Emojis in Lexicon-Based Sentiment Analysis: Creating Emoji Sentiment Lexicons from Unlabeled Corpora

Fabian Haak[1]

[1]Technische Hochschule Köln (TH Köln), Claudiusstraße 1, Köln, 50678, Deutschland

Abstract

Emojis represent an essential means of expressing sentiments such as opinions and attitudes in computer-mediated communication, especially in chats and social media. Knowledge about the sentiments expressed with emojis is therefore highly relevant for sentiment analysis. However, most previous approaches use labor-intensive manual annotation to determine the sentiments associated with emojis. Thus, for many emojis, especially platform-specific emojis, studies on expressed sentiments do not exist. Hence, the majority of emojis are not considered in sentiment analyses.

In this paper, a method to effectively and efficiently determine the sentiments expressed by emojis without the need for manual annotation is presented. Sentiments expressed by emojis are statistically derived via occurrences in sentiment-bearing texts. Two emoji sentiment lexicons for UTF-8 emojis and platform-specific emojis (Twitch emotes) have been constructed using unlabeled corpora. A comparison with gold standard emoji sentiment lexicons has shown that the developed method achieves qualitatively similar results as a manual annotation.

Keywords

Sentiment Analysis, Emojis, Sentiment Lexicon, Natural Language Processing

1. Introduction

Emojis are used to enrich computer-mediated communication. Their usage follows fixed patterns [1]. Emojis are primarily used to replace the functions of nonverbal communication in electronic communication, including the expression of sentiment [2, 3, 4]. Nevertheless, they have received little attention in sentiment analysis. Due to the ambiguous properties and the large number of emojis, approaches used so far to determine connotative meanings of emojis involve a great deal of time and effort. Moreover, the usage patterns of emojis may differ between contexts and domains and over time. Previous efforts for emoji sentiment determination, including the emojis sentiment ranking [5], which represents the gold standard for emoji sentiment lexicons, require laborious manual annotation. However, the large number of available emojis makes this impractical for UTF-8 and especially platform-specific emojis. Thus, this paper presents an approach to derive emojis' sentiments from cooccurrence with sentiment-laden messages.

LWDA'21: Lernen, Wissen, Daten, Analysen September 01–03, 2021, Munich, Germany
fabian.haak@th-koeln.de (F. Haak)
0000-0002-3392-7860 (F. Haak)

Definition and Types of Emojis. Emojis are small images that, like the simpler emoticons composed of text characters, are used in electronic communication to express ideas or feelings [6]. In addition to the standard Unicode emojis, many platforms have proprietary emojis. On many platforms, these platform-specific emojis take a central role in communicating emotions. However, they can differ significantly from Unicode emojis in appearance and can be challenging or impossible to interpret for people who do not know how the emojis are used. Consequently, few studies have been conducted to determine the sentiments associated with platform-specific emojis (Kobs et al. [7] represents one of the few exceptions). Platform-specific emojis are not only relevant for sentiment analysis of platform texts; many of these emojis have become part of general internet culture [8]. In this study, we consider the so-called Twitch emotes, the platform-specific emojis of the streaming platform Twitch.tv [9].

Emojis in Sentiment Expression. Although emojis perform a variety of functions in speech, their primary function is to serve as a vehicle to establish conceptual orality [10]. Via iconographic properties, emojis can be understood mostly independently of age, language, and cultural background, enabling them to effectively carry the tasks of nonverbal communication [6, 11]. Hu et al. [3] investigated the intention and impact of emoji use in digital text communication. In terms of sentiment expression, they identified three main functions [3]:

1. Expressing sentiment in otherwise neutral text using emojis
2. Reinforcing the sentiment of positive or negative text through emojis of the same polarity
3. Reversing the sentiment of non-neutral text with emojis of the opposite polarity (e.g., to denote irony and sarcasm)

2. Related Work

Na'aman et al. [12] examined different uses of emojis, identifying the categories function, content and multimodal. The latter is the most frequently used category of emojis. It also includes emojis that express, reinforce or change sentiment as described by Hu et al. [3].

Kralj Novak et al. [5] have conducted the first detailed study on emoji sentiment for use in lexicon-based sentiment analysis. In their Emoji Sentiment Ranking (ESR), 751 UTF-8 encoded emojis are each assigned a sentiment value in the form of a valence value ($valence = polarity * intensity$, cf. [13]). The ESR was developed with a corpus of over 1.6 million Twitter tweets, which 83 annotators labeled in terms of expressed polarity. Based on these labels, the emojis were assigned a valence based on the distribution of polarities of the containing texts [5]. Despite its age of five years, the ESR represents the gold standard emoji sentiment lexicon to date.

Using representation learning, Eisner et al. [14] used the names and descriptions of Unicode emojis to generate two-dimensional representations of the emojis to use with Word2Vec. Rice and Zorn [15] use a machine learning approach to generate domain-specific sentiment lexicons. They used a minimum-supervised approach to determine co-occurrences and TFIDF values for corpus words and translate them to embeddings. Kimura and Katsurai [16] derived the sentiment content of emojis in terms of Ekman and Plutchik's basic emotions theory from the co-occurrence of emojis with sentiment words. Kobs et al. [7] performed sentiment analysis of platform-specific texts (chat messages of the platform Twitch.tv) using emoji sentiment lexicons. For this purpose, using manual annotation, they developed [7], to my knowledge, the first sentiment lexicon for platform-specific emojis.

3. Methodological Approach

The methodological approach for determining emoji sentiments presented in this paper consists of deriving the emojis' sentiments from the sentiments of sentiment-laden texts in which they appear. This approach is based on the intentions of the use of emojis for expressing sentiments described in section 1 [3], as well as the methods of Kralj Novak et al. [5] and [16]. Based on the intentions of using emojis, the following assumptions on the co-occurrence of emojis with sentiment-bearing texts were made:

1. Emojis in texts with neutral polarity either serve to express the sentiment of the text on their own or are emojis of the categories function or content according to Na'aman et al. [12] and express no sentiment.
2. Emojis in texts with a clear polarity reinforce the sentiment of the texts, reverse it, or carry no sentiment-identifying function.

By the distribution of the valence values of texts in which an emoji occurs, we can thus infer the sentiment connoted by the emoji. Suppose an emoji appears almost exclusively in texts of one polarity and neutral texts. In that case, it can be assumed that the emoji is used to express and reinforce sentiments of this polarity. If an emoji is used mainly in neutral texts and the valences of the non-neutral texts do not show a clear polarity, the emoji is not used to express sentiments. The last case is emojis that occur in texts whose valence distribution shows bimodal traits with high intensities in both polarities. For these emojis, it is reasonable to assume that they are used to indicate irony or sarcasm.

Corpora. To test the effectiveness of the method for both UTF-8 emojis and platform-specific emojis, two corpora have been created. The first corpus comprises a publicly available collection of 1.48 million Twitter messages (tweets) collected in April 2018 [17]. The second corpus consists of chat messages from Twitch streams. These were taken from a publicly available collection of chat logs by Harvard Dataverse [18]. The corpus contains six chat logs of popular streamers from different topics with a total of 2.86 million messages. Before analysis, the corpus texts are filtered and preprocessed. First, spam messages are deleted. Next, all texts that do not contain emojis, and third, texts that do not have sentiment-bearing words are removed. Finally, any duplicate texts are deleted from the corpora. The preprocessing steps reduced the corpora to 13.359 texts in the Twitter corpus and 92.500 texts in the Twitch corpus.

Sentiment Analysis and Emoji Valences. The valences of the emojis are derived via the valences of texts containing them. Thus, sentiment analysis for all emoji-containing texts has to be performed. Valences are determined using the VADER tool [13]. It was chosen because of its suitability for short, informal texts from chats and social media. Before sentiment analysis, the VADER tool has been modified. All emojis have first been removed from the VADER sentiment lexicon to prevent the valence values of the emojis in the VADER lexicon from influencing the valence value of produced lexicons.

All UTF-8 emojis, a selection of emoticons (f.e. ":)" and ":P"), and a wide range of Twitch emotes have been taken into account in the development of the sentiment lexicons. The emoticons were included in the analyses because it was shown that they are used very similarly to UTF-8 emojis [4, 3]. Furthermore, Twitter transforms them into emoji-like images and the VADER sentiment lexicon contains entries for them. The included Twitch emotes consist of all global Twitch emotes available to all users and the 100 most used channel-specific emotes, which require a paid subscription to the associated Twitch channel. For each emoji, the standard deviation and arithmetic mean of all valence values of all texts containing the emoji are calculated. All emojis whose standard deviations are below 0.625 and for which there are more than ten occurrences are considered valid. The threshold for the standard deviation is derived from Hutto and Gilbert [13]. They chose the same value as a boundary for the means of human-annotated sentiment values for entries of their sentiment lexicon. All emojis that meet the criteria are exported as a sentiment lexicon with their corresponding assigned mean valence values. Thus, produced lexicons can be easily integrated into lexicon-based sentiment analysis approaches like VADER. Doing so, the sentiment analysis model is extended by information on platform-specific emoji valences, thus increasing the effectiveness and domain specificity of sentiment analysis of texts containing these emojis. The developed method also determines additional information such as TFIDF values and n-grams about emojis. Along with exported plots of the distributions of valence values of each emojis' texts, this information allows for further qualitative judgments of the use of emojis in the analyzed corpus.

4. Results

Analyses of the two corpora (Twitch, Twitter) were performed, producing two emoji sentiment lexicons. Analyzing the Twitch corpus, 555 emotes and emojis were found in chat messages with sentiment-laden text. Of these, 186 met the criterion of appearing in at least 10 texts, one of these 186 did not meet the required standard deviation requirement. In the Twitter corpus, 211 emojis appeared at least in the required amount of texts. For 13 of these emojis, the limit for the standard deviation was exceeded; in total, 198 emojis were included in the lexicon. Table 1 shows descriptive statistics for both lexicons. Both lexicons and a script that incorporates them into the VADER sentiment lexicon are available at Zenodo [19]. The average valence value of emojis is slightly higher for the lexicon produced by analyzing the Twitch Corpus (0.116 compared to 0.069), but both are lower that the average valence value in the ESR (0.28). Some emojis show bimodal distributions of valence values of the texts they appear in. As discussed in section 1, these emojis, such as the "face with tears of joy" emoji (🤣), are often used to mark sarcasm or irony. They should therefore not be assigned a high valence in either polarity. As can be seen in Figure 1, but also in the valence value of the "Kappa" Twitch emote (), that is known to be used for signaling sarcasm and irony in Twitch chats [8], the developed method tends to assign neutral sentiment values to those emojis.

	Twitch Corpus and Lexicon	Twitter Corpus and Lexicon
Number of emojis in produced sentiment lexicon	185	198
Avg. valence value	0.116	0.069
Avg. standard deviation of valences of texts for each emoji	0.42	0.53
Avg. number of appearances in sentiment-laden texts	517	101
Texts in preprocessed corpus (with emojis and sentiment)	13,359	92,500
Avg. number of words in preprocessed corpus texts	8.52	34.28
Avg. number of emojis in preprocessed texts with emojis	1.12	2.32

Table 1
Descriptive statistics of the two generated emoji sentiment lexicons and the corresponding corpora.

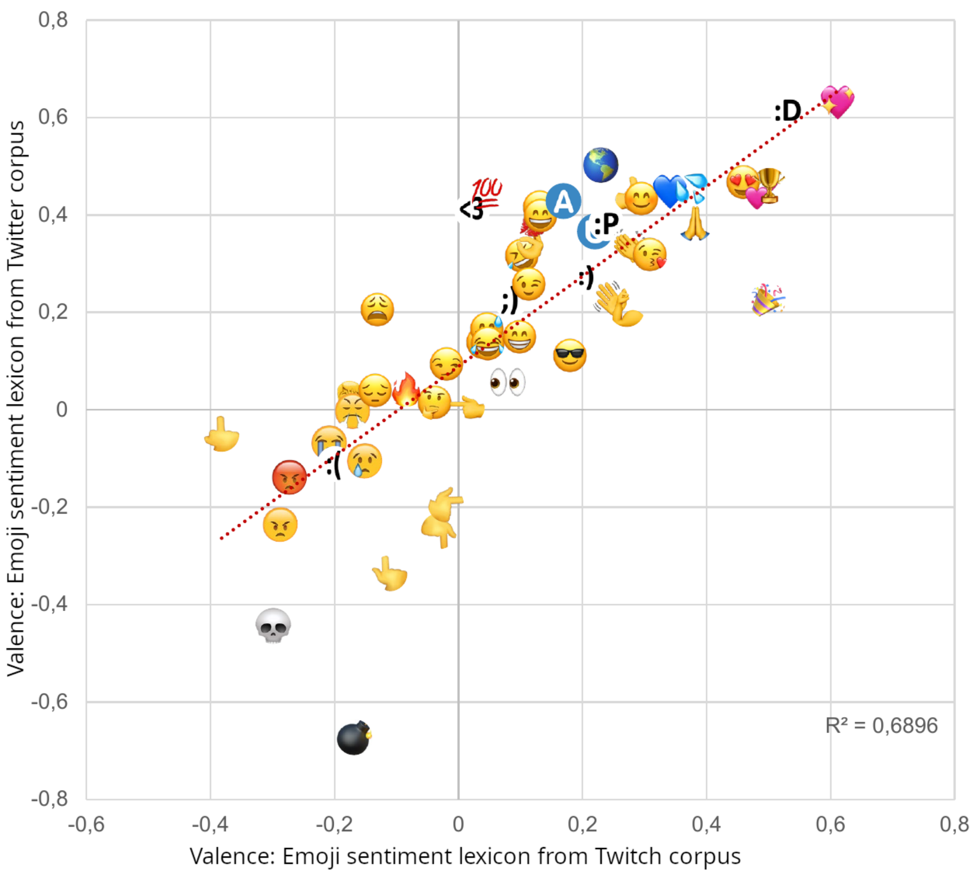

Figure 1: Comparison of valence values of the produced emoji sentiment lexicons. Only those emojis are shown, for which both lexicons contain entries. With few exceptions, both produced lexicons assigned the same polarity and comparable values to these emojis.

5. Evaluation

To evaluate the effectiveness of the developed method, the two produced emoji sentiment lexicons are analyzed. First, valence values of emojis with valence values in both lexicons are compared. Since these mutual emojis consist of UTF-8 emojis and six emoticons, we can generally assume very similar domain-independent use patterns. Therefore, similar values in both lexicons can be expected if the method is effective. The valence values of the mutual emojis are visualized in Figure 1. With few exceptions, both produced lexicons assigned the same polarity and comparable values to these emojis. Their Spearman's rank correlation and Pearson correlation show a statistically significant correlation between the two dictionaries. This indicates that the determined valences represent the actual emoji valences and that the method is reliable. For a better evaluation of the quality of the generated lexicons and the developed method, the lexicons were compared with the ESR, and a sentiment lexicon for Twitch emotes developed by Kobs et al. [7], both produced with manual annotation. Despite the higher average valence values of the ESR, correlation analyses between the lexicons show promising results. The emoji sentiment lexicon generated using the Twitter corpus shows a strong positive Spearman's rank correlation ($r = 0.74$, $p < 0.01$) and Pearson correlation ($r = 0.723$, $p < 0.01$) with the ESR. The comparison between the ESR and the Twitch corpus sentiment lexicon shows fewer correlations. However, only around five percent of the Twitch corpus texts contain the UTF-8 emojis shared with the ESR that the correlation analysis is based on. Comparing the emoji sentiment lexicon generated using the Twitch corpus with the emote lexicon produced by Kobs et al. also shows a strong Pearson correlation ($r = 0.717$, $p < 0.01$) as well as rank correlation ($r = 0.744$, $p < 0.01$). This much higher correlation with another lexicon based on the same domain demonstrates the method's effectiveness.

6. Conclusion and Outlook

The developed method can effectively determine the sentiment valences of emojis based on the texts containing these emojis and generate sentiment lexicons that improve sentiment analysis of texts containing emojis. Hence, the method represents a promising new approach to sentiment analysis, especially for short texts such as chat messages where sentiments are expressed primarily through emojis. Furthermore, the comparisons with the gold standard emoji sentiment lexicon ESR by Kralj Novak et al. [5] and the emote sentiment lexicon by Kobs et al. [7] have shown that the method produces sentiment lexicons that are qualitatively comparable to lexicons made using manual annotation. Especially the correlations and the high correspondences to the polarities of the existing lexicons speak for an accurate valence determination by the method. The successful determination of the twitch emote valences further suggests that the method can effectively derive non-Unicode emojis' valence.

Although it was shown that the method produces usable results, no universal emoji sentiment lexicon that could replace the ESR was created. As suggested by the results, using a much larger corpus, creating a new gold standard emoji sentiment lexicon is possible using the presented approach. Furthermore, domain-specific use of emojis could be researched by producing lexicons based on domain-specific texts.

References

[1] S. Wijeratne, L. Balasuriya, A. Sheth, D. Doran, Emojinet: An open service and api for emoji sense discovery, 2017. arXiv:1707.04652.

[2] D. Derks, A. Bos, J. von Grumbkow, J. Von, Emoticons and online message interpretation, Social Science Computer Review. 26 (2008). doi:10.1177/0894439307311611.

[3] T. Hu, H. Guo, H. Sun, T. vy Thi Nguyen, J. Luo, Spice up your chat: The intentions and sentiment effects of using emoji, 2017. arXiv:1703.02860.

[4] J. B. Walther, K. P. D'Addario, The impacts of emoticons on message interpretation in computer-mediated communication, Social Science Computer Review 19 (2001) 324–347. doi:10.1177/089443930101900307.

[5] P. Kralj Novak, J. Smailović, B. Sluban, I. Mozetič, Sentiment of emojis, PLoS ONE 10 (2015) e0144296. URL: http://dx.doi.org/10.1371/journal.pone.0144296.

[6] M. Danesi, The Semiotics of Emoji - The Rise of Visual Language in the Age of the Internet, Bloomsbury Publishing, New York, 2016.

[7] K. Kobs, A. Zehe, A. Bernstetter, J. Chibane, J. Pfister, J. Tritscher, A. Hotho, Emote-controlled: Obtaining implicit viewer feedback through emote-based sentiment analysis on comments of popular twitch.tv channels, in: Transactions on Social Computing, volume 3, Association for Computing Machinery, New York, NY, USA, 2020. doi:10.1145/3365523.

[8] Dictionary.com, Kappa, 2017. URL: https://www.dictionary.com/e/pop-culture/kappa/.

[9] Twitch, 2020. URL: https://www.twitch.tv/creatorcamp/de-de/learn-the-basics/emotes/.

[10] S. Pappert, Zu kommunikativen Funktionen von Emojis in der WhatsApp-Kommunikation, De Gruyter, 2017, pp. 175–212. doi:10.1515/9783110567786-007.

[11] B. Siebenhaar, Funktionen von Emojis und Altersabhängigkeit ihres Gebrauchs in der Whatsapp-Kommunikation, De Gruyter, 2018, pp. 749–772. doi:10.1515/9783110472226-034.

[12] N. Na'aman, H. Provenza, O. Montoya, Varying linguistic purposes of emoji in (Twitter) context, in: Proceedings of ACL 2017, Student Research Workshop, Association for Computational Linguistics, Vancouver, Canada, 2017, pp. 136–141. URL: https://www.aclweb.org/anthology/P17-3022.

[13] C. J. Hutto, E. Gilbert, Vader: A parsimonious rule-based model for sentiment analysis of social media text, in: Proceedings of the 8th International Conference on Weblogs and Social Media, ICWSM 2014, 2015.

[14] B. Eisner, T. Rocktäschel, I. Augenstein, M. Bošnjak, S. Riedel, emoji2vec: Learning emoji representations from their description, in: Proceedings of The Fourth International Workshop on Natural Language Processing for Social Media, Association for Computational Linguistics, Austin, TX, USA, 2016, pp. 48–54. doi:10.18653/v1/W16-6208.

[15] D. R. Rice, C. Zorn, Corpus-based dictionaries for sentiment analysis of specialized vocabularies, in: Political Science Research and Methods, volume 9, Cambridge University Press, 2021, pp. 20–35. doi:10.1017/psrm.2019.10.

[16] M. Kimura, M. Katsurai, Automatic construction of an emoji sentiment lexicon, in: Proceedings of the 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2017, ASONAM '17, Association for Computing Machinery, New York, NY, USA, 2017, pp. 1033–1036. doi:10.1145/3110025.3110139.

[17] S. Kramer, Trump bot detection april 2018, 2018. URL: https://data.world/drstevekramer/trumpbotdetectionapril2018.
[18] J. Kim, Twitch.tv Chat Log Data, 2019. doi:10.7910/DVN/VE0IVQ.
[19] F. Haak, Emoji sentiment lexicons, 2020. doi:10.5281/zenodo.4159573.

A. Online Ressources

The complete emoji sentiment lexicons are available via

- Emoji Sentiment Lexicons.