socher, R., Manning, C.D.: Glove: Global vectors for word representation. In: Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP). pp. 1532–1543 (2014)
18. Riordan, M.A.: The communicative role of non-face emojis: Affect and disambiguation. Computers in Human Behavior **76**, 75–86 (2017)
19. Sim, J., Wright, C.C.: The kappa statistic in reliability studies: use, interpretation, and sample size requirements. Physical therapy **85**(3), 257–268 (2005)
20. Tufekci, Z.: Social movements and governments in the digital age: Evaluating a complex landscape. Journal of International Affairs pp. 1–18 (2014)
21. Wijeratne, S., Balasuriya, L., Sheth, A., Doran, D.: Emojinet: Building a machine readable sense inventory for emoji. In: International conference on social informatics. pp. 527–541. Springer (2016)
22. Wood, I., Ruder, S.: Emoji as emotion tags for tweets. In: Proceedings of the Emotion and Sentiment Analysis Workshop LREC2016, Portorož, Slovenia. pp. 76–79 (2016)