Emoji as Emotion Tags for Tweets

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Abstract

In many natural language processing tasks, supervised machine learning approaches have proved most effective, and substantial effort has been made into collecting and annotating corpora for building such models. Emotion detection from text is no exception, however research into this area is in it's relative infancy, and few emotion annotated corpora exist to date. A further difficulty with developing emotion annotated corpora is the difficulty of the annotation task and corresponding inconsistencies in human annotations. One approach to address these problems is to use self-annotated data, using explicit indications of emotions included by the author of the data in question. This approach has had success with using text emoticons and selected hash tags for sentiment annotation (Davidov et al., 2010) and emotion-specific hash tags for emotion annotation (Mohammad, 2012; Mohammad and Kiritchenko, 2015). We present a study of the use of unicode emoji as self-annotation of a tweeters emotional state. Emoji are found to be used far more extensively than hash tags and we argue that they present a more faithful representation of a tweeters emotional state. We present an evaluation plan including training a supervised emotion detection model and applying it to the SemEval2007 data set as well as manual annotation of a subset of collected tweets.

Keywords: Twitter, hash tags, emotion annotation, emotion detection, emoji, emoticons

1. Emotion Expression in Text Only Communication

Facial expressions, voice inflection and body stance are all significant communicators of emotion (Johnston et al., 2015). Indeed research into emotion detection from video and voice has found that arousal (the level of excitement or activation associated with an emotional experience) is difficult to detect in text transcripts, implying that those aspects are not strongly expressed in text. One might think, therefore, that text-only communication would be emotion-poor, containing less expression of emotion than face to face or vocal communication.

Research into text-only communication has, however, found that people find ways to communicate emotion, despite the lack of face, voice and body stance, and that text only communication is no less rich in emotional content than face to face communication (Derks et al., 2008). Other research has found that text emoticons (text sequences that indicate facial expressions, such as "(-:") produce similar brain responses to faces (Churches et al., 2014), and it is not unreasonable to expect that facial expression emoji (unicode characters that whose glyphs are small images, such as "😅") to function similarly.

In recent years, marketing researchers have observed significant and continuing increases in the use of emoji in online media. This increase was not constrained to young internet users, but across all ages. Facial expression emoji have become a common method for emotion communication in online social media that appears to have wide usage across many social contexts, and are thus excellent candidates for the detection of emotions and author-specified labelling of text data.

2. Collecting Emoji Tweets

A selection of commonly used emoji[1] with clear emotional content were hand selected as emotion indicators and

joy	😀😂😃😄😆😇😉😊😋😌😍😎😏🌞☺😘😜😝😛😹😸😺🐱❤💖💕💓😁❤
anger disgust	😬😠😐😑😠😡😖😤😾 💩
fear	😅😦😧😱😨😰🙀
sad	😔😕☹😫😩😢😥😪😓😭🙀💔
surprise	😳😯😵😲

Table 1: Selected Emoji

joy	U+1F600, U+1F602, U+1F603, U+1F604, U+1F606, U+1F607, U+1F609, U+1F60A, U+1F60B, U+1F60C, U+1F60D, U+1F60E, U+1F60F, U+1F31E, U+263A, U+1F618, U+1F61C, U+1F61D, U+1F61B, U+1F63A, U+1F638, U+1F639, U+1F63B, U+1F63C, U+2764, U+1F496, U+1F495, U+1F601, U+2665
anger disgust	U+1F62C, U+1F620, U+1F610, U+1F611, U+1F620, U+1F621, U+1F616, U+1F624, U+1F63E, U+1F4A9
fear	U+1F605, U+1F626, U+1F627, U+1F631, U+1F628, U+1F630, U+1F640
sad	U+1F614, U+1F615, U+2639, U+1F62B, U+1F629, U+1F622, U+1F625, U+1F62A, U+1F613, U+1F62D, U+1F63F, U+1F494
surprise	U+1F633, U+1F62F, U+1F635, U+1F632

Table 2: Selected Emoji Code Points

tweets that contained at least one of the selected emoji were collected. We used Ekman's emotion classification of 6 basic emotions (Ekman, 1992). The selected emoji are indicated in Tables 1 and 2.

There are a few choices and difficulties in selecting these emoji that should be noted. First, it was difficult to identify emoji that clearly indicated disgust. An emoji image with green vomit has been used in some places, including Face Book, however this is not part of the Unicode official emoji set (though is slated for release in 2016) and does not currently appear in Twitter.

The second difficulty concerns the interpretation and popular usage of emoji. All emoji have an intended interpretation (indicated by their description in the official unicode

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[1] as indicated by http://emojitracker.com/

list), however it is not guaranteed that their popular usage will align with the description. The choices made in this study were intended as a proof of concept, drawing on the personal experiences of a small group of people. Though these choices are likely to be, on the whole, reasonably accurate, A more thorough analysis of emoji usage through the analysis of associated words and contexts is in order.

The "sample" endpoint of the Twitter public streaming API was used to collect tweets. This endpoint provides a random sample of all tweets produced in twitter. Tweets containing at least one of the selected emoji were retained. The "sample" endpoint is not an entirely unbiased sample, with a substantially smaller proportion of all tweets sampled during times of high traffic (Morstatter et al., 2013). This was considered to be of some benefit for this study, as it reduces the prominence of individual significant effects and associated bias in the collected data.

Twitter has a streaming endpoint to which search phrase can be supplied (the"filter" endpoint), providing only tweets that mach the search criteria. This endpoint has two disadvantages: first, you can only search on whole (whitespace delimited) words, and not individual unicode glyphs, thus only emoticons surrounded by whitespace are retrieved. Second the volume of data for an emoji search phrase build from the above list is very large. A substantial data set could be collected in a single day, however this would be subject to biases resulting from the particular trending topics during that day. Collecting a smaller proportion of tweets over a longer period mitigates this problem. As an illustration of the trending topic problem, in our initial experiment with the "filter" endpoint, the most common hash tag (in 35 thousand tweets) was "*#mrandmrssotto*", which relates to a prominent wedding in the US Philipino community.

We also considered a set of emotion-related hash tags (similar to in (Mohammad, 2012)), however we found that the number of such tweets was orders of magnitude less than tweets with our emotion emoji. That combined with the evidence from psychology that connects emoji to emotion expression (see Section 1.) prompted us to focus on emoji for this study.

3. Data Summary

Over a two week collection period, we collected a total of over half a million tweets, of which 190,591 were tagged by Twitter as English. Note that all the tweet counts provided below do not include retweets. These are considered to bias the natural distribution of word frequencies due to the power-law distribution of retweet frequencies and the fact that a retweet contains verbatim text from the original tweet.

4. Evaluation Plan

Two forms of evaluation will be carried out. First, we will train support vector machine models on the collected data for each basic emotion. Cross-validation will be carried out on the collected data and a final model will be applied to the SemEval2007 data set (Strapparava and Mihalcea, 2007) then compared to results from that competition as well as

Language	total	joy	sad	anger
en	190591	136623	36797	7658
ja	99032	68215	17397	4595
es	65281	45809	11773	3877
und	56597	42535	9217	1959
ar	44026	29976	11216	1114
pt	29259	21987	4894	1208
tl	20438	14721	4096	752
in	18910	13578	3175	1018
fr	13848	10567	1821	651
tr	8644	6935	773	419
ko	7242	5980	916	142
ru	5484	4024	646	411
it	4086	3391	376	156
th	3828	2461	857	227
de	2773	2262	235	119

Table 3: Top 15 Languages; total tweet counts and tweets containing joy, sad and anger emoji ("und" = undetermined language).

Language	fear	surprise	disgust
en	6060	2943	510
ja	4585	3631	609
es	2532	1176	114
und	1624	1033	229
ar	1084	572	64
pt	889	233	48
tl	656	176	37
in	738	323	78
fr	572	213	24
tr	305	201	11
ko	113	87	4
ru	317	74	12
it	119	34	10
th	156	124	3
de	81	69	7

Table 4: Top 15 Languages; tweets containing fear, surprise and disgust emoji ("und" = undetermined language).

cross validation results for the same model trained on SemEval2007 data. Features for these model will include word, ngram, hash tag and emoji tokens as well as emotion scores calculated with the hash tag emotion lexicon (Mohammad, 2012). Note that there is evidence that term usage in social media can be useful for detection of emotions in media such as news articles (Mohammad, 2012). For the second evaluation, we will provide manual annotations of a small subset of tweets (with emotion-indicative emoji removed).

Note to reviewers: It is unfortunate that we have not been able to perform these evaluations prior to writing this abstract, however we submit in any case due to the important prospect of new and easily obtainable labelled data. It is also likely that during the coming week, at the end of which final papers for the workshop should be completed, that we will complete the automated evaluation and a small manual

evaluation. If not, I propose to withdraw the paper and wait for a future venue. This would be a shame, as this workshop would seem the most appropriate venue for this work.

5. Conclusion

We have collected a substantial and multilingual data set of tweets containing emotion-specific emoji in a short time. We argue that we can expect these emoji to perform well as ground truth indicators of tweet emotion content and propose evaluations of that claim. The lack of large, quality annotated data for emotion detection in social media and other text is a substantial barrier to continued research efforts in that area, and the approach presented here promises to provide some relief.

Acknowledgements

6. Bibliographical References

Churches, O., Nicholls, M., Thiessen, M., Kohler, M., and Keage, H. (2014). Emoticons in mind: An event-related potential study. *Social Neuroscience*, 9(2):196–202.

Davidov, D., Tsur, O., and Rappoport, A. (2010). Enhanced sentiment learning using twitter hashtags and smileys. In *Proceedings of the 23rd International Conference on Computational Linguistics: Posters*, COLING '10, pages 241–249, Stroudsburg, PA, USA. Association for Computational Linguistics.

Derks, D., Fischer, A. H., and Bos, A. E. R. (2008). The role of emotion in computer-mediated communication: A review. *Computers in Human Behavior*, 24(3):766–785.

Ekman, P. (1992). An argument for basic emotions. *Cognition and Emotion*, 6(3-4):169–200.

Johnston, E., Norton, L. O. W., Jeste, M. D., Palmer, B. W., Ketter, M. D., Phillips, K. A., Stein, D. J., Blazer, D. G., Thakur, M. E., and Lubin, M. D. (2015). *APA Dictionary of Psychology*. Number 4311022 in APA Reference Books. American Psychological Association, Washington, DC.

Mohammad, S. M. and Kiritchenko, S. (2015). Using hashtags to capture fine emotion categories from tweets. *Computational Intelligence*, 31(2):301–326.

Mohammad, S. M. (2012). #emotional tweets. In *Proceedings of the First Joint Conference on Lexical and Computational Semantics*, SemEval '12, pages 246–255, Stroudsburg, PA, USA. Association for Computational Linguistics.

Morstatter, F., Pfeffer, J., Liu, H., and Carley, K. M. (2013). Is the sample good enough? comparing data from twitter's streaming api with twitter's firehose. *arXiv preprint arXiv:1306.5204*.

Strapparava, C. and Mihalcea, R. (2007). Semeval-2007 task 14: Affective text. In *Proceedings of the 4th International Workshop on Semantic Evaluations*, pages 70–74. Association for Computational Linguistics.