Emojinating: Representing Concepts Using Emoji

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Abstract. Emoji system does not currently cover all possible concepts. In this paper, we present the platform *Emojinating*, which has the purpose of fostering creativity and aiding in ideation processes. It lets the user introduce a concept and automatically represents it, by searching for existing emoji and generating novel ones. The system combines the exploration of semantic networks with visual blending, and integrates data from EmojiNet, ConceptNet and Twemoji. To evaluate the system in terms of production efficiency and output quality, we produced emoji for a set of 1509 nouns from the *New General Service List*. The results show a coverage of 75% of the list.

Keywords: Computational Creativity, Computational Generation, Concept Representation, Computational Design, Visual Representation, Emoji

1 Introduction

Emoji are often associated with the meaning "picture-word", as *e* can be translated to "picture", *mo* to "writing" and *ji* to "character"[1]. Their increasing importance is well documented by statistical data (e.g. [17]) and some authors even discuss a possible shift towards a more visual language [23, 12]. The integration of emoji in written language can be easily observed in the growing number of emoji-related tools and features – e.g. search-by-emoji[2], and the Emoji Replacement and Prediction features implemented in iOS 10[3]. These features explore the relation between concepts and their representation in emoji.

Despite the constant addition of new emoji, there are still a large number of concepts that do not have a representation. Several attempts have been made to complement emoji lexicon, some of which resulted in new emoji being officially added to Unicode Standard. The nature and goals of such attempts are not always the same. Some examples are: to propose culture-specific emoji[4]; to

[1] unicode.org/reports/tr51/proposed.html, retr. 2018
[2] blogs.bing.com/search/2014/10/27/do-you-speak-emoji-bing-does, retr. 2018.
[3] macrumors.com/how-to/ios-10-messages-emoji/, retr. 2018.
[4] finland.fi/emoji/, retr. 2018

increase the scope of a certain trait (e.g. curly hair[5]); to help abuse victims communicate[6]; or even to just propose "missing emoji" (e.g. *condom*[7] and *taco*[8]).

In 2015, the Unicode Consortium decided to add "skin tone" modifiers (characters that could modify other emoji) to Unicode core specifications. One year later, the ZWJ (Zero-Width-Joiner) mechanism was also implemented – an invisible character to denote the combination between two characters [1]. This development meant that new emoji could be created by combining others.

By having these combination mechanisms as inspiration and following the idea presented in [9], we believe that the connection between the pictorial character of emoji and its associated semantic knowledge can be explored in the generation of visual representations for concepts. In this paper, we present *Emojinating* – a tool which allows the user to introduce a concept and automatically presents emoji that represent it. Three resources are used: Twemoji[9], EmojiNet [34] and ConceptNet [31]. By combining semantic network exploration with visual blending, it not only searches for existing emoji but also produces new ones. There is great potential for its usage in brainstorming activities, leading to creativity stimulation and ideation fostering. The system behind *Emojinating* was thoroughly described in [10]. For this reason, we will not go into much detail, but will instead focus on the analysis of the generation and representation for single-word concepts – in [10] only double-word ones were addressed.

The remainder of this paper is organised as follows: section 2 summarises the related work; section 3 describes our approach; section 4 analyses the results obtained in the representation of 1509 nouns from the *New General Service List* [4]; and section 5 presents our conclusions and directions for future work.

2 Related Work

Previous research on emoji can be divided into five main topics: Meaning, Sentiment, Interpretation, Role in communication, Similarity, and Generation. Concerning emoji meaning, word embedding techniques are normally used with different data sources (e.g. [13, 3, 16]). Emoji sentiment is often calculated from the sentiment of the text in which they occur (e.g. [25]) and has been used to study the intentions for using emoji [21]. Miller et al. [24] described how the interpretation of meaning and sentiment of emoji change within and across-platforms, and Rodrigues et al. [30] studied interpretation differences between users and developers. Research on the role of emoji in written communication addresses several topics: e.g. redundancy and part-of-speech category [14], emoji function [15], effect on reading time [19], emoji as semantic primes [33], among

[5] adage.com/article/digital/dovelaunchescurlyhairedemojisaddressvoid/301203/, retr. 2018
[6] webcollection.se/bris/abusedemojis/, retr. 2018
[7] businessinsider.com/durexs-condom-emoji-for-safe-sex-2015-11, retr. 2018
[8] tacobell.com/stories/Tacoemoji, retr. 2018
[9] github.com/twitter/twemoji, retr. 2018

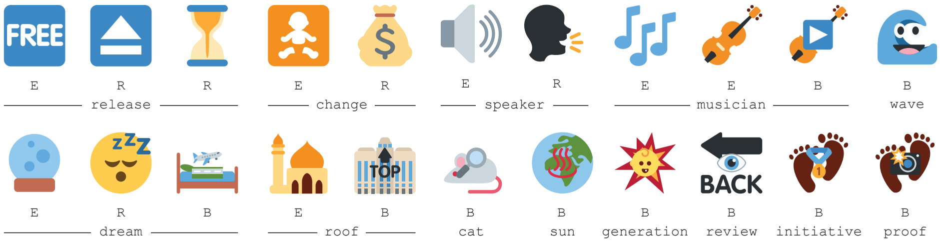

Fig. 1. Examples of retrieved emoji: existing (E), related (R) and blended (B)

others [22, 7, 20]. In terms of similarity between emoji, Ai [2] semantically measured emoji similarity. Other authors used emoji vector embeddings to identify clusters of similarity [16, 3]. Pohl et al. [27] organised emoji in a relatedness-hierarchy. Wijeratne et al. [35] built a dataset of human-annotated semantic similarity scores – EmoSim508.

Literature is scarce on emoji generation and most work uses Generative Adversarial Networks to replicate existing emoji, e.g. [28, 29]. The quality of the results is significantly lower when compared to the one of official emoji.

2.1 Variation and blending

Several applications allow some degree of variation in emoji (or equivalent graphicon), e.g. Windows Live Messenger[10] enabled the creation of emoticons through image uploading and Slack[11] currently has the same feature. Moreover, there are other applications that consist in face-related customisation, e.g. Bitmoji[12]. These examples and the emoji proposals (presented in the introduction section) show that there is potential in emoji combination and generation. It is our belief that visual blending can be used to represent novel concepts.

Current computational approaches to visual blending can be divided into two groups according to the type of rendering used: (i) picture or photorealistic rendering; and (ii) non-photorealistic (e.g. pictograms or icons). Examples of the first group are: Steinbrück [32] who combined image processing techniques with semantic knowledge gathering to produce images in which elements are replaced with similar-shaped ones (e.g. round medical tablets are transformed into globes); and Vismantic [36] – a semi-automatic system that produces visual compositions for specific meanings (e.g. *Electricity is green* is represented as the fusion between an electric light bulb and green leaves).

On the other hand, a categorisation can also be done in terms of where the blending process occurs: some interpret or visualise previously produced conceptual blends, e.g. Pereira and Cardoso [26] experimented with conceptual

[10] news.microsoft.com/2003/06/18/msn-messenger-6-allows-im-lovers-to-express-themselves-with-style/,retr. 2018
[11] get.slack.help/hc/en-us/articles/206870177-Create-custom-emoji, retr. 2018
[12] bitmoji.com, retr. 2018

blends produced for the input spaces *house* and *boat*; others use blending only at the visual level, e.g. Correia et al. [6] generated faces out of existing ones by recombining face parts; and in others, which can be called hybrid, the blending process starts at the conceptual level and only ends at the visual level, e.g. Cunha et al. [8] generated visual conceptual blends for the concepts *pig, angel* and *cactus*. In addition, some authors combine entire signs, e.g. [5], while others combine parts, e.g. the blend of Pokémon[13].

The project most similar to ours is Emojimoji[14], an emoji generator which randomly merges two emoji. However, none of abovementioned work addresses our main subject – using existing emoji and associated semantic knowledge for developing a tool to aid in ideation.

3 The approach

Before emoji, emoticons were used to express emotions in Computer-Mediated Communication. One of their advantages is the potential for customisation and variation. Whereas emoji are inserted as a whole in the text, emoticons are the result of a combination of individual components [15] – e.g. ":" + ")" = ":)". The changeable parts not only allow a high degree of visual variability but also the exchange of a component leads to a change in the meaning. This is one of the reasons why they are still being used as alternative to emoji [18]. We follow a similar approach in the generation of novel emoji, having the modifier and ZWJ mechanisms as inspiration. By taking advantage of the emoji connection between pictorial representation and associated semantic knowledge, we aim to develop a computer-aiding tool for creativity fostering and icon design.

Emojinating has two main functionalities: (i) search for existing emoji and (ii) generation of new ones. In order to implement these two functionalities, we combined data from the following online resources: Twitter's Twemoji 2.3 – a dataset of fully scalable vector graphics with 2661 emoji; EmojiNet – a machine readable sense inventory for emoji built through the aggregation of emoji explanations from multiple sources [34], containing 2389 emoji; and ConceptNet – a semantic network originated from the project Open Mind Common Sense [31], which we use to obtain concepts related to the one introduced by the user.

Twitter's Twemoji dataset, despite allowing an easy blending process due to the layered structure of the vector images, does not have any semantic data associated. For this reason, EmojiNet was used. We extract, for each emoji, the *name*, *definition*, *keywords*, *senses* and *unicode* from EmojiNet, which are used as criteria in the search for emoji. These are afterwards matched with the images from Twemoji and used to retrieve emoji related to the user-introduced concept.

3.1 How it works

The system searches for existing emoji semantically related to the introduced concept (T1) and complements this search with a visual blending process which

[13] pokemon.alexonsager.net, retr. 2018
[14] emblemmatic.org/emojimoji, retr. 2018

generates new emoji (T2). After gathering the emoji, it presents them to the user. The blending process is useful in cases when there is no existing emoji that matches the concept but also to suggest possible alternatives. The system output is a variable number of visual representations for the introduced concept, composed of existing (E) emoji, related (R) emoji and generated blends (B). The system makes use of three main components:

1. **Concept Extender (CE)**: based on a given concept, uses ConceptNet to search for related concepts;
2. **Emoji Searcher (ES)**: searches for existing emoji that are semantically related to a given word, using semantic knowledge provided by EmojiNet;
3. **Emoji Blender (EB)**: receives two emoji as input and returns a list of possible blends.

In this paper, we decided to only address single-word concepts. The blends for single-word concepts are generated using double-word related concepts. The different components are used in the gathering and production of emoji. For the retrieval of existing emoji the ES component is used. In the gathering of related emoji, CE and ES are used. The search is currently being conducted for two levels: directly related concepts (1st), and second degree concepts – i.e. indirectly related (2nd). Regarding emoji blending, the system firstly collects related concepts (using CE), then searches for existing emoji for the concepts (using ES) and finally blends them (using EB).

Knowledge from the different resources is used to generate novel representations. One example is the blend for *generation* (Fig. 1). Firstly, CE is used to retrieve the related concept *baby boom*. Then, semantic knowledge associated with emoji is used by ES to obtain matching emoji: the *baby* (from the name) and the *collision* emoji (from the keyword "boom"). Finally, the blending process makes use of attribute-based and positioning knowledge, which is retrieved from existing emoji (i.e. the *baby* emoji is placed according to the position of the *collision* emoji).

3.2 Interface

The aim of the *Emojinating* platform is to allow the user to input a concept and receive emoji that represent it. As such, the interface has two main areas: the *search area* and the *results area*. The *search area* contains a search field in which the user writes words to search. After conducting the search and generation of emoji, the results are presented to the user in the *results area*. This area is divided into four sections: (i) the generated blends section which shows the blended emoji; (ii) the existing emoji section which shows emoji retrieved from the search for the introduced word(s); (iii) the related emoji (1st level) section which shows emoji for directly related concepts to the one introduced; and (iv) the related emoji (2nd level) section which shows emoji for indirectly related concepts (directly related to related concepts).

The user is able to download any emoji by clicking on it. Despite being a simple interface, we consider that it serves its purpose as it allows the input to be given and presents the results in a perceptible way.

	R 1st	R 2nd	B	or RB	nor RB
E	927	853	683	707	921	6
$\overline{\textbf{E}}$	582	414	529	336	578	4
	1509	1267	1212	1043	1499	10

Table 1. Number of nouns with each type of emoji – related (R) 1st and 2nd level, blended (B), either R or B, and neither R or B – and the presence of existing emoji (E). The number of emoji considered in R does not include the ones that also exist in E.

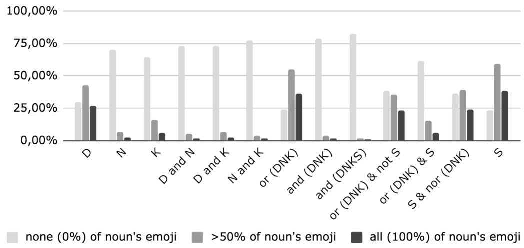

Fig. 2. Percentage of nouns in relation to the percentage of noun's existing emoji in terms of semantic information source, e.g. 29,45% of the nouns with existing emoji have none of their emoji (0%) with "definition" as source of their semantic information (first bar on the left). Sources are: Definition, Name, Keywords and Senses.

4 Results and discussion

In this section, we present and discuss the experimental results. We begin by describing the setup of a test for the assessment of the system's quality in terms of gathering existing emoji and generation of new ones. Afterwards we present and analyse the results.

In order to evaluate the system, we used a list of concepts, containing concepts with and without official emoji representation. The list selected was the *New General Service List* [4] as it consists of a core vocabulary of 2801 words for second language learners. As most emoji represent nouns, we decided to apply this restriction to the list. Using RiTa[15] library (part-of-speech tagging function), the list was reduced to 1509 nouns. The system was used to produce emoji for each concept of the list and output was analysed in terms of production and quality. Given the large number of nouns, we are still conducting user evaluation on output quality, and at this stage we tested the full set with two users.

4.1 Analysing the production of emoji

In general, the system is able to produce emoji that reflect the meaning of the noun, both related (e.g. change) and blended (e.g. generation) – see Fig. 1. From the 1509 input names the system is only unable to produce emoji for 4 nouns (protein, incentive, immigrant and refugee), as observed in Table 1. It produces existing emoji for 927 nouns, 1st level related emoji for 1267 nouns, 2nd level related emoji for 1212 nouns and blends for 1043 nouns.

The most significant source of semantic information is *senses*, with 59.44% of nouns have the majority of their emoji related to senses, 38.3% have all the emoji (100%), and only 23.3% have none of the emoji (0%) related to senses (Fig. 2).

[15] rednoise.org/rita/

(a)

	1	2	3	4	5	
Related	692	253	287	215	31	1478
Blended	668	187	108	74	6	1043

(b)

		Gs	**G$\overline{s}$**	$\overline{\mathbf{G}}$	
E	*good*	112	675	4	791
	bad	65	69	2	136
$\overline{\mathbf{E}}$		288	290	4	582
		465	1034	10	1509

Table 2. ***(a)*** Quality of Related and Blend emoji – (1) none represents the noun, (2) bad, (3) neutral, (4) good and (5) obvious, expressed in number of nouns. ***(b)*** Usage of generated emoji (related and blends) vs presence of existing emoji (E), expressed in number of nouns. Nouns with existing emoji were divided into: *good* (at least one existing emoji represents the noun) and *bad* (no existing emoji represents the noun). It shows the number of nouns in which one of the generated emoji was selected to represent the noun (s); and in which none of the generated emoji was selected ($\overline{s}$).

It is also important to notice the value of *definition*, with 43.04% of nouns with the majority of their emoji related to *definition*, 26.86% with all the emoji, and 26.86% with none of the emoji. These two sources highly contrast with the rest, as well as, with combinations among them.

4.2 Analysing the quality of generated emoji

The system's ability to retrieve related emoji and produce blends does not mean that produced emoji correctly represent the concept. We firstly evaluated the results from gathering of related emoji and blending of new ones, associating an integer from 1 (does not represent the noun) to 5 (represents in a obvious way). This value concerns the best exemplar (if such exists). The obtained results can be seen in Table 2 (side a).

On the other hand, some of the sources used to retrieve existing emoji are not official but result from user attribution (e.g. senses). For this reason, there is no guarantee that they represent the concept well. To evaluate the quality of the existing emoji we attributed a binary value corresponding to wether it represents (*good*) or not (*bad*) the concept. Afterwards, we identified if at least one of the generated emoji (related or blended) can be selected to represent the noun (S) – i.e. it is as good or better than the existing emoji.

From this analysis it is possible to divide the nouns into several groups (see Table 2, side b):

1. **Gs & E** – a generated emoji was selected to represent the noun (S) despite the presence of existing emoji (E). Three situations occur: **(a)** *Good E* but the generated ones are even better. This is the best case scenario and had an incidence of 112 out of 921 emoji with Existing and Generated emoji (12.16%), which we consider a good result – e.g. *musician*, *release*, *roof* and *wave* in Fig. 1; **(b)** *Bad E* and the generated ones are better. We do not

consider the results for this group very good as the generated were only selected in 65 from a total of 134 nouns with generated and bad existing emoji. One reason for this may be the abstract nature of nouns; **(c)** *Equally good*. The generated emoji are as good as the existing emoji. This is often related to different meanings for the same noun – e.g. *change* and *speaker* in Fig. 1;

2. **Gs & $\overline{\mathbf{E}}$:** There are no existing emoji and the system is able to generate emoji that represent the noun well – e.g. *initiative*, *proof*, *generation* and *review* in Fig. 1;
3. **G$\overline{\mathbf{s}}$ & E:** The system is not able to generate anything better than the existing emoji. Two situations occur: **(a)** *Good E*. This is the case with most incidence (675 nouns). This is easy to justify as some nouns have officially associated existing emoji (we did not determine which and we consider it as future work) – e.g. *cat* and *sun* in Fig. 1. The fact that the generated were not selected, does not mean their quality is not good – it was just not enough to surpass the existing emoji. This may be due to the metaphoric quality of generated emoji; **(b)** *Bad E*. Despite the bad quality of existing emoji, the generated ones are not considered better. One reason for this may be the abstract nature of the nouns;
4. **G$\overline{\mathbf{s}}$ & $\overline{\mathbf{E}}$**: the system does not produce anything good enough to represent the noun. This is the worst situation.

Despite stating that the number of nouns with existing emoji is 927 (Table 1), the number of nouns well-represented with existing emoji is only 791 (Table 2, side b). The number of nouns for which the system is not able to produce an adequate emoji is 365 ((*bad*E G$\overline{\text{s}}$) + ($\overline{\text{E}}$ G$\overline{\text{s}}$) + (*bad*E $\overline{\text{G}}$) + ($\overline{\text{E}}$ $\overline{\text{G}}$)). This means that the system is able to present the user with representative emoji for 1144 nouns out of 1509 (an increase of 44.63% when compared to the initially well-represented 791 nouns) – see examples in Fig. 1. It is important to bear in mind that the initial number of well-represented nouns would be even lower if we did not consider the emoji retrieved using non-official semantic knowledge (gathered from EmojiNet). Moreover, some of the nouns are abstract and thus highly difficult to represent (e.g. *everyone*). Other nouns do not have any representative emoji, despite having a great number of retrieved ones.

5 Conclusion and future work

We presented and described *Emojinating* – a platform which searches for existing emoji and automatically generates new ones, based on a user-introduced word. It combines Semantic Network exploration with visual blending. In order to assess the system's quality in terms of production and output, we produced representations for 1509 nouns from the New General Service List. The system was able to produce emoji for the majority of the nouns, achieving novelty and good quality of representation.

We consider that there is a large range of possible applications for the system, e.g. aiding in ideation, helping in icon design (generated representations should not be seen as final result as adjustment may be necessary, e.g. legibility issues) or even providing resources for information visualisation (as described in [11]).

Future enhancements include: (i) extending the evaluation to double-word concepts, (ii) increasing the number of evaluators, (iii) studying the relation between nature of nouns and system's performance, and (iv) distinguishing between official emoji and user-associated ones.

Link *Emojinating* will be available at `http://rebrand.ly/emojinatingICCBR`.

Acknowledgements This research is partially funded by: Fundação para a Ciência e Tecnologia (FCT), Portugal, under the grant SFRH/BD/120905/2016. This work includes data from ConceptNet 5, which was compiled by the Commonsense Computing Initiative. ConceptNet 5 is freely available under the Creative Commons Attribution-ShareAlike license (CC BY SA 4.0) from http://conceptnet.io. The included data was created by contributors to Commonsense Computing projects, contributors to Wikimedia projects, Games with a Purpose, Princeton University's WordNet, DBPedia, OpenCyc, and Umbel.

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