ArSarcasMoji Dataset: The Emoji Sentiment Roles in Arabic Ironic Contexts

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Abstract

In digital communication, emoji are essential in decoding nuances such as irony, sarcasm, and humour. However, their incorporation in Arabic natural language processing (NLP) has been cautious because of the perceived complexities of the Arabic language. This paper introduces **ArSarcasMoji**, a dataset of 24,630 emoji-augmented texts, with 17. 5% that shows irony. Through our analysis, we highlight specific emoji patterns paired with sentiment roles that denote irony in Arabic texts. The research counters prevailing notions, emphasising the importance of emoji's role in understanding Arabic textual irony, and addresses their potential for accurate irony detection in Arabic digital content.

1 Introduction

Irony, sarcasm, and humour are intricate forms of expression that craft messages in nuanced, playful, or mock-serious tones. Although they might intersect in their application, each has a unique meaning and utility. Irony portrays situations or statements contrary to what is expected, manifesting verbally or situationally (Abrams and Harpham, 2009). **Sarcasm**, a specific facet of irony, employs language with a sharp, often bitter tone to mock or critique, often with exaggerated emphasis (Partridge, 1997). Within the Arabic social media sphere, sarcasm often serves as a tool for social commentary or political satire, acting as a medium to challenge authority and examine social norms and values (Zidjaly, 2017; Mohammed et al., 2020; Abu Farha and Magdy, 2022). **Humour**, while encompassing elements of irony, specifically denotes the ability to evoke amusement or laughter (Martin and Ford, 2018). It manifests itself in diverse formats, from jokes and puns to witty remarks. In Arabic digital communication, humour is praised for its prowess in communicating intricate emotions and fostering positive sentiments in a light-hearted and engaging manner (Banikalef et al., 2014; Alkhalifa et al., 2022).

In today's digital age, emoji have emerged as powerful tools in the linguistic landscape. These are small digital icons that are used to convey emotions or ideas. Although once dismissed as mere decorative elements, they are now acknowledged for their crucial role in amplifying and clarifying textual sentiments, moods, and intentions (Danesi, 2017; Cohn et al., 2019; Hakami et al., 2020). By providing much needed context, especially on platforms where vocal tonalities and facial cues are absent, emoji enrich the emotional depth of a message. They have become instrumental in detecting nuances such as sarcasm and humour, underscoring their importance in contemporary studies of natural language processing (NLP) (Rohanian et al., 2018; Hayati et al., 2019; Chiruzzo et al., 2020; Castro et al., 2018).

Although the importance of emoji in the deciphering of textual context is undeniable, there exists a contrasting trend in Arabic NLP. Given the inherent intricacies of the Arabic language, characterised by its rich morphological structures and multifaceted semantics, many researchers opt to exclude emoji when analysing irony. This practise stems from the belief that emoji could introduce an additional layer of complexity, potentially diverting the focus from the linguistic nuances unique to Arabic. As such, despite the global trend of integrating emoji into textual analysis, there is a cautious approach within Arabic NLP circles, underscoring the challenges and distinctiveness of the Arabic linguistic landscape.

In response to this observed gap in Arabic NLP research, this paper presents the community with a unique dataset (**ArSarcasMoji**) consisting of **24,630** short texts enriched with emoji (**4,320** are ironic and **20,310** are not) [1]. Our exploration goes beyond conventional analyses to illustrate the cru-

[1] Click here to download ArSarcasMoji.

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cial role these emoji play in discerning sarcasm and humour within the texts. Through careful analysis, we show that emoji are not just additional symbols, which goes against common beliefs. Instead, they often hold the key to unmasking the ironic intent behind a statement.

In this paper, we test this claim as follows. For a text to be labelled as ironic, it must feature a specific emoji pattern with distinct sentiment roles. Accordingly, our research focuses on three main questions:

- **Q1:** Which emoji patterns are indicative of irony in Arabic texts?
- **Q2:** In what manner do these emoji convey irony through their sentiment roles?
- **Q3:** How effectively does the synergy of these emoji patterns and their associated sentiment roles pinpoint irony?

Providing **ArSarcasMoji** dataset along with this analysis underscores the indispensable value of emoji in enhancing our understanding of textual irony in the Arabic informal social media language.

The remainder of this paper is organised as follows. Section 2 reviews related work; Section 3 presents the study methodology; Section 4 presents the analysis of the dataset. Finally, in Section 5 we draw conclusions from this work along with some recommendations for future work as well as highlight its limitations.

2 Related Work

Sarcasm and humour, two intricate linguistic phenomena, have garnered significant attention in the field of NLP. Their detection in textual data is paramount for improved sentiment analysis, better content recommendation, and the promotion of nuanced human-machine interactions.

In the fast-evolving domain of NLP, the challenge of irony detection in Arabic stands out, given the language's diverse dialects and rich linguistic intricacies. Sentiment analysis has long wrestled with this complexity, primarily due to the nuances of spotting indirect phrasing that often conveys meanings contrary to their overt expressions. Taking steps in this area, Abu Farha and Magdy (2020) introduced the ArSarcasm dataset. Derived from reannotating existing Arabic sentiment datasets, ArSarcasm features 10,547 tweets with 16% labelled sarcastic. The research highlighted the subjective challenges of sentiment annotation and the diminished efficacy of modern sentiment analysis systems when confronted with sarcasm. Furthermore, a BiLSTM-based model they developed for sarcasm detection achieved an F1 score of 0.46, underscoring the task's complexity. However, a notable limitation in their study was the neglect of the roles of emoji, which often play a pivotal role in conveying and deciphering sarcasm in textual communications.

In the following step, a research study by Al-Mazrua et al. (2022) unveiled the *Sa'7r*, a Saudi-specific irony dataset derived from 19,810 tweets (8,089 of which were labelled ironic). In their endeavour, they trained an array of classifiers, encompassing machine learning models like KNN, LR, SVM, and NB, as well as deep learning contenders such as BiLSTM and AraBERT. Among these, the SVM algorithm emerged as the most proficient in traditional techniques, boasting an accuracy of 0.68, while in the deep learning arena, AraBERT led with an impressive 0.71 accuracy. This establishes AraBERT as a primary tool for discerning irony within the nuances of Saudi dialects. However, the study did not highlight the feature of emoji in this task.

In parallel, Alkhalifa et al. (2022) paved the way with a distinctive dataset of 10,039 tweets, covering various Arabic dialects and Modern Standard Arabic, meticulously annotated for humourous and non-humourous content. With rigorous pre-processing steps, including Arabic normalisation and the pruning of unrelated text, the CAMeLBERT-DA model achieved an accuracy of 72.11%. Despite that, a critical gap was the dataset's exclusion of emoji.

In today's digital era, emoji are instrumental in relaying sentiments, particularly in the realm of irony. This oversight in the already-existing Arabic datasets might hint at the datasets' potential limitation in truly capturing the intricacies of contemporary Arabic sarcasm and humour, marking an area ripe for further research and development. Hayati et al. (2019) explored the central role of emoji in irony detection in English texts. Observing the under-representation of emoji in ironic tweets in existing English datasets, they proposed an automated pipeline for more balanced data. Their findings highlighted how emoji can transform text sentiment, converting straightforward statements into ironic ones. They augmented the datasets, making the models attuned to text and emoji signals, and,

#	Dataset Source	Reference	Initial Emoji-Texts	ArSarcasMoji
1	AraSenCorpus	(Al-Laith et al., 2021)	280,739	20,657
2	ArCovid_19	(Haouari et al., 2021)	45,440	5
3	ASAD	(Alharbi et al., 2020)	11,969	1
4	TEAD	(Abdellaoui and Zrigui, 2018)	11,950	1,343
5	ArSAS	(Elmadany et al., 2018)	6,070	1,113
6	ATSAD	(Abu Kwaik et al., 2020)	3,775	666
7	Kawarith	(Alharbi and Lee, 2021)	2,975	208
8	ArSarcasm	(Abu Farha and Magdy, 2020)	1,093	19
9	SS2030	(Alyami and Olatunji, 2020)	1,061	244
10	SemEval_2018_Task1_Task2	(Mohammad et al., 2018) (Barbieri et al., 2018)	668	196
11	DART	(Alsarsour et al., 2018)	599	89
12	ArSenTD-Lev	(Baly et al., 2018)	389	51
13	SemEval_2017_Task4	(Rosenthal et al., 2017)	263	20
14	L-HSAB Dataset	(Mulki et al., 2019)	65	8
15	SyriaTweets	(Salameh et al., 2015)	64	10
Total			**367,120**	**24,630**

Table 1: ArSarcasMoji dataset resources.

when analysing the SemEval 2018 dataset (Mohammad et al., 2018), observed distinct patterns of emoji usage between ironic and non-ironic tweets, highlighting the vital role of emoji in sentiment interpretation.

Hakami et al. (2022b) explored similar emoji behaviour in Arabic texts. Their research posited an innovative approach towards understanding the sentiment implications of emoji, particularly within Arabic textual frameworks. The findings reaffirm that an emoji's sentiment role can oscillate among three paradigms: negative, neutral, or positive. Specifically, an emoji can function as an *Emphasizer*, *Indicator*, *Mitigator*, *Reverser*, or *Trigger* of negative or positive sentiments within a textual context. There was also an intriguing proposition that certain emoji can exert a *Neutral Effect* essentially leaving the text with a neutral sentiment. In distilling the gamut of roles that emoji can play in sentiment analysis, this research provided invaluable insights for scholars seeking to understand the nuanced interplay of emoji and text.

Expanding on the emoji-sentiment-roles model by Hakami et al. (2022b), we formulated an irony classification technique that allowed the creation of the **ArSarcasMoji** dataset. Details are as follows.

3 Methodology

3.1 Data Resources and Pre-processing

To create our comprehensive dataset, we began by amalgamating data from 15 distinct Arabic social media datasets, as referenced in Table 1. This aggregation resulted in **367,120** emoji-inclusive tweets from Twitter, which we designated as the Emoji-Text dataset. From this rich collection, we derived a parallel Plain-Text dataset by extracting the same tweets while removing their emojis. Following the cleaning and normalisation procedures outlined in (Hakami et al., 2021), both data sets were subjected to sentiment annotation using five Arabic sentiment classifiers: Mazajak (Abu Farha and Magdy, 2019), CAMeL-Tools (AraBERT and mBERT) (Obeid et al., 2020), ASAD (Hassan et al., 2021), and the lexicon-based method presented by (Hakami et al., 2022b). Only tweets with sentiment labels that garnered unanimous agreement across all classifiers were preserved, narrowing our data set to concise **24,630** tweets. Conclusively, we applied the methodology delineated by Hakami et al. (2022b) to pinpoint the sentimental roles of different emoji patterns present within these concise tweets.

3.2 Irony Classification Model

Our irony detection model within textual content is based on two primary features: the presence of a distinct emoji pattern (referred to as the "*ironic emoji pattern*") and the sentiment role this pattern assumes in the text. They are detailed below.

3.2.1 Ironic Emoji Patterns Identification

In addressing the first research question of this study on the identification of ironic emoji patterns, we primarily anchored our approach on a curated set of emoji, termed as '*seed*' emoji. These emoji were selected due to their inherent ironic characteristics, previously validated as markers of irony

Sentiment	Emoji													
Positive	😂	🙂	😅	😁	🤣	😉	😎	😬	😜	😹	😆	😝	😛	🤪
Negative	🙃	😒	🤔	😑	😏	🤦	🙄	🤥	🤨					

Table 2: Emoji seeds for ironic patterns extraction.

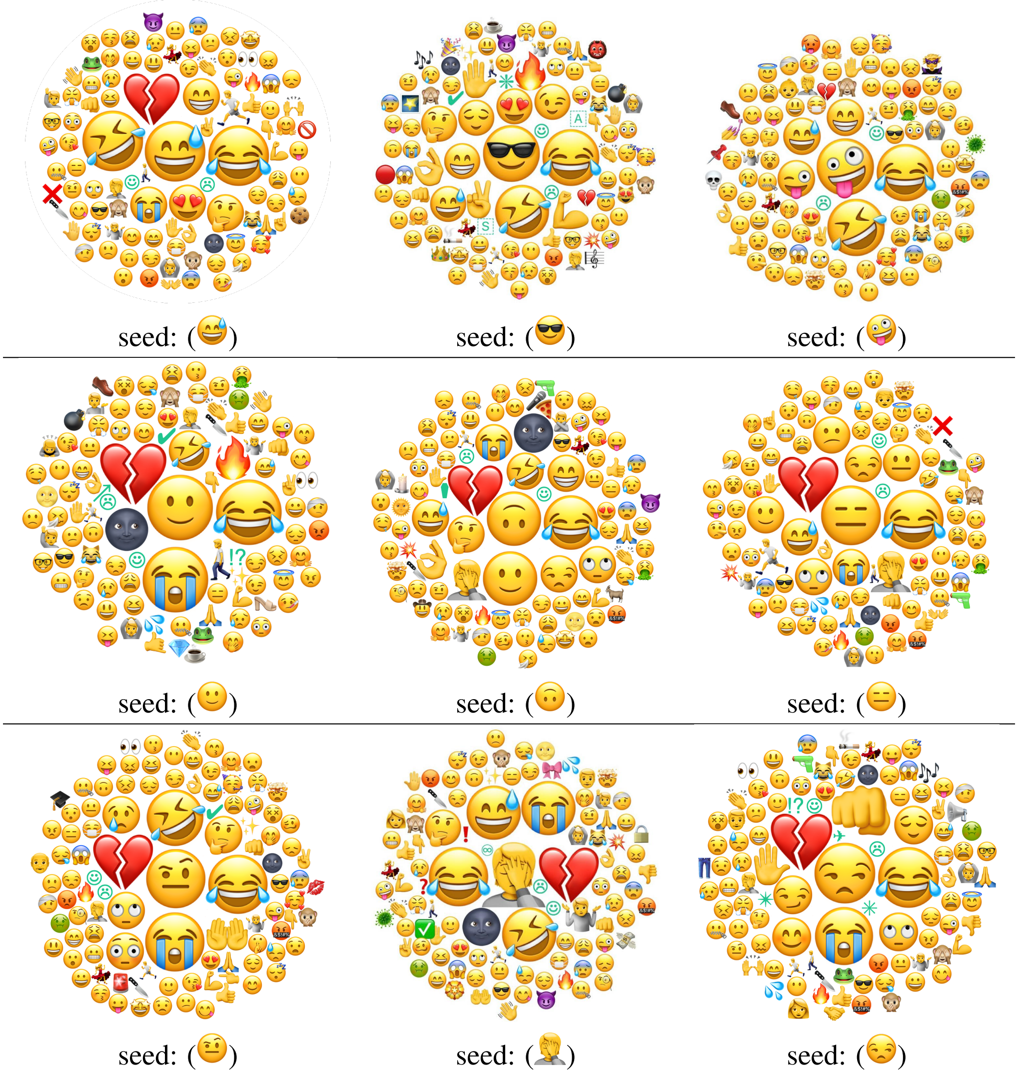

Table 3: The most 100 correlated emoji to nine of the seed ironic emoji.

in studies such as (Wiguna et al., 2021; Weissman and Tanner, 2018; Wang, 2022). Specifically, we curated **23** emoji, both positive and negative according to Hakami et al. (2021) and Hakami et al. (2022a), presented in Table 2, hypothesising their deliberate use in Arabic contexts as irony markers (Mahzari, 2017; Abbas and Ubeid, 2021; Alshboul and Rababah, 2021; Etman and Elkareh, 2021). Merging these seed emoji with a selection from the original 1,272 emoji in our initially collected dataset (excluding all *Flags*, select *Natures*, and the majority of *Hearts* emoji), we identified **15,101** distinct ironic emoji patterns. This ensemble comprises **8,990** positive, **543** neutral, and **5,568** negative patterns, each possessing various sentiment roles with an ironic tilt. To improve clarity, we illustrate the co-occurrence of the top 100 emoji with nine foundational ironic seed emoji in Table 3, demonstrating the diverse sentiment-laden emoji employed in Arabic ironic scenarios. We have made these patterns openly accessible for future research purposes[2]

[2]Click here to download Arabic ironic emoji patterns.

3.2.2 Sarcasm/Humour Classifications

Addressing the second research question of the study, we utilised the sentiment roles of the ironic emoji patterns within the texts to determine their ironic undertones.

To identify sarcastic texts, the classification was based on the existence of certain predetermined ironic emoji patterns tied to negative sentiment roles in a rule-based manner. This was formulated as follows:

$$\textbf{Plain Text} + \left\{\begin{array}{c} \text{Negativity Emphasizer Ironic Emoji} \\ \text{Negativity Indicator Ironic Emoji} \\ \text{Negativity Mitigator Ironic Emoji} \\ \text{Negativity Trigger Ironic Emoji} \\ \text{Negative Reverser Ironic Emoji} \\ \text{No-Effect (Negative | Neutral Ironic Emoji)} \end{array}\right\} = \textbf{Sarcastic Text}$$

On the other hand, for identifying humorous texts, the classification centred on the existence of certain predefined ironic emoji patterns that played positive sentiment roles. This was formulated as follows:

$$\textbf{Plain Text} + \left\{\begin{array}{c} \text{Positivity Emphasizer Ironic Emoji} \\ \text{Positivity Indicator Ironic Emoji} \\ \text{Positivity Mitigator Ironic Emoji} \\ \text{Positivity Trigger Ironic Emoji} \\ \text{Positive Reverser Ironic Emoji} \\ \text{No-Effect (Positive Ironic Emoji)} \end{array}\right\} = \textbf{Humorous Text}$$

3.2.3 Model Evaluation

Addressing the third research question of the study, to evaluate this irony classification model, we utilized two publicly available Arabic ironic datasets: Sa'7r (AlMazrua et al., 2022) and ArSarcasm (Abu Farha and Magdy, 2020). From the merged datasets, we retained only those texts containing emoji, amounting to 6,738 texts. Of these, 2,727 were labelled as ironic/sarcastic, while 4,011 were not. To establish a balanced sample, we arbitrarily chose 1,000 texts from both ironic and non-ironic categories, resulting in a total of **2,000** evaluation texts. Using the predefined ironic emoji patterns, we categorized this sample into ironic and non-ironic groups. We then gauged the efficacy of this classification by comparing its resulting labels with the benchmark's labels. Impressively, our analysis reported an **accuracy** of **0.91** when juxtaposed with the benchmark set. The Cohen's (κ) (McHugh, 2012) agreement between our classifications and the benchmark annotations was also substantial, scoring a **0.83**.

While the pre-defined emoji patterns clearly indicated irony in the texts, differentiating between sarcasm and humour was not clear. To address this ambiguity, we first identified the sentiment roles of these emoji patterns, using the machine's fusion sentiment annotation technique, mentioned in the data pre-processing step above, for both texts with and without emoji. Based on the sentiments roles plied by these emoji, we labelled the texts as either *sarcastic* or *humorous*. To validate these labels, we hand-annotated the sentiment of **600** representative texts, split equally between the humorous and sarcastic categories. Our irony classification model's analysis of this subset yielded impressive consistency: a Cohen's κ coefficient of **0.97** for humorous (positive) texts and **0.95** for sarcastic (negative) texts. These results underscore our model's capability to discern between humorous and sarcastic undertones in ironic Arabic texts.

Consequently, we employed this irony classification model to categorize the 24,630 tweets in the ArSarcasMoji dataset into sarcastic, humorous, and not_ironic categories.

4 ArSarcasMoji Dataset Analysis

To the best of our knowledge, ArSarcasMoji is the premier dataset in Arabic dedicated to the analysis of emoji, with a particular focus on ironic behaviours. This dataset encompasses **24,630** Arabic texts with emoji, as well as parallel versions of these texts devoid of emoji. Both categories of texts—with and without emoji—have undergone sentiment annotation. Moreover, the sentiment roles of emoji patterns and the ironic demeanour of each emoji-inclusive text are clearly defined. Delving into the ironic nature of emoji use, the dataset boasts **4,320** ironic texts (**3,573** classified as *sarcastic* and **747** as *humorous*), in contrast to **20,310** *non-ironic* texts. The sentiment roles of the emoji patterns, juxtaposed with their irony-induced effects, are visualized in Figure 1. For a more illustrative insight, Figure 2 presents samples of both sarcastic and humorous texts. A more in-depth exploration of the dataset is provided subsequently.

4.1 Positive Texts

Of the dataset, 54.64% represents texts with a positive sentiment. Within this positive cohort, emoji play pivotal roles, notably:

- *Positivity Emphasizer*: A substantial 53.26% of emoji in these entries function as non-verbal amplifiers of the text's positive sentiment. From this pool, 5.39% are indicative of humour. A tangible example showcasing an

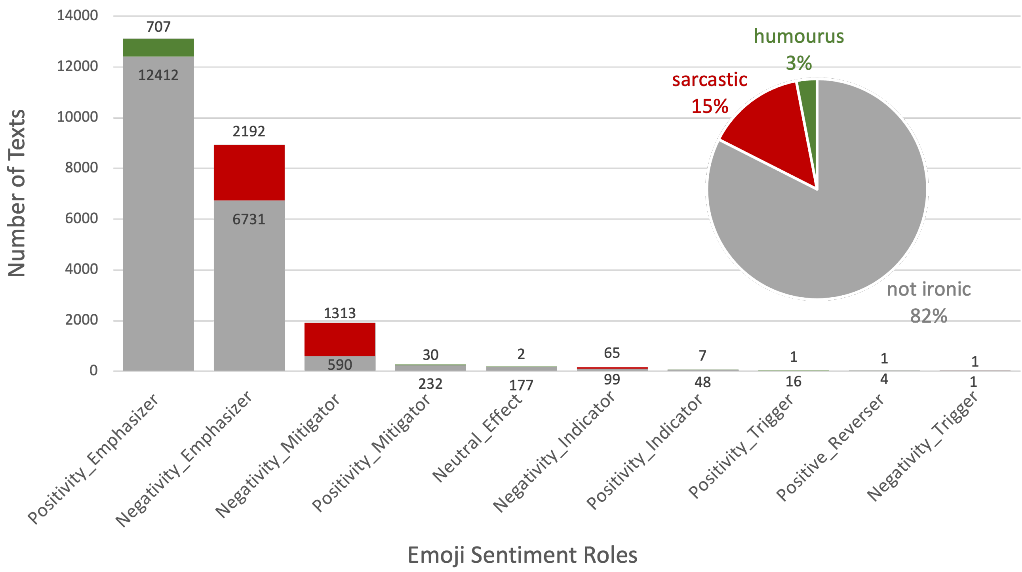

Figure 1: The distribution of *sarcastic* and *humorous* texts along with their emoji sentiment roles in the ArSarcasmoji Dataset.

Positive Norm

#	Text	Emoji	Emoji Role	Irony Label
1	ممكن صباح الخير 🤣 😁 Can I get a 'good morning'? 😁 🤣	😁 🤣	Positivity Emphasizer	Humourus
2	احب اشكر بيضه كندر لانها الوحيدة الي اعطتني هديه 😏 I'd like to thank the Kinder egg because it's the only one that gave me a gift 😏	😏	Positivity Mitigator	Humourus
3	بكل فخر 🤦‍♂️ 😂 😂 🙋‍♂️ With all pride 🙋‍♂️ 😂 😂 🤦‍♂️	🙋‍♂️😂😂🤦‍♂️	Positivity Indicator	Humourus
4	نيدو 👌 👌 😂 😂 😂 😂 Nido 😂 😂 😂 😂 👌 👌	😂😂😂😂👌👌	Positivity Trigger	Humourus
5	😍 😍 😍 😍 نفسي اوصل لهذي المرحله طفشت 👌 😅 😍 😍 😍 😍 I wish I could reach this stage; I'm bored 😅 👌	😍😍😍😍😅👌	Positive Reverser	Humourus

Neutral Norm

#	Text	Emoji	Emoji Role	Irony Label
6	بوفون وبونوتشي وفيراتي براكاس العالم الحضري ورامي ربيعه وطارق حامد حينورو روسيا 😅 تصفيات كاس العالم Buffon, Bonucci, and Verratti are out of the World Cup, while Rami Rabia and Tarek Hamed are going to shine in Russia 😅. World Cup qualifiers	😅	Neutral Effect	Humourus
7	داخل الكتاب حصلت الفاصل عباره عن لوحه منمنمه صغيره ما قدرت اقراها وين اصحاب المخطوطات 🤔 Inside the book, I found a bookmark that's a small miniature board; I couldn't read it. Where are the manuscript experts? 🤔	🤔	Neutral Effect	Sarcastic

Negative Norm

#	Text	Emoji	Emoji Role	Irony Label
8	اين ذاك النيزك الذي سيصطدم بالارض مللت الانتظار 😑 Where is that meteorite that will hit the Earth? I'm tired of waiting 😑	😑	Negativity Emphasizer	Sarcastic
9	الناس بقت بتحط اكونت البابجي البايو بتاعهم 😂 😂 😑 People are now putting their PUBG account in their bio 😑 😂 😂	😑 😂 😂	Negativity Emphasizer	Sarcastic
10	بس انا مش زيك يعني لو احتجتني هتلاقيني للاسف 😉 But I'm not like you; if you need me, you'll unfortunately find me 😉	😉	Negativity Mitigator	Sarcastic
11	لو يجي منخفض اقوي شوي بتسحل الاردن عالسعوديه 🙃 سيول الأردن If a slightly stronger low air pressure comes, Jordan will slide into Saudi Arabia 🙃 Jordan's floods	🙃	Negativity Indicator	Sarcastic
12	اصلا مبين تركيب 😒 It's obviously fake 😒	😒	Negativity Trigger	Sarcastic

Figure 2: Examples of the resulting ironic texts and their corresponding emoji sentiment roles.

emoji pattern's humorous undertone is available in example (1) of Figure 2.

- *Positivity Mitigator*: 1.06% of the emoji serve to tone down the text's positive sentiment. Interestingly, 11.45% of these convey humour, demonstrated in example (2) of Figure 2.

- *Positivity Indicator*: 0.22% of emoji signal the inherent positive sentiment of the text. Of these, 12.73% bear a humorous intonation, as seen in example (3) of Figure 2.

- *Positivity Trigger*: A mere 0.069% of emoji initiate a positive sentiment in the text, with 5.88% insinuating humour. This is exemplified in example (4) of Figure 2.

- *Positive Reverser*: 0.020% of emoji intriguingly transform negative sentiments into positive ones. Among these, one pattern expresses humour, illustrated in example (5) of Figure 2.

4.2 Neutral Texts

In the ArSarcasmoji dataset, neutral texts—including those with mixed emotions or devoid of sentiment—account for 0.73% of the total. The emoji within these texts exclusively serve a *Neutral effect*, with the same percentage of 0.73%. The ironic nuances of these emoji patterns vary depending on their sentiment labels, as detailed below:

- *Positive Emoji Patterns with Neutral Effect*: Within the set of texts featuring *Neutral effect* emoji patterns, 0.55% convey humour in a positive context. This humorous manifestation of the emoji pattern can be observed in example (6) of Figure 2.

- *Neutral or Negative Emoji Patterns with Neutral Effect*: Among the texts showcasing *Neutral effect* emoji patterns, 1.1% exude sarcasm with a negative undertone. An exemplification of this sarcastic tone can be found in example (7) of Figure 2.

4.3 Negative Texts

Within the ArSarcasmoji dataset, 44.63% of the texts convey a negative sentiment. In these texts, emoji serve distinct roles, primarily:

- *Negativity Emphasizer*: A notable 36.23% of emoji in this subset act as non-verbal enhancers, magnifying the text's negative sentiment. Of these, 24.57% have sarcastic implications. Examples (8) and (9) from Figure 2 provide clear demonstrations of this sarcastic undertone.

- *Negativity Mitigator*: 7.73% of the emoji appear to modulate, reducing the intensity of the text's negative sentiment. Fascinatingly, 68.99% among these exhibit sarcasm, as showcased in example (10) of Figure 2.

- *Negativity Indicator*: 0.67% of the emoji directly indicate the text's inherent negative sentiment. Within this category, 39.63% possess a sarcastic tone, as illustrated in example (11) of Figure 2.

- *Negativity Trigger*: An exceptional 0.008% of emoji seem to spark a negative sentiment in the text. Half of these (i.e., one text) carry a sarcastic nuance, as depicted in example (12) of Figure 2.

5 Conclusion and Future Work

This study ventured into the relatively uncharted territory of emoji-augmented Arabic texts to discern nuances like humour and sarcasm. With the introduction of the ArSarcasMoji dataset, we have taken a pivotal step towards understanding the interplay of emoji patterns and sentiment roles in Arabic digital content. Our investigation has revealed that contrary to established beliefs, emoji play an indispensable role in accurately decoding Arabic textual irony. Their integration does not simply add another layer of complexity but rather serves as an essential tool to unmask the true intent behind statements.

Several avenues beckon exploration in the realm of Arabic NLP. One promising direction is to delve deeper into the multi-faceted semantics of the Arabic language and how emoji can further contribute to understanding other linguistic nuances, beyond irony. Another avenue would be to expand our dataset by incorporating different social media platforms, thereby ensuring a holistic understanding of emoji usage across the digital landscape. Furthermore, a comparative study between emoji-augmented Arabic texts and those of other languages might shed light on cultural nuances and their implications in NLP. Lastly, it would be insightful to develop machine learning models that can leverage the rich insights offered by the **ArSarcasMoji** dataset for automated irony detection, sentiment analysis, and beyond.

Limitations

While our study provides valuable insights into the relationship between texts and emoji in the context of irony detection on Twitter, it is crucial to acknowledge its boundaries and constraints. These limitations stem from both the dataset's intrinsic characteristics and the methodological choices we made during the research process. Recognizing these constraints not only underscores the areas where caution should be exercised when interpreting the results but also offers potential avenues for future research. Here, we delineate some of the principal limitations of our study:

- The dataset inadequately represents certain emoji sentiment roles such as the *Positivity Trigger*, *Positive Reverser*, *Negativity Trigger*, and *Negative Reverser* due to the inclusion of very few or even no texts corresponding to these roles.

- The dataset restricts ironic emoji patterns solely to facial expressions. However, the irony in textual conversations can be conveyed through various other emoji types, including hand gestures, body language, objects, and symbols, contingent on the context.

- The scope of irony detection in this study is confined to the relationship between texts and emoji. Incorporating other modalities like images, voice notes, and videos could significantly enrich irony detection by providing a more holistic understanding of a conversation's nuances.

- The dataset sources texts exclusively from Twitter. A more comprehensive irony detection dataset might consider incorporating texts from diverse platforms, such as WhatsApp or Telegram, to capture full conversational contexts.

- Linguistic nuances, regional dialects, and cultural contexts were not thoroughly accounted for in the dataset. This could lead to misinterpretations or overlooking of ironic constructs specific to certain cultures or languages.

- The dataset does not capture the temporal evolution of emoji meanings. Emoji can adopt new connotations over time, and a static dataset might not accurately reflect these dynamic shifts.

- The potential influence of trending topics or events on Twitter, which can temporarily modify the typical usage or meaning of certain emoji, was not factored into our analysis.

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