On the Context-Free Ambiguity of Emoji: A Data-Driven Study of 1,289 Emojis

Justyna Czestochowska*1, Kristina Gligorić1, Maxime Peyrard1, Yann Mentha1, Michal Bien1, Andrea Grütter2, Anita Auer3, Aris Xanthos3 and Robert West1

1EPFL, 2University of Zurich, 3University of Lausanne
{justyna.czestochowska, kristina.gligoric, maxime.peyrard, yann.mentha, michal.bien, robert.west}@epfl.ch, andrea.gruetter@es.uzh.ch, {anita.auer, aris.xanthos}@unil.ch

Abstract

Emojis come with prepacked semantics making them great candidates to create new forms of more accessible communications. Yet, little is known about how much of this emojis semantic is agreed upon by humans, outside of textual contexts. Thus, we collected a crowdsourced dataset of one-word emoji descriptions for 1,289 emojis presented to participants with no surrounding text. The emojis and their interpretations were then examined for ambiguity. We find that with 30 annotations per emoji, 16 emojis (1.2%) are completely unambiguous, whereas 55 emojis (4.3%) are so ambiguous that their descriptions are indistinguishable from randomly chosen descriptions. Most of studied emojis are spread out between the two extremes. Furthermore, investigating the ambiguity of different types of emojis, we find that an important factor is the extent to which an emoji has an embedded symbolic meaning drawn from an established code-book of symbols. We conclude by discussing design implications.

1 Introduction

Emojis have been playing an increasingly important role in online communication since they gained popularity in 2011. As of January 2022, there are 3,521 emojis in the Unicode Standard, and the number is only growing, providing users with more ways to express increasingly complicated concepts. Emojis have thus received a lot of attention from researchers. Various fields, including natural language processing, human-computer interaction, and Web and social media research, study emoji usage and functions.

Beyond current usage patterns (mostly, social media and messaging), emojis have an untapped potential for being used for supporting goals and communication of individuals and communities. While letters, syllables, and words are arbitrary and highly abstract constructs that require a long time to master, emojis come already packed with a lot of semantics. Emojis can thus be leveraged, for instance, in learning and education (Gilles Doiron 2018) or to describe complex ideas to broad audiences (Andy Thomason 2014).

However, it is unknown which emojis can be used for such goals. As the first step towards the ambitious use of emojis, it is necessary to establish how much people agree about their context-free interpretations. Doing so has broad implications within social media and Web research. Beyond research communities, identifying which emojis are ambiguous is helpful to online communities and emoji designers to prevent introducing emojis with a high potential for miscommunication. Additionally, studying context-free emoji semantics informs us which concepts can vs. cannot be easily communicated with emojis.

Despite these questions’ practical importance, it is difficult to approach them with available datasets. Social media content carries inherent selection biases and emoji studies leveraging social media are questioned for their generalizability (Herring and Dainas 2020). Additionally, as emojis are almost only used in context, it is difficult to infer context-free interpretations. To complicate the matter further, the meaning of emojis on social media evolves (Alexander Robertson et al. 2021), making it difficult to study their intrinsic semantics.

We ask the following: Do individuals interpret emojis in the same way? Which emojis have the potential to be used in future communication scenarios, to what extent? Previous work on the ambiguity of emojis focused on differences between platforms (Shurick and Daniel 2020) and their usage in context (Miller et al. 2017). Most closely related past studies focused on frequently used and anthropomorphic emojis (Shurick and Daniel 2020; Miller et al. 2017, 2016), discarding many available emojis. While a lot is known about emoji sentiment and usage in context (Novak et al. 2015), emoji semantics and standalone understanding remain limited.

To bridge this gap, we designed and executed a crowdsourced study examining an exhaustive set of emojis, many of which are rarely used in online communication. We studied their interpretation, stripped from any textual context. Using a novel dataset of emoji annotations, we address the following research questions:

RQ1: To what degree do people agree in their interpretation of emojis?
RQ2: What types of emojis are most and least ambiguous?

2 Related Work

Emojis: interpretation and meaning. Previous research has shown that emojis are often misunderstood (Miller et al. 2016, 2017). Misunderstanding is sometimes related to how the emoji’s design is interpreted in context or the way it is shown on the receiving side. In particular, in 2016, Miller
et al.] examined interpretations of the 25 most popular anthropomorphic emojis without context, across 5 popular platforms. The study compared differences in sentiment and semantics to identify the most ambiguous emojis. In 2017, Miller et al. conducted a similar study comparing sentiment variability with and without context, for 10 anthropomorphic emojis. An extensive dataset of emoji senses was created by [Wijeratne et al.] linking Unicode emoji representations to their meanings extracted from the Web. Recent studies of emoji meaning provide a longitudinal perspective [Barbieri et al. 2018b; Alexander Robertson et al. 2021]. Our work studies the intrinsic ability of emojis to convey information, independent of the textual context they are used in. In contrast to [Miller et al. 2016; 2017], focusing on small subsets of anthropomorphic emojis, we consider many available emojis (see Table 1).

The aspiration of an emoji-based language. There is a growing interest in the linguistic purposes of emojis [Na’aman, Provenza, and Montoya 2017] and their potential to emerge as a graphical language [Ge and Herring 2018]. Informal initiatives exist aiming to create an emoji language. Kickstarter, a popular crowdfunding platform, hosts a project: “Emoji Dick—a never-before-released translation of Herman Melville’s classic Moby Dick in Japanese emoji icons”. Such efforts demonstrate the potential for viewing emojis as the atomic units of graphical and intuitive languages that could remove accessibility barriers inherent to standard symbolic natural languages. This work serves as an initial step in this direction, by investigating how much humans agree on the semantic interpretation of emojis.

Emojis, social media, and natural language processing. Social Media researchers have been examining the ways social media users use, interpret, and express emotions and information through emojis. It is known that emojis shape online language (Feldman et al. 2021; Pavalanath and Eisenstein 2016). Emoji usage is a proxy to study human behavior—emojis are a powerful indicator in the context of crisis events (Santhanam et al. 2018) and can be used to identify group belonging (Jones, Nurse, and Li 2021). Researchers have also been analyzing the use of gender and skin-tone modifiers (Barbieri and Camacho-Collados 2018; Robertson, Magdy, and Goldwater 2020; 2021). As emojis became a standard element of online language, a need to computationally process them emerged. Creating meaningful, latent emoji representations (Eisner et al. 2016) and emoji prediction tasks (Felbo et al. 2017; Barbieri et al. 2018a) became important NLP tasks. Our annotations can be used to compute or augment emoji representations and thus support Social Media and NLP research communities.

3 Methods and Data

Emoji selection. We selected studied emojis in the following way. Starting from all available emojis, we removed letters, numbers, flags, and anthropomorphic emojis of varying colors, as we aimed at using only neutral versions of gendered and skin-toned emojis. We also removed variations of the same emoji (e.g., family with three or four members). This resulted in the final set of 1289 emojis. Furthermore, we collected emoji categories from Emojipedia (https://emojipedia.org/) and hand-crafted a categorization extending 7 existing categories to 20 fine-grained types, outlined in Table 1.

Annotation process. We collected emojis’ interpretations using Amazon Mechanical Turk (AMT). Each participant was asked to: “Describe emojis with a single, accurate word”. One task consisted of ten emojis. All participants had to be at least 18 years old, speak English, reside in the USA, have a 99% approval rate, and have already had completed at least 500 tasks on AMT. Our annotator compensation was in line with ethical guidelines for AMT (Whiting, Hugh, and Bernstein 2019). Each emoji was annotated by 30 unique participants. This number was chosen via pilot studies (150 annotations for 12 emojis), showing that as the number of annotations increases beyond 30, the word distribution remains robust. Overall, we collected 38670 annotations. One participant annotated on average 82.46 emojis. In total, there were 445 unique participants. We asked participants to provide their age, gender, mother tongue. The majority of annotators were native English speakers (97%). Participants’ gender was balanced (55% female, 44% male, 1% other or not stated). Average age was 38.79 (SD = 11.95).

Post-processing. To improve the quality of annotations, we performed three post-processing steps: low quality annotator detection, validation of honeypots, and spelling correction. We performed detection of annotators with low annotation quality by identifying those who used the same word for all emojis in a task. We discarded one annotator whose vocabulary size was less than 80% of the number of assigned emojis. To further ensure the quality, one unquestionably non-ambiguous emoji was placed in every task. Annotations whose answers did not match any words from the expected set (e.g., “apple” for 🍎, “pizza” for 🍕, “carrot” for 🥕) were excluded. Finally, to account for spelling mistakes, we cross-checked word validity using PyEnchant library.

Measuring semantic variation. To measure the extent to which annotators agree about emoji meaning, we calculate the dispersion of emoji’s annotations in a similar spirit to Miller et al. We used GloVe word embeddings (Pennington, Socher, and Manning 2014) of size 200 (Rehurek and Sojka 2011). Let V denote the set of distinct words used by respondents to annotate the considered emoji, which we will call the emoji’s vocabulary; f v stands for the frequency of word v in the emoji’s annotations (e.g. ⅓ for “heart” in the vocabulary of ♡, and MoV := arg maxv∈V f v is the mode annotation, i.e. the most frequent word in V (e.g. “love” for ♡). We then define the emoji’s semantic variation as the weighted average of the cosine distance between the embedding e v of each word v ∈ V and the embedding eMoV of the mode annotation in V:

\[
\text{semantic variation} = \sum_{v \in V} f_v \cdot (1 - \cos(e_v, e_{MoV}))
\]
4 Results

RQ1: To what degree do people agree in their interpretation of emojis? For each emoji, we measure the consistency among the words chosen to describe it. Consider the example of the fire emoji 🔥, for which one annotator used the word “hot” and another the word “fire”. Since the terms are different, the annotators—strictly speaking—do not agree. Yet, the words “hot” and “fire” are semantically close, and we would like to capture such similarities via the semantic variation (Eq. 1).

To detect semantic variations significantly different from random, we compute the semantic variation of the random baseline. We sample random words (n = 30) from the union vocabulary of all annotations and calculate its semantic variation. We repeat the process 1000 times to compute 95% confidence intervals.

Our results bring nuances to findings of Miller et al., who claim that anthropomorphic emojis can be more likely to be ambiguous compared to emojis characterizing “things”. The “faces” category occupies one of the middle places in the average variation ranking. Still, it is more ambiguous than objects. Categories with the lowest average variation are food-drink, clothes & accessories, nature, and hearts.

Figure 1: Top: the relationship between semantic variation (on the x-axis), and vocabulary size (on the y-axis). Bottom: average semantic variation across emoji categories (cf. Table 1). Color-bar represents the extent to which emojis within a category can be seen as belonging to an established system of symbols. Black dashed lines represent random baselines and gray bands their bootstrapped 95% confidence intervals.

emojis are likely to be useful—they are unlikely to introduce misunderstanding.

Third, semantic variation of 55 out of 1289 (4.3%) emojis falls into the random baseline confidence interval. Given the intuition that emojis come with built-in semantics, it is striking that some of them exhibit such low agreement. For future communication applications, these emojis are unlikely to be useful as they introduce high levels of ambiguity.

In summary, human agreement about the context-free meaning of emojis ranges from completely unambiguous (16 emojis) to indistinguishable from random (55 emojis), with emojis covering the whole spectrum of ambiguity. Our dataset can guide communication applications in choosing appropriate emojis to facilitate understanding.

RQ2: What types of emojis are most and least ambiguous? We further investigate discrepancies in ambiguity, expecting different categories of emojis to exhibit different average variations. We report average semantic variation per category in Fig. 1.

Our results bring nuances to findings of Miller et al., who claim that anthropomorphic emojis can be more likely to be ambiguous compared to emojis characterizing “things”. The “faces” category occupies one of the middle places in the average variation ranking. Still, it is more ambiguous than objects. Categories with the lowest average variation are food-drink, clothes & accessories, nature, and hearts.

Table 1: Emoji categorization. Twenty categories, category descriptions, number of emojis, and three examples.

| Category | Category description | Num. | Examples |
|----------|----------------------|------|----------|
| objects  | household items, celebrations, stationery, and miscellaneous objects | 202  | 🎄🎁 babys |
Interestingly, the top five most ambiguous categories are the ones that emerged from further division of the original “symbols” category. In particular, astrological signs form the only category as ambiguous as the random baseline. Astrological signs were described with very different words or, often, with names of other astrological signs. One could argue that astrological signs have an unambiguous mapping to their names. However, without the background knowledge, they yield ambiguous standalone interpretations. Emojis representing Japanese signs or having origins in Japanese culture ( japan, japanese, asian, sign), occupy the third place when it comes to average variation, likely due to annotators’ demographics and cultural background (USA residing, native English speakers). To describe emojis of Chinese, Japanese and Korean characters ( japanese, chinese, asian, sign), annotators consistently used words such as: japanese, chinese, asian, sign. This was not the case for some emojis ( japanese, japanese, sign) where annotators might have not been aware of the Japanese origin.

Following these insights, we investigate in more detail symbolic emojis. In our data, emojis designed to represent symbols are the most ambiguous. Indeed, describing an emoji with an unknown symbol or a symbol that requires cultural background is not any easier than trying to translate a piece of text into an unknown foreign language. Thus, it is important to establish how close an emoji is to simply being a symbol within an established code-book of symbols. We can then measure whether more symbolic emojis bring less intuitive and universally shared meaning.

Arguably, every emoji is a symbol, and its interpretation always refers to some shared background or cultural knowledge (e.g., Japanese emojis would be unambiguous to Japanese speakers). However, we aimed to establish “symbolicalness” of an emoji. Two authors independently annotated emojis with “symbolic levels”. We rated levels of agreement with the statement: “This emoji is a symbol,” on a five-level Likert scale where 1 corresponded to “absolutely disagree” and 5 to “absolutely agree”.

We pre-established an annotation framework where we assigned levels from 5 to 1 respectively, to emojis representing objects and concepts that are established symbols and can be encountered in everyday or specialized activities such as: , that can have a symbolic meaning and be encountered in everyday or specialized activities such as: , that may or may not have a symbolic meaning such as: , that typically do not have a symbolic meaning such as: , that are not established symbols (faces, gestures, people) such as: , .

Following this framework, we obtained Kendall’s $\tau = 0.8$, $p = 1.55 \times 10^{-26}$ between the authors. Then, we computed an average symbolicalness between annotations for each emoji. Afterward, we averaged the values for emojis within a category to obtain category’s symbolicalness rating. We represent the rating with a color scale in Figure [11] There is a weak but significant positive correlation (Spearman correlation $0.25$, $p = 1.61 \times 10^{-19}$) between semantic variation and the symbolicalness rating. In addition, the most ambiguous categories of emojis indeed are the ones with the highest symbolicalness rating. Even though symbols are designed to facilitate communication, our results indicate that symbolic emojis can, unintuitively, be ambiguous since their interpretation requires specific knowledge.

In summary, we find that human agreement about the interpretation of emojis varies across different emoji types. The symbolicalness, or the extent to which an emoji is a symbol from an established code-book of symbols, is an important dimension explaining the differences.

5 Discussion

Summary of main findings. Investigating whether people interpret emojis in the same way (RQ1), we find that emojis come with very different amounts of prepacked semantics. Some emojis are completely unambiguous, with most annotators describing them with the same word. On the opposite, others are as ambiguous as if their descriptions were drawn at random. To support the broader goals of using emojis to improve communications, unambiguous emojis seem to be clear candidates to bring direct benefits. Investigating what types of emojis are ambiguous (RQ2), we find that different types of emojis have very different levels of agreement. An important dimension explaining the agreement differences is the degree to which an emoji belongs to an established code-book of symbols. Emojis referring to symbols require background knowledge for interpretation and are less likely to be unambiguously recognized.

Concrete objects and things can easily be illustrated by an emoji, while abstract ideas and concepts are harder to represent without referring to symbolic ideas from shared cultural knowledge. Yet to support complex communication goals, it is necessary to refer to abstract ideas. This has to be done symbolically since there is no descriptive way to represent in one emoji abstract societal concepts such as peace ( peace, peace, peace, peace, peace), or resistance ( peace, peace, peace, peace, peace). However, there exist ubiquitous symbols whose interpretations are widely agreed upon. For instance, peace is an unambiguous symbol for love. These symbols can be leveraged to convey complex ideas universally.

Design implications. We highlight two mechanisms likely fueling measured variation in ambiguity and discuss their implications. First, the fact that concrete objects can more easily be universally described with emojis highlights the importance of considering the intended participants and their shared cultural background to appropriately choose the symbolic emojis to use. Second, emoji design is known to contribute to misinterpretations (Miller et al. 2017), since emojis are limited in size and need to be comprehensible even if displayed tiny. For example, a “pine decoration” emoji ( decoration, decoration) contains a fair amount of details that are difficult to display on a small scale, further jeopardizing the understanding of the concept. Our findings of ambiguity can thus help make emojis more accessible, user-friendly, and versatile.

Limitations and future work. Our goal is to provide initial measurements of the ambiguity of emojis. Therefore, our study is not without its limitations. All annotators provided a single word to describe an emoji. In the future, it will be interesting to extend to descriptions beyond one word. All annotators were English speakers who reside in the USA. Future work should generalize to other cultures and languages.
References

Alexander Robertson; Farhana Ferdousi Liza; Dong Nguyen; Barbara McGillivray; and Scott A. Hale. 2021. Semantic Journeys: Quantifying Change in Emoji Meaning from 2012–2018. In Workshop Proceedings of the 15th International AAAI Conference on Web and Social Media.

Andy Thomason. 2014. Finally! Academics Describe Their Research in Terms We Can Understand. URL https://www.chronicle.com/blogs/ticker/finally-academics-describe-their-research-in-terms-we-can-understand

Barbieri, F.; Anke, L. E.; Camacho-Collados, J.; Schockaert, S.; and Saggion, H. 2018a. Interpretable Emoji Prediction via Label-Wise Attention LSTMs. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, EMNLP 2018, 4766–4771. Association for Computational Linguistics.

Barbieri, F.; and Camacho-Collados, J. 2018. How Gender and Skin Tone Modifiers Affect Emoji Semantics in Twitter. In Proceedings of the 7th Joint Conference on Lexical and Computational Semantics, 101–106.

Barbieri, F.; Maruo, L.; Karuturi, P.; and Brendel, W. 2018b. Exploring Emoji Usage and Prediction Through a Temporal Variation Lens. Proceedings of the 1st International Workshop on Emoji Understanding and Applications in Social Media 2130.

Eisner, B.; Rocktäschel, T.; Bošnjak, M.; and Riedel, S. 2016. emoji2vec: Learning Emoji Representations from their Description. In Proceedings of The Fourth International Workshop on Natural Language Processing for Social Media, 48–54.

Felbo, B.; Mislove, A.; Søgaard, A.; Rahwan, I.; and Lehmann, S. 2017. Using millions of emoji occurrences to learn any-domain representations for detecting sentiment, emotion and sarcasm. In EMNLP 2017 - Conference on Empirical Methods in Natural Language Processing, Proceedings, 1615–1625. Association for Computational Linguistics (ACL).

Feldman, L. B.; Barach, E.; Srinivasan, V.; and Shaikh, S. 2021. Emojis and Words Work Together in the Service of Communication. Workshop Proceedings of the 15th International AAAI Conference on Web and Social Media.

Ge, J.; and Herring, S. C. 2018. Communicative functions of emoji sequences on Sina Weibo. First Monday 23(11). URL https://firstmonday.org/ojs/index.php/fm/article/view/9413

Gilles Doiron, J. A. 2018. Emojis: Visual Communication in Higher Education. International Journal of Teaching, Education and Learning J. A. Gilles Doiron 2(2): 1–11.

Herring, S. C.; and Dainas, A. R. 2020. Gender and Age Influences on Interpretation of Emoji Functions. ACM Transactions on Social Computing 3(2): 1–26.

Jones, K.; Nurse, J. R.; and Li, S. 2021. The Shadowy Lives of Emojis: An Analysis of a Hacktivist Collective’s Use of Emojis on Twitter. In Workshop Proceedings of the 15th International AAAI Conference on Web and Social Media.

Miller, H.; Kluver, D.; Thebault-Spieker, J.; Terveen, L.; and Hecht, B. 2017. Understanding Emoji Ambiguity in Context: The Role of Text in Emoji-Related Miscommunication. AAAI Conference on Web and Social Media (ICWSM).

Miller, H.; Thebault-Spieker, J.; Chang, S.; Johnson, I.; Terveen, L.; and Hecht, B. 2016. "Blissfully happy" or "ready to fight": Varying Interpretations of Emoji. AAAI Conference on Web and Social Media (ICWSM).

Na’a’man, N.; Provenza, H.; and Montoya, O. 2017. MojiSem: Varying linguistic purposes of emoji in (Twitter) context. Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics-Student Research Workshop 136–141.

Novak, P. K.; Smailović, J.; Sluban, B.; and Mozetič, I. 2015. Sentiment of Emojis. PLoS ONE 10(12). doi: 10.1371/journal.pone.0144296.

Pavalanathan, U.; and Eisenstein, J. 2016. View of More emojis, less :) The competition for paralinguistic function in microblog writing | First Monday. URL https://firstmonday.org/article/view/6879/5647

Pennington, J.; Socher, R.; and Manning, C. D. 2014. GloVe: Global Vectors for Word Representation. In EMNLP 2014 Conference on Empirical Methods in Natural Language Processing, Proceedings of the Conference, 1532–1543. Association for Computational Linguistics (ACL).

Rehurek, R.; and Sojka, P. 2011. Gensim—python framework for vector space modelling. NLP Centre, Faculty of Informatics, Masaryk University, Brno, Czech Republic 3(2).

Robertson, A.; Magdy, W.; and Goldwater, S. 2020. Emoji Skin Tone Modifiers. ACM Transactions on Social Computing 3(2): 1–25.

Robertson, A.; Magdy, W.; and Goldwater, S. 2021. Identity Signals in Emojis do not Influence Perception of Factual Truth on Twitter. In Workshop Proceedings of the 15th International AAAI Conference on Web and Social Media.

Santhanam, S.; Srinivasan, V.; Glass, S.; and Shaikh, S. 2018. I Stand With You: Using Emojis to Study Solidarity in Crisis Events. In Wijeratne, S.; Kiciman, E.; Saggion, H.; and Sheth, A., eds., Proceedings of the 1st International Workshop on Emoji Understanding and Applications in Social Media.

Shurick, A. A.; and Daniel, J. 2020. What’s behind those smiling eyes: Examining emoji sentiment across vendors. Workshop Proceedings of the 14th International AAAI Conference on Web and Social Media.

Whiting, M. E.; Hugh, G.; and Bernstein, M. S. 2019. Fair Work: Crowd Work Minimum Wage with One Line of Code. Proceedings of the AAAI Conference on Human Computation and Crowdsourcing 7: 197–206.

Wijeratne, S.; Balasuriya, L.; Sheth, A.; and Doran, D. 2017. EmojiNet: An Open Service and API for Emoji Sense Discovery. Proceedings of the 11th International Conference on Web and Social Media, ICWSM 2017 437–446.