Emoji as Sentiment Indicators: An Investigative Case Study in Arabic Text

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***Abstract*—With the explosion of social media usage, researchers have become interested in understanding and analysing the sentiment of the language used in textual digital communications. One particular feature is the use of emoji. These are pictographs that are used to augment the text. They might represent facial expressions, body language, emotional intentions or other things. Despite the frequency with which they are used, research on the interpretation of emoji in languages other than English, such as Arabic, is still in its infancy. This paper analyses the use of emoji in Arabic social media datasets to build a better understanding of sentiment indicators in textual contents. Seven benchmark Arabic datasets containing emoji were manually and automatically annotated for sentiment value. A quantitative analysis of the results shows that emoji are sometimes used as true/direct sentiment indicators. However, the analysis also reveals that, for some emoji and in some contexts, the role of emoji is more complex. They may not act as sentiment indicators, they may act as modifiers of the sentiment expressed in the text or, in some cases, their role may be context dependent. It is important to understand the role of emoji in order to build sentiment analysis systems that are more accurate and robust.**

***Keywords*—*Emoji*; *Social Media*; *Arabic*; *NLP*; *Sentiment Analysis*.**

I. INTRODUCTION

Natural human communication involves both verbal (natural language) and nonverbal channels. In face-to-face communication, nonverbal cues are often the meta-messages that instruct receivers on how to interpret verbal messages. These cues can be either visual/mimogestual (the use of the body), like head nodding, facial expressions, posture, mime, gaze, and eye contact [1]; or oral/prosodic (the use of the voice), like pitch contour, tone, stress, pause, rhythm, tempo and vocal intonation [2]. Ambady et al. [3] also consider these nonverbal cues as reliable indicators for attributes of the speaker, such as gender, personality, abilities, and sexual orientation. The main feature of nonverbal cues, however, is their "ability to convey emotions and attitude" as well as to "emphasize, contradict, substitute or regulate verbal communication" [4]. From a Psycholinguistic perspective, Mehrabian [5] argues that 93% of human communication takes place non-verbally.

In text-based communication, it has been argued that many of these nonverbal cues are missed, which potentially makes the communication ambiguous and inefficient and can lead to misunderstandings [6]. To address this issue, people often use many kinds of text-based surrogates, such as nonstandard/multiple punctuation (e.g., '...', or '!!!'), lexical surrogates (e.g., 'hmmm', or 'yummm'); asterisks (e.g., '*hug*' or '*grin*'), emoticons (e.g., ':)' or ':('), and emoji (e.g., '😊' and '😡'). Carey [7] categorized these nonverbal cues into five types: vocal spelling, lexical surrogates, spatial arrays (e.g., using the textual layout to aid understanding or provide emphasis), manipulation of grammatical markers, and minus features. Emoticons, and later emoji, are sometimes considered as examples of spatial arrays that are used to convey emotion or sentiment. Sentiment analysis can be defined as a process that analyses text and builds an interpretation of the sentiment that it is intended to convey. Usually, this is a one dimensional measure from negative to positive and often it is quantized to just three values: negative, neutral or positive. Sentiment analysis has become an important tool in classifying and interpreting text. It has important applications in social media analysis, consultation systems, text classification and many other areas.

Generally, there are two broad approaches to analyzing sentiment in text: a machine learning approach and a lexicon-based approach. The conventional automated sentiment analysis, that takes account of emoji, especially in the Arabic language, works as follows: the text is analysed to calculate a value representing the sentiment of the text, any emoji are analysed to derive their sentiment values, and then the two values are combined to build an overall interpretation of the sentiment of the whole text.

This conventional assumption might not always be correct. Emoji do not always just indicate additional emotional content. It has been noticed in [8]–[11] that emoji often play sentiment roles other than as a direct indication. For instance, a negative emoji (e.g., broken-heart 💔) can disambiguate an ambiguous sentiment in a text (i.e., add negativity to neutral sentiment texts), it can also complement it in a relatively positive text. Kunneman et al. [11] discussed a similar duality of sentiment role in the use of emotional hashtags such as #nice and #lame. Since this information is not explicit, we assume that the role of emoji as a sentiment signal needs to be examined using various approaches and in different contexts, in order to build a better understanding.

In this work, we seek to investigate the interpretation of the sentiment expressed in informal Arabic texts, which contain emoji and are drawn from a Twitter dataset. This is done

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by trying to answer, from a broad perspective, the following questions:

> **Q1:** When is it appropriate, in sentiment analysis, to use the conventional techniques for interpreting emoji (i.e., when are they a true sentiment indicator within the text)?
>
> **Q2:** What are the other, unconventional, cases of emoji in sentiment analysis, and when do they apply?

To answer these questions, we borrow from [8] the argument that each emoji has three different norms of sentiment within itself. These are positivity, neutrality, and negativity. Thus, we cannot merely consider a single emoji to be a representative or an indicator of one absolute sentiment (positive, negative, or neutral) unless we examine its sentiment state within that related context. Indeed, arguably, within a textual context, some emoji can mislead the sentiment analysis process.

Here, we propose an investigation that uses a comparison between the sentiment of text with and without emojis as well as of the sentiment of the emoji on its own. We apply this approach with 496 different emojis that are used in a corpus of 5204 Arabic texts, annotated with sentiment labels. As a result, we identify four cases for the roles of emoji as sentiment indicators. These cases are as: true sentiment indicators, multi-sentiment indicators, ambiguous sentiment indicators, and not sentiment indicators.

The rest of this paper is organized as follows. Section II reviews related work upon which we build; Section III presents the study's design; Section IV presents the results, analysis and discussion. Finally, in Section V we draw conclusions from this work along with its weaknesses and limitations as well as some recommendations for future work.

II. Related Work

Previous studies on emoji within texts have attempted to explore their roles as nonverbal cues and as sentiment indicators.

A. *Emoji as Textual Nonverbal Cues*

Emoticons are a sequence of keyboard characters (ASCII characters) that represent nonverbal behaviors, such as facial expressions. Emojis are, in many ways, a successor to emoticons with more sophisticated rendering and a wider repertoire but they often play a similar role. In practice, emoji are actual icons that appear on physical or virtual keyboards and can be used across various platforms, such as WhatsApp, Twitter, Facebook, Instagram, and others. These icons can represent facial expressions, body language, food, animals, places, and natural objects like flowers and trees. As discussed by Denis [12] and Zwaan and Singe [13], the human brain instantly analyzes image elements whilst it processes language linearly. That is to say: the human brain processes visual elements faster than written text. Many major technology companies, like Apple and Microsoft, have realized this importance of emoji and have taken considerable strides towards developing them in their systems.

Dresner and Herring [14] and Skovholt et al. [15] have observed that including emoticons, as well as emojis, in text not only helps the receivers to infer some contextual information, but it also eases understanding of the expressed sentiment. Therefore, it has become necessary to integrate the analysis of textual content and emoji in order to properly undertake sentiment analysis. Accordingly, Evans [16] defined emoji as a form of developed punctuation (the way of encoding nonverbal prosody cues in writing systems) that supplements written language to facilitate the writers articulating their emotions in text-based communication.

Also, Miller et al. [17] considered the use of emoji to be understood as ”visible acts of meaning”. As defined by Bavelas and Chovil [18], visible acts of meanings are analogically encoded symbols that are sensitive to a sender-receiver relationship, and they are fully integrated with the accompanying words. Indeed, the sender-receiver cultural background is one of the essential contextualization aspects that might affect emoji-text sentiment analysis. For that, Gao and VanderLaan [19] presented a study suggesting that Eastern and Western cultures are different in their use of mouth versus eye cues when interpreting emotions. According to the study, the norm in Western cultures is to display the overt emotion while in Eastern cultures, the norm is to present more subtle emotion to other people. Westerners interpret facial emotional expressions through the mouth region. Conversely, Eastern cultures focus more on the eyes. The researchers of the study also found that such differences extend to written paralinguistic signals such as emojis and, consequently, this has implications for digital communication.

B. *Emoji as Textual Sentiment Indicators*

Studies on emoji within textual context mainly focus on three directions: the usages of emoji, their meaning and the sentiment they convey. Researchers have found that emoji can be used to disambiguate the intended sense [20], manipulate the original meaning [21][22], or add sentiment to a message [23].

Regarding sentiment analysis, some studies' findings suggest that the level of sentiment perceived from a text increases with the inclusion of facial-emojis [8][23][24] and [25]. Moreover, Rathan et al. [26] considered facial-emoji as a direct sentiment indicator. In their approach, they used emoji as a sentiment source to evaluate social media messages containing particular brands' names. Furthermore, Riordan [20] found that even non-facial emoji can increase the sentiment and improve the clarity of texts.

Going a step further, many studies have assumed emoji to be a reliable ground truth for the sentiment. For example, researchers in the work [27]–[29] followed the same approach by constructing datasets for sentiment prediction and using a set of emoji to label their datasets automatically. Despite its intuitiveness, this assumption seems insufficient since it ignores that the emoji-text sentiment correlation is context-sensitive. Therefore, approaches relying on such an assumption might yield arbitrary and inaccurate sentiment annotation. Besides, it

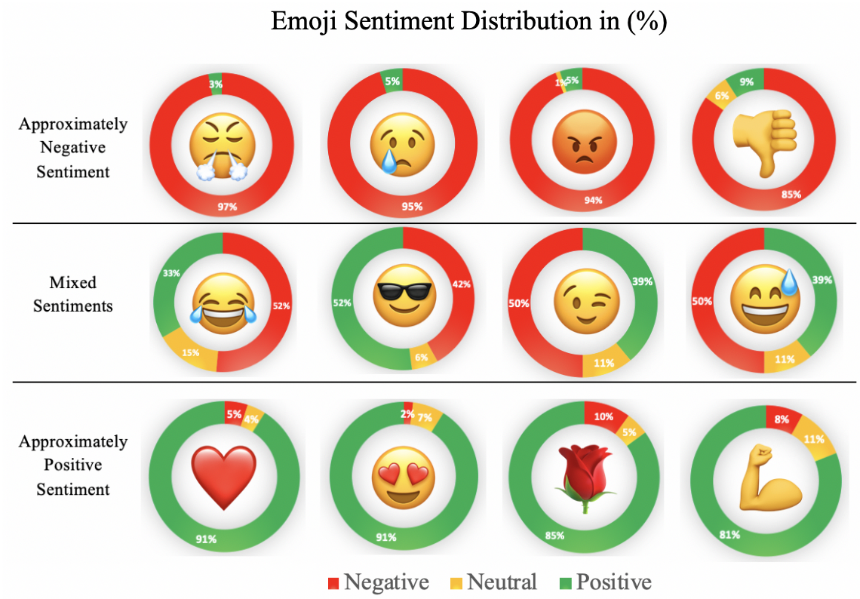

Figure 1. Examples of the Most Representative Emoji for Each Sentiment in Emoji-Text Dataset. The Percentage (%) Shows the Relative Frequency of the Sentiment Class of the Text within Which Each Emoji Occurs.

has been shown that the sentiments of surrogates for nonverbal cues (like emoji) and verbal messages (the accompanying text) are not isolated, and they should be integrated as a whole forming a context with a particular sentiment [30][31].

In line with this hypothesis, Novak et al. [8] conducted a study, which considers context-sensitivity when analyzing the sentiment of emoji and texts. In the study, the researchers annotated a collection of tweets containing at least one emoji, with sentiment labels (negative, neutral, positive). From that textual content, the researchers computed and presented sentiment ranking scores for 751 emoji. Their work illustrated that while some emoji have very high sentiment scores with little variance, others were often used to denote both positive and negative sentiment. These observations suggest that treating emoji as a direct sentiment signal is misleading because they are often full of nuanced details that are highly context dependent.

Overall, it is clear that the conventional approach of performing separate sentiment analysis of text and emoji and then combining the two to generate an overall value, is inadequate. Sometimes this approach will work. However, often and in particular with some frequently used emoji and in some critical cases, this approach fails. Furthermore, in some language such as Arabic, there is little research and also there is evidence that emoji play an especially strong sentiment indication role. The aim of this research is to close that gap.

III. Study Design

We argue that each emoji can have a different sentiment effect on a text, depending upon the context in which it appears. This is a micro-level linguistic phenomenon so, along with the standard natural language processing approach (sentiment analysis), we also used a technique from computer-mediated discourse analysis: "Coding and Counting" [32]–[34]. This is defined by Herring et al. [35] as consisting of three phases: observe, code, and count. It starts with purely qualitative observation and ends with a set of relative frequencies.

A. Data for Observation

To observe how emoji behave as a sentiment indicator for a text, content with specific criteria is needed. The content should be from a social media platform, written in the Arabic language, multi-dialect, multi-aspect, and, more importantly, should contain emoji. Therefore, the main focus of our observation was on 5402 texts (tweets from the Twitter platform), each with at least one emoji. These were extracted from seven different public datasets of Arabic social media [36]–[43]. We refer to this as the Emoji-Text dataset.

Then, we extracted all of the emoji from the Emoji-Text dataset to form a collection of 496 unique emoji. We refer to this as the Emoji-only dataset.

Lastly, a third dataset was constructed, which consists of all the texts in the Emoji-Text dataset, with the emoji removed. We refer to this dataset as the Plain-Text dataset.

B. Coding with Sentiment

In order to understand the way in which the emoji affects the interpretation of the sentiment of each text, we need to have a sentiment annotation for each item in each of the datasets.

All of the texts in the Emoji-Text dataset were human annotated with either sentiment labels (negative, positive, or neutral), or emotional labels (angry, sadness, or joy). For simplicity, we unified all the labels to be in the sentiment label form. The negative emotional labels 'angry' and 'sadness' were labelled as *negative*, and the positive emotional label 'joy' as *positive*.

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TABLE I. THE TOP 5 EMOJI IN EMOJI-ONLY DATASET WITH SENTIMENT FREQUENCY (Fr.) AND RELATIVE FREQUENCY (RelFr.).

Emojis	Name	Class	Sentiment	Total	W/ Negative Texts Fr.(RelFr.)	W/ Neutral Texts Fr.(RelFr.)	W/ Positive Texts Fr.(RelFr.)
😂	Face with Tears of Joy	Facial Expression	Positive	2,270	1,229 (54.14%)	92 (4.05%)	949 (41.80%)
❤️	Red Heart	Heart	Positive	765	45 (5.88%)	20 (2.61%)	700 (91.50%)
🇸🇦	Saudi Arabia	Flag	Positive	733	89 (12.14%)	29 (3.95%)	615 (83.90%)
😍	Smiling Face with Heart-Eyes	Facial Expression	Positive	426	21 (4.93%)	15 (3.52%)	390 (91.55%)
💔	Broken Heart	Heart	Negative	410	286 (69.75%)	16 (3.90%)	108 (26.34%)

TABLE II. THE FREQUENCY (Fr.) AND RELATIVE FREQUENCY (RelFr.) OF SENTIMENTS IN THE PLAIN-TEXT, EMOJI-TEXT AND EMOJI-ONLY DATASETS.

Sentiment Label	Plain-text Fr.(RelFr.)	Emoji-text Fr.(RelFr.)	Emoji-only Fr.(RelFr.)
Negative	2045 (39%)	1885 (36%)	4016 (31%)
Neutral	1119 (22%)	965 (19%)	2547 (20%)
Positive	2040 (39%)	2354 (45%)	6244 (49%)
Total	5,204	5,204	12,807

TABLE III. THE FREQUENCY (Fr.) AND RELATIVE FREQUENCY (RelFr.) OF SENTIMENTS IN THE EMOJI-TEXT DATASET WITH DIFFERENT EMOJI LOAD.

Emoji Load	Total Text Fr(RelFr.)	Neg. Text Fr.(RelFr.)	Neut. Text Fr.(RelFr.)	Pos. Text Fr.(RelFr.)
1	2283 (44%)	908 (40%)	436 (19%)	939 (41%)
2	1358 (26%)	467 (34%)	233 (17%)	658 (48%)
3	652 (12%)	261 (40%)	77 (12%)	314 (48%)
4	393 (8%)	112 (28%)	94 (24%)	187 (48%)
5 or more	518 (10%)	137 (26%)	125 (24%)	256 (49%)

For the emoji, each emoji in the Emoji-only dataset was manually annotated. This was done independently by three native Arabic speaking annotators, two females and one male. To test the reliability of this coding process, we used the inter-rater Fleiss' Kappa agreement test [44]. The test resulted in k = 0.85, which is interpreted as a general high agreement among the three annotators. In cases where two annotators disagreed on a specific sentiment, the annotation from the third annotator was considered to determine the decision.

Lastly, for the text only, we labelled each text in the Plain-text dataset with sentiment. An automatic sentiment annotation process was applied using the Python based Arabic sentiment analysis model, Mazajak [45].

C. Frequency and Relative Frequency Counting

To understand how each emoji is associated with each sentiment class, we undertook a frequency analysis of the Emoji-Text dataset. This identifies the frequency with which each emoji is associated with (human annotated) text labelled as negative, neutral and positive. We calculate two measures, the frequency (Fr), which is the absolute number of times that that emoji occurred within text of that sentiment class and also the relative frequency (RelFr), which is the proportion of the occurrences of that emoji that fall into that class. Table I shows the results for the 5 most common emojis in our data.

A similar process was repeated for each of the datasets Emoji-Text, Plain-Text and Emoji-only, in order to understand how the distribution of the sentiment annotation varied between the three sentiment classes. The results are shown in Table II.

Finally, the number of emoji occurring in each text is counted. This is referred to as the "emoji load" of that text. The Fr and RelFr distributions of each emoji load for each of the three sentiment norms is then calculated to explore how sentiment varies with emoji load. This is shown in Table III.

IV. Results Analysis and Discussion

Table II shows the results of counting the frequency of texts in each sentiment class, both with and without emoji, besides the counting of the emoji only. The results show that for the negative and neutral classes there was a decrease in frequency of 3% when the emoji were included in the text. However, the number of texts classified as positive was increased by 6% when the emoji were included. In Table III, we show the emoji load across all texts and broken down by sentiment class. It is clear that the most usual usage is to include just one or sometimes two emoji in a text. The number of texts in the dataset with three or more emoji is much lower. It is also clear that, as the number of emoji in a text increases, the balance between the sentiment classes changes significantly. The proportion of negative texts is much lower when there are 3 or more emoji than when there are just 1 or 2. Similarly, the proportion of neutral or positive texts increases. This may reflect that, for negative texts, it is sufficient to use one emoji to signal the negative sentiment in Arabic. Whereas, for a positive sentiment, additional emoji are used to provide more emphasis.

Based on this quantitative observation, we analyzed the emoji textual behavior as sentiment indicators and noticed the following significant cases.

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TABLE IV. EXAMPLES FROM EMOJI-TEXT DATASET (1).

Sentiment	Tweets
(1) Negative	من تيران وصنافير لسد النهضه يا قلبي احزن علي البلد 😡 From Tiran and Sanafir islands to Al Nahdha dam, Oh my heart feels sad for the country 😡
(2) Positive	شفته يا ساره حلو اوي فعلا يدي تفاؤل وبهجه كده برافو بجد عل ال عمله ده 😍 😍 Sara, I watched it. It is nice and it really gives the viewers optimism and cheer. Bravo to what he did 😍 😍
(3) Negative	اطفال سوريا طفوله ☹️ تستنجد انسانيه عالم تواطئ علي دمائهم 😡 اغتال احلامهم واغتال ارواحهم 💔 دون ان يرف لهم جفن او يرق لهم قلب Syria's children are the childhood ☹️ that seeks help from the humanity of the world that colludes for their blood 😡 and assassinates their dreams and souls 💔 without any blink of eye or heartily kindness
(4) Positive	كل لما شوفك واسمع صوتك بتفكريني باول حب كانت شبهك في كل حاجه حتي ضحكتك وصوتك 😍 😍 بالتوفيق دايما ومتالقه يانجمه مصر 👌 🙏 Every time I see or hear you, I remember my first love, she was similar to you in everything even in your laugh and your voice 😍 😍 God bless you, and you are always a brilliant Egyptian star 🙏 👌
(5) Positive	امتلات فخرا وانا اقرا النيويورك تايمز وهي تنصح قاده ايران بعدم استفزاز ولي العهد السعودي 😡 صحيفه لها وزنها العالمي وكتابها عالميين I was proud when I read the New York Times advises Iran leaders not to provoke the Saudi crown prince 😡 advice comes from such a well-known newspaper that has a global value and international writers
(6) Negative	انتهي منتدي شباب العالم لزعماء الدول المعاديه انتهي الدرس ياغبياء مصر تقود وتقاد 😍 The World Youth Forum for the leaders of the antagonist countries is over. The lesson is finished, you stupid. Egypt leads and is led 😍
(7) Positive	👌 💔خوي السعد وافي وانا للخوي معكاز وانا محزمه كان الزمن عقد احجاجه نبض العراق 🍃 اخوي الغالي عازف ربي يطول عمره👌 👌 💔 He is my trustworthy friend and I am his weapon and his wand on which he leans in times of his need. The Iraq's beat 🍃 my beloved brother Aazef, may God prolong his life 👌

TABLE V. EXAMPLES FROM EMOJI-TEXT DATASET (2).

Sentiment	Tweets
(8) Positive	نفسي مفاجاه تخليتي منشكح انشكاح منشكحهوش منشكح في تاريخ المنشكحين او اي حاجه تفك عني شويه 😂 😂 I wish I could get a surprise that makes me feel happy in a way that no one felt it in the history of hapeness. Or anything that makes me feel better 😂 😂
(9) Positive	احلا فرحه فرحه النجاح الف مبروك 😎 فرحتي نجاحي The best happiness is the happiness of success. Congratulation 😎 My success is my happiness
(10) Positive	ابتسم 😉 فالبعض عندما يرون حزنك يفرحون Smile 😉 some people become happy when they see your sadness
(11) Negative	كريستيانو لاعب مريض نفسيا والله اجل تزعل عشان خويك سجل هدف 😂 Cristiano, I swear to God, is a psychopathic player, he is upset because his teammate scored a goal 😂
(12) Negative	خليك ببرميل الزباله يا وهيدا بلوك ه😎 Keep yourself in the rubbish barrel and here is a block 😎
(13) Negative	جرح السيف خفيف وبيستخبا بس جرح اللسان رخيص وبينهي المحبه 😉 The sword's wound is simple and can be hidden, but the tongue's wound is cheap, and ends the love 😉
(14) Negative	بت مش ناقصه رعب انا 😡 😡 تتبحي خير وسلميلي اللي وراكي😂 😂 😘 😘 Hay girl, I am already scared 😡 😡 Good night and say hi to the one behind you 😂 😂 😘 😘

A. True Sentiment Indication

In Figure 1, the analysis shows the relationship between particular emoji and the sentiment of the text. The table uses the most representative examples of each sentiment class for illustration. It is clear that some emoji are overwhelmingly negative indicators, for instance: 😤, 😢, 😡 and 👎. Others are mostly positive indicators, like ❤️, 😍, 🌹 and 💪. With this kind of emoji, the indicated sentiment is usually explicit and clear, for two reasons:

First, the messages delivered within the text are, themselves, clear and unambiguous. So, these messages do not express irony, sarcasm or other more complex phenomena. Moreover, most of the cases in our dataset where these emoji occur, include sentiment words or phrases, like the words: "love", "hate", or the phrases: "I agree with" or "I am against". We find that Arabic speakers (perhaps, like others) usually use these emoji to directly articulate their feelings of sadness or anger (example 1) or love, cheerfulness, and satisfaction (example 2) in Table IV.

The second reason is that these emoji often co-occur with other emoji from the same sentiment class (i.e., positive with positive and negative with negative). Thus, the combination of these emoji works together to strengthen the sentiment indication (examples 3, and 4) in Table IV.

Note that, in examples 1 and 3, the sentiments of the text-only, the emoji-only, and the text with emoji (i.e., the tweet) are identical, and they all are negative. The same occurs in examples 2 and 4, but with positive sentiment. This means that when all the components of a tweet (i.e., text and each emoji) share the same sentiment class, they will end up reinforcing the effect and so the result will, clearly, belong to that same sentiment class. Therefore, in this condition, emoji can be considered as direct (true) sentiment indicators for a tweet.

B. No-Sentiment Indication

For some of the emoji in our dataset, they do not appear to convey any sentiment indication. This is the case for examples 5 and 6 in Table IV. This may be because, in our examples, the sentiment of the text (i.e., the sentiment of the words) or of the other emoji in the same text dominates.

However, often these emoji are used randomly with some other emoji in a way that is not intended to convey any sentiment. For instance, they may be used as 'decoration' rather than to serve any real purpose. Example 7 in Table IV, which uses the emoji 💔, is an example.

C. Multi-Sentiment Indication

In Figure 1, there are examples of emoji that we classify as "Mixed Sentiment". We considered emoji, like 😂, 😎, 😉, and 😅 as multi-sentiment indicators.

These emoji can be considered as being true sentiment indicators, but with cases with two opposite sentiments, exemplified in Table V. As positive indicators, these emoji have been found playing a significant role in cases similar to example 8 where the 😂 emoji indicates being funny. In example 9, the 😎 emoji indicates being proud, and example 10 where the 😉 emoji indicates being a positive adviser.

In other cases, the same emoji as in examples 8, 9 and 10 are found playing the opposite sentiment role (i.e., a negative sentiment). This can be seen, in Table V, in example 11 where the 😂 emoji indicates being a mocker, example 12 where the 😎 emoji indicates being arrogant, and example 13 where the 😉 emoji indicates embedded threatening advice.

D. Ambiguous Sentiment Indication

Beyond the cases mentioned above, there can also be an ambiguous sentiment indication for a text arising where an emoji exists, not only as a single, stand-alone emoji, but also in combination with emoji with different sentiments. For instance, in example 14 in Table V, human annotators agreed on annotating this tweet with negative sentiment. However, when re-reading the tweet, it could also be interpreted as a positive tweet, depending on context.

This confusion in judging the tweet sentiment is because of the complexity of the sentiment of the text itself. In this example, the sentence “Hey girl, I am already scared” is negative, while the following sentence, “Good night and say hi to the one behind you”, is positive. Besides, the combination of the negative emoji (i.e., 😡), the positive emoji (i.e., 😘), and the multi/mixed-sentiments emoji (i.e., 😂) increase the complexity of deciding the sentiment of the tweet as a whole. Hence, none of the involved emoji can be considered the true/direct sentiment indicator for this tweet.

V. Conclusion, Limitations, and Future Work

In this work, we have undertaken an empirical investigation of the phenomenon of emoji as a sentiment indicator within text. We have applied this in a study of an Arabic, social media corpus using the “Coding and Counting” approach.

Emoji can be a true sentiment indicator, which is the conventional assumption of existing sentiment analysis approaches with emoji. This is the approach used by most of the existing work and implementations of software to perform sentiment analysis of text with embedded emoji. There are many cases in our data where this interpretation is the correct one.

However, some of the most frequently used emoji also occur in many other, unconventional, cases. They may either act as multi-sentiment indicators or as ambiguous sentiment indicators. This is because, according to the context, emoji sometimes are very negative, and sometimes are very positive. Besides, in some cases, our investigation identified examples where the sentiment of an emoji can be neglected within a text. They may be dominated by the sentiment of the text or be dominated by the sentiment of the other emoji in that text. In this case, we considered such emoji as No-sentiment indicators.

It is worth mentioning that the emoji sentiment indications stated above have been found within the dataset that we collected and sampled for this investigation. We are aware that the sentiment behavior of emoji is context-sensitive. This means that in a different context, (for instance, in a different country or in a different social group), the emoji sentiment might reflect the sentiment or usage of that context. Therefore, one of the weaknesses of this work is that, if the same investigative approach was applied on a different dataset, from a different context, then these emoji may be found to behave differently as sentiment indicators.

What is clear, is that the sentiment role of emoji in Arabic social media is complex. Our analysis shows that the conventional approach is sometimes appropriate. However, it also shows that (especially for some of the most frequently used emoji) the conventional approaches are inadequate and that a more sophisticated technique is needed.

Another constraint of this work is the source of the text that was analysed. Whilst Twitter provides a useful source for data, there may be differences between different social media platforms. Furthermore, different classes of conversation (e.g., purely social, political, business and so on), may have an influence upon how emoji are used. Again, further research is required to investigate this.

In conclusion, using emoji solely, as a feature of sentiment indication for text is not a reliable approach, and it might yield arbitrary, noisy, and incorrect sentiment annotation. For that, we need to understand, in detail, the different sentiment states in which emoji can occur, and also the associated sentiment roles that emoji can play within different textual and social contexts.

In the future, our work will expand upon the analysis presented here, develop a model based upon this understanding and then evaluate it, empirically, against human annotated text, and compare the performance of this approach against existing methods. Also, the focus of the work presented here has been on the interpretation of the sentiment effect of emoji in Arabic text. We would expect that similar phenomena would be found in other languages. However, there are likely to be some differences with language and culture. Further work is necessary to confirm whether this is true.

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