Emojinator: An Emoji Generator to Represent Emotions

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Abstract

In recent years, emojis have become a key part of computer-mediated communication (CMC). This stems from the fact that they act as nonverbal cues which are difficult to convey when communicating using simple text. Just as a picture is worth a thousand words, the same can be said for an emoji. In this paper, we present a creative system, *Emojinator*, that generates emojis using visual blending to represent a diverse range of emotions. Unlike previous emoji generation work, fuzzy logic was incorporated to enable Emojinator to make decisions. A user study was conducted to evaluate the output, along with the creative tripod method to assess Emojinator's creativity. The results from the survey show that for more than half the emojis, at least 50 percent of participants agreed or strongly agreed that the emoji represented the stated emotion. Evaluation through the creative tripod method showed that the system is skillful and imaginative but could be more appreciative. Therefore, further refinement may be needed to make the system more creative. However, the success of this novel approach to emoji creation opens up new directions for future work.

Introduction

In recent years, the use of emojis has increased rapidly. Literally meaning "picture-word" in Japanese, their popularity in written language can be seen in the rise in the number of emoji-related tools such as search-by-emoji and emoji replacement or prediction features. The emoji language has also been proposed as the fastest-growing language in the UK (Doble 2015), referencing how a large proportion of 18 to 25-year-olds find it easier to express their feelings through emojis instead of through text. Emojis gained more popularity after the Unicode standard incorporated them, and after Apple added the emoji keyboard to iOS in 2011, with new emojis released every year since (Dimson 2015). Since then, their number has increased continuously with the addition of new characters in Unicode, comprising not just faces but also pictographs depicting vehicles, buildings, food, drinks, activities like dancing and running, and animals and plants (Pavalanathan and Eisenstein 2015).

The increasing number of emojis does not indicate a corresponding increase in emojis with visual representations of emotion. Based on recent numbers, there are a total of 3633 emojis in the Unicode Standard; out of these 157 are single-character smileys representing emotions (EmojiList 2022). Consequently, developing new emojis to represent a greater number of emotions seems to be a laborious task. With the growth of computational creativity, it therefore makes sense to delegate this task to a creative system.

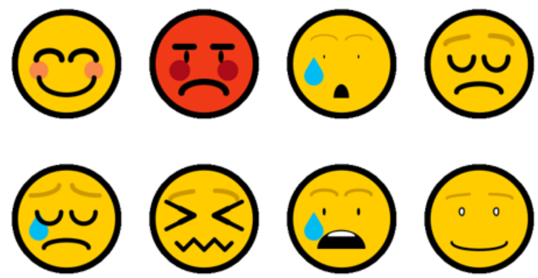

Figure 1: Examples of emojis generated by Emojinator. From left to right and top to bottom: *Joyous, Bitter, Anxious, Disappointed, Dissatisfied, Miserable, Worried, Satisfied*.

In this paper, we develop a system that uses *visual blending* to generate new emojis. Visual blending, based on the idea of the Conceptual Blending (CB) theory (Fauconnier and Turner 2002) is the creation of new visuals, such as images, by combining at least two current ones (Cunha, Martins, and Machado 2018b). The *Emojinator* system creates new emojis by blending features from an emoji (Figure 1). The system uses fuzzy logic to make decisions on what kind of features an emoji should have to depict a particular emotion. To evaluate the results and understand how the system can be improved, a user study was conducted. We also evaluate the creativity of the system using the creative tripod (Colton 2008). Before discussing *Emojinator* further, it is important to explore the significance of emojis to understand why this area is important.

Importance of Emojis

It is a well-known fact that emojis have become an important part of digital communication. Major technological companies have realised their significance as well and have taken several steps to incorporate emojis in their systems. Alongside the business importance of emojis, there are psychological, sociological and linguistics-related aspects to emojis.

Psychological Aspects Before the introduction of emojis, emoticons were used to display emotions in communication through texting, email, and other forms of computer-mediated communication. Emoticons, unlike emojis, are letters, punctuation marks or numbers that usually represent an emotion, for instance, a smiling face would be ':)'. As computer-mediated communication is devoid of nonverbal cues, the primary objective of emoticons was to translate emotions to convey facial expressions (Walther and D'Addario 2001). It has been found that similar parts of the brain are activated when a person sees a smiling emoticon or emoji, as when they see someone smiling in real life (Churches et al. 2014).

This function has developed with time with the growth of online systems and emojis. In a study on how emojis impact emotional communication and information processing, it was found that understanding of verbal messages and processing speed were found to have been improved by adding emojis (Boutet et al. 2021). The results of this study thus supported use of emojis, especially positive ones, to enhance communication.

Sociological Aspects In face-to-face settings, nonverbal cues help in communicating information which impacts our perception of other people and our behaviours towards them as well (Stewart et al. 2012). For instance, individuals who smile more frequently may be considered 'warmer' (Wang et al. 2017). A similar effect is seen when emoticons and emojis are used.

Linguistics-related Aspects In recent years, research has extensively examined the role of emoticons in communication. These symbols are believed to convey emotions and thoughts by mimicking nonverbal cues (Crystal 2006). Nonverbal cues are usually the main piece of information processed by the brain and when an emoticon or emoji is seen, it is identified as an emotional interaction (Yuasa, Saito, and Mukawa 2011). Emojis are perceived as not words but emotional information as they help to articulate the tone of voice and gestures which are usually only possible when people are communicating vocally.

Consequently, emojis play a significant part in helping people express their emotions and helping others in understanding them. It then becomes crucial to understand emotions and how they can be modelled to represent emotions.

Computational Modelling of Emotions

Emotions are one of the key significant unconscious mechanisms that affect human behaviours, decision making and attention (Phelps 2006). As there are several elements and facets which underly emotions, they can be approached from various perspectives. The multi-faceted nature of emotions has resulted in them being the focus of study in various disciplines such as neuroscience, cognitive informatics, psychology, philosophy and computer science (Wang 2007b). This multidisciplinary study has led to the development of several computational, cognitive and theoretical models.

While there are several theories of emotions, Ekman's model, Wang's Hierarchical model of emotions and Russell's circumplex model will be discussed as these are some of the main theories in this field.

Ekman's Model

One of the most well-known theories of emotions is Ekman's model of six basic emotions comprising sadness, surprise, fear, happiness, disgust and anger (Ekman 1999), based on different facial expressions. However, these are usually not used in the development of cognitive computational models of emotions (Rodríguez, Ramos, and Wang 2012). According to Cohen (2005), the model of basic emotions does not have the conceptual room to consider emotional experiences and therefore, is not an adequate theory of emotion. The fact that it depicts only six emotions also limits its usability for this system since these emotions are already depicted in emojis currently.

Wang's Hierarchical Model of Emotions

A hierarchical model of emotions was developed by Wang (2007a). In this model, human emotions were classified into two categories: unpleasant and pleasant. Emotions in the two categories can be further classified into five levels based on the intensity of subjective feelings where every level consists of a pair of pleasant and unpleasant emotions. While the hierarchical model of emotions is wider in scope in comparison to Ekman's model, its focus on the link between emotions, attitudes and motivations makes it difficult to apply this model to this study; the primary objective here is to use emojis to depict emotions, not to study the underlying motivations and attitudes behind emotions.

Russell's circumplex model

In Russell's circumplex model of affect, emotions are modelled spatially in which eight variables are plotted on a two-dimensional graph (Russell 1980). The dimensions used in this graph are:

- **Valence:** the extent to which an emotion is positive or negative. E.g. delighted is a positive valence emotion in Russell's model, while sad is a negative valence emotion.
- **Arousal** the intensity of emotion. It ranges from calm (low) to excited (high).

Scherer's update to the Russell model A problem which arises in Russell's model is how certain emotional states may fall under a similar area of the two-dimensional space – for instance, both angry and tense would have negative valence and high arousal. In such a situation, verbal labels help to identify key components of the stimulating event and the integrated interpretation of reaction patterns (Scherer 2005). Using emotional labels, and incorporating goal conduciveness, coping potential, and appraisal dimensions with the strongest impact on emotions, Scherer (2005) superimposed a two-dimensional structure on Russell's model with various emotion terms (indicated with a +, lower-case words). This addition by Scherer led to a wider variety of emotions being represented in this model.

Paltoglou and Thelwall (2013) used Scherer's model for measuring the emotional content of blog posts. During this

Figure 2: Scherer's updates to Russell's model converted into quantitative data. Source: (Paltoglou and Thelwall 2013). The diagram has been used with permission from the authors. Upper-case notation represents the terms that were used by Russell (1980).

application, they converted the graphical data into quantitative data to use in their study. This conversion makes the model quite useful for implementation in this project. The model contains a wide and diverse range of emotions across the full range of dimensions of valence and arousal – a total of 97 emotions. Therefore, the Russell model, as updated by Scherer (2005) and Paltoglou and Thelwall (2013) was used in the development of this system (Figure 2).

The Approach

Computational creativity work on emoji generation is mostly focused on two approaches: Generative Adversarial Networks (GANs) which have been used to replicate existing emojis (Radpour and Bheda 2017; Puyat 2017) (Figure 3) and visual blending (Cunha, Martins, and Machado 2018a; 2018b; Cunha et al. 2019; 2020) (Figure 4). As GANs have not been able to achieve the same level of sophistication, visual blending has been used here. In this section, the process of visual blending is discussed, followed by an explanation of the key components of this system.

Visual Blending

Visual blending, based on the idea of the Conceptual Blending (CB) theory (Fauconnier and Turner 2002) is the creation

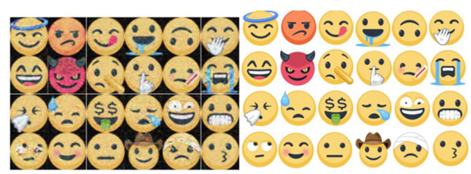

Figure 3: Emojis generated by conditioning the network (left) with actual emojis (right). Source: (Radpour and Bheda 2017). The image has been used here with permission from the authors.

of new visuals, such as images, by combining at least two current ones (Cunha, Martins, and Machado 2018b). There are several examples of visual blending. The two relevant ones are: character blending for Pokémon (name and image) in which mappings exist between attributes, such as colour and shape and type, resulting in a new type of Pokémon (Liapis 2018). In addition, the X-Faces system generates new faces by merging different face parts to enhance data augmentation in face detection (Joao Correia and Machado 2016). Similar work has been done with emojis as well.

Emoji Generation using Visual Blending Before emojis, emoticons were used and the ease with which individual parts of an emoticon could be changed, for instance, chang-

Figure 4: Blends for *peace accord, car factory, security, house, market depression, health risk* and *airline bureaucracy*. Source: (Cunha et al. 2020). The image has been used here with permission from the authors.

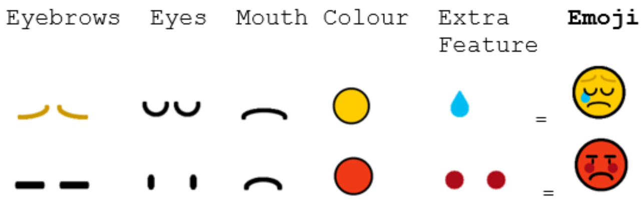

Figure 5: Examples of two emojis created by blending features

ing a bracket from ")" to "(" to make an emoticon ":(" could mean a sad face, has led to the development of different blending approaches to generate emojis.

In 2016, the Unicode Consortium decided to introduce the ZWJ (Zero-Width-Joiner) method which mainly consisted of an invisible character to describe the combination between two characters (Abbing, Pierrot, and Snelting 2017). A key example of emoji generation using visual blending is the *Emojinating* system that blends existing emojis to generate new ones to enhance creativity and assist in the idea generation process (Cunha, Martins, and Machado 2018a). This system has a wide range of applications such as helping in idea generation and designing icons (Cunha, Martins, and Machado 2018a). Another emoji generator, *Emojimoji*, generates new emojis by randomly combining two existing ones (EmojiMoji 2022).

Cunha et al. (2020) further worked in this area by assessing the Emojinating system to gauge the suitability of this approach for the visual depiction of concepts. However, the focus of Emojinating is quite different from this system in the sense that it does not specifically focus on emotions and mainly used emojis as a case study to gauge the effectiveness of visual blending for concept representation. By focusing on emotions, our system addresses a gap in existing research. The visual representation of emotions through emojis interlinks with the psychological aspect of emojis helping in communication and enabling people to express emotions more easily.

Visual blending was also used in this project because of similarities between existing emojis. For example, most emojis had common features such as eyes, face, mouth, and eyebrows and were yellow in colour. There were different types of each feature. For instance, if we focused on eyes,there are oval, smiling and x-shaped eyes. This similarity meant that once common features were identified they could be used in different emojis based on the emotion.

However, the question then arose of how exactly should visual blending be done? What can be blended to create a new emoji and what tools should be used?

Features of an Emoji To identify the similarities between emojis, we mapped the existing emojis to the circumplex model using *Emojipedia* (Emojipedia 2022) as a guide (see Figure 6). This helped to make links in features between different emojis. Blending these features, would therefore result in the generation of new emojis (see Figure 5).

The artwork selected for emojis was the one that is visible in a browser. This was to ensure ease and standardization as the artwork varies according to each platform. For face colour, yellow and red were selected. Yellow is used in most emojis and red was chosen as other emotions in the second quadrant, such as *jealous* and *indignant* had a similar meaning associated with them as *enraged*. While the *disgusted* emoji has a green colour face, this was not incorporated as disgust has a distinct relationship with the colour green and no other emotion in the model has a similar meaning.

Fuzzy logic was then used to represent the overlap across various features to represent different emotions.

Computational Tools and Fuzzy Logic

Py5 (py5coding 2022), a new version of *Processing* for Python, was used. Py5 is a widely used software sketchbook that is used to create images with code. To ensure that the system is autonomous and is not completely following the rules set by a human being, fuzzy logic was incorporated. Fuzzy logic can be used in situations where there is a possibility for imprecision (Zadeh 1996). This was needed in this system since it is difficult to classify emotions based on just crisp logic. The below examples demonstrate the difference between the two logical processes using emotions:

- **Crisp logic:** If Sarah passes her dissertation (gets a mark above 50), she will be happy, otherwise she will be sad.
- **Fuzzy logic:** The degree to which Sarah is sad or happy will depend on her overall mark instead of being binary. If she scores above 70, she will probably be ecstatic but there is a small possibility she might be sad as she wanted a 90. Otherwise, if she scores a 50, she will be sad, but also relieved about passing her final module.

Fuzzy logic provided a way to convert the two-dimensional data on emotions (valence and arousal) to a one-dimensional space, while also making the system *artificially intelligent*. An agile software development process was also followed to allow more room for flexibility. The objective of this was to give the system *creative* freedom.

Fuzzy Logic Architecture The first step in fuzzy logic architecture is *fuzzification* in which a crisp input value is used to determine the extent to which the input belongs to a fuzzy set (Guo and Wong 2013). To depict fuzzy sets graphically, trapezoidal membership functions (MF) were used. Two linguistic variables were defined based on the circumplex model – valence and arousal, which would determine the output, that is, emotional state. A trapezoidal membership function was used, since it covered a larger area.

Five membership functions were defined for valence and arousal: very low, low, medium, high and very high (Figure 6). This was predominantly to capture a diverse range

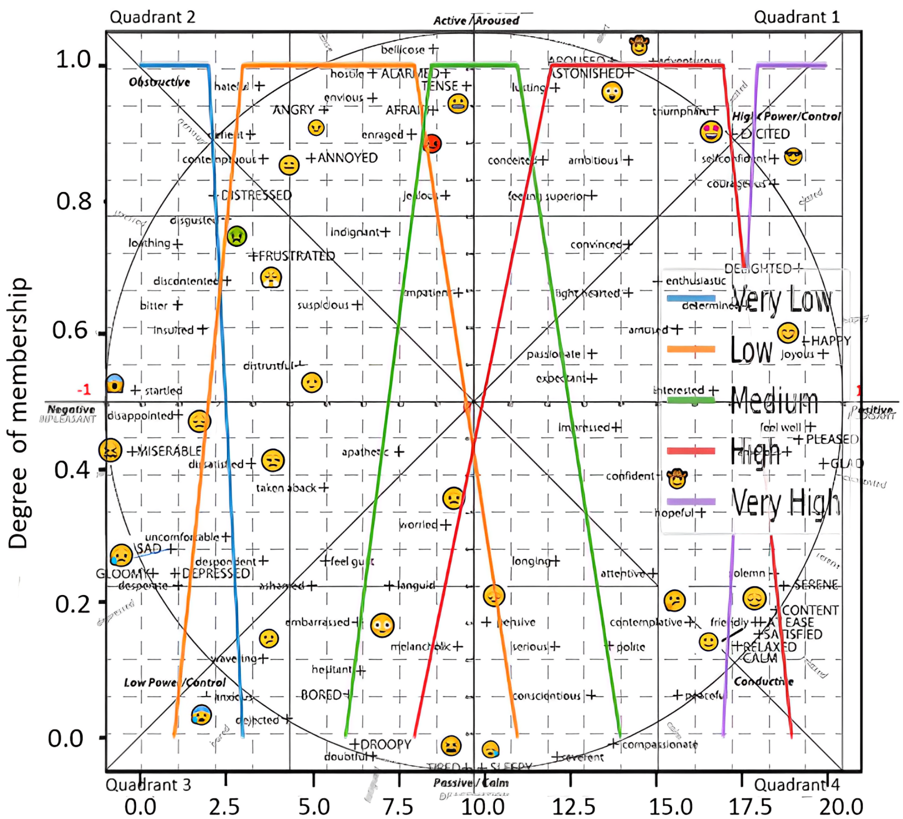

Figure 6: Fuzzy logic membership functions for Valence and existing emojis mapped on to the circumplex model

of emotions from the circumplex model more effectively. A neutral MF was incorporated to effectively represent emotions such as tired and sleepy which have a very low valence on the circumplex model but lie on the negative and positive sides respectively of the x-axis due to the slightly different connotations of the two words. A similar process was followed for output fuzzy sets for emotional state: very unpleasant, unpleasant, neutral, pleasant and very pleasant.

After fuzzification, fuzzy rules had to be defined. For simplicity, these were split into various combinations of valence and arousal and what emotional state they would lead to, using the fuzzy operators AND, NOT and OR which were available in the Simpful library (Spolaor et al. 2020). The Mamdani Inference system was used as it is better suited to human inputs, with a more interpretable rule base, making it more appropriate for this project. On the other hand, the Sugeno inference system is better suited to mathematical analysis and makes use of a singleton output MF that is a linear function (mathworks.com 2022).

Once an emotional state value was determined, it was assigned a positive or negative sign based on the quadrant it fell under. For example, in quadrant 2, the overall output value would be negative since valence is negative, while arousal is positive, and in quadrant 1, the overall value would be positive as both valence and arousal values are positive.

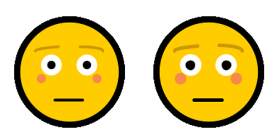

Figure 7: Emojis for *embarrassed* (left) and *felt guilt* (right)

Rules and Uniqueness

Once an emotional state value is calculated, if-then rules use these values to decide what feature every emoji should have.

To ensure that every emoji looked unique, a weight parameter, determined by the arousal value was added to the features (eyes, mouth etc). This would impact stroke thickness and the qualities of features depending on their attributes. For example, in Figure 7, stroke thickness for mouth and eyebrows, and diameter for eyes and flushed cheeks are slightly different for the two emojis. We recognize that some of the emojis look very similar and this is a limitation of this work.

How it Works A user has two options to create an emoji:

- Entering valence and arousal values
- Selecting an emotion from the dropdown box (a list of all the emotions from the circumplex model).

Figure 8: Emojis used in Section 1 of the survey. From left to right and top to bottom: *Light Hearted, Lusting, Passionate, Frustrated, Tense, Insulted, Taken Aback, Droopy, Embarassed, Contemplative, Confident* and *Serious*

Based on the values entered between the ranges of -1 to 1 or selection of the emotions, an emoji is generated.

Results and Discussion

In this section, we present and discuss the results generated. Following this, the system is evaluated using the *creative tripod* approach.

User Testing

Emojis are mostly used in computer-mediated communication to help individuals communicate more easily. Thus, it becomes essential to acquire responses from human participants to understand how they would be interpreting an emoji. A survey was created to get feedback from participants about the emojis generated by the *Emojinator* system. The survey was split into three sections.

In the first section, participants had to evaluate emojis based on how accurately they represented the stated emotion. A five-point Likert scale was used in which participants had to select their level of agreement: (1) Strongly agree (2) Agree (3) Neutral (4) Disagree and (5) Strongly disagree. A Likert scale was used, as ratings are ordinal values (Yannakakis and Martinez 2015); therefore, assigning relative values to emotions is a better approach than using absolute values due to the ordinal nature of emotions (Yannakakis, Cowie, and Busso 2018). At the end of the section, participants were asked to share any comments they had about the emojis to acquire qualitative feedback as well. A total of 12 emojis were used in this section with three from every quadrant of the circumplex model. They were selected randomly using a random word selector website (textfixer.com 2022) to avoid bias on our part in selecting emojis (Figure 8).

The second section involved a comparison of system-generated and existing emojis with the objective of understanding which emoji better represented the specific emotion. Here we compare to existing emojis, as we are treating existing emojis as the benchmark for this work. Participants were not told which ones were system-generated and which ones are the existing ones.

Finally, in the third section, participants were told which emojis were system-generated and which are the existing ones. They were again asked which emoji better represented the emotion mentioned and to provide a reason for their choice. This was to gauge if opinions had changed. The objective of adding a comment box was to get both quantitative and qualitative results to analyze the output of Emojinator. The same rendering of emojis was used for comparison with existing emojis to keep the results consistent.

Analysis of Responses A total of 45 responses were received in the survey.

Looking at Figure 9 shows that for 7 out of 12 emojis at least fifty percent of participants agreed or strongly agreed about how effectively an emoji represented a given emotion. The top-rated emojis were *embarrassed*, followed by *frustrated*, *light-hearted* and *insulted* emojis. In terms of the lowest ranked emoji, 69 percent of participants disagreed or strongly disagreed about how effectively the emoji for *passionate* depicted the emotion. This was followed by the *lusting*, *serious* and *droopy* emojis.

Out of the 12 emotions listed in this section, *frustrated, tense, embarrassed* and *contemplative* have existing emojis to represent them. Out of these, *embarrassed* closely resembles its existing counterpart. This could be a possible explanation for why the system-generated emoji for embarrassed ranked the highest out of all these emojis suggesting that participants were more used to existing emojis. There was also an interesting comment about how the frustrated emoji should have clenched teeth. This again proves to some extent that individuals are used to seeing existing emojis and this could potentially impact their opinions. However, participants did score *frustrated* (73 percent of participants agreeing or strongly agreeing) and *tense* (58 percent of participants agreeing or strongly agreeing) highly in terms of their effectiveness in representing their respective emotions despite them looking quite different from their existing counterparts. This suggested that *Emojinator* was producing emojis that represented emotions well.

The comment box at the end of this section also had some insightful feedback with comments about specific emojis such as *insulted* looking angry and *tense* looking sad. Another respondent mentioned how neutral was selected as a response as the emoji could represent a particular emotion but was more representative of another emotion. This showed there was some ambiguity regarding interpretation.

Comparison with Existing Emojis Four emotions were selected in this section, one from each quadrant – *happy*, *worried*, *enraged* and *pensive* using a random word selector (textfixer.com 2022). Users were not told which emojis were system-generated and which were the existing ones and had to decide which emoji better represented an emotion. Figure 10 shows the results from this section.

The results show overwhelming support for existing emojis with the only exception being *pensive*. In the next section, participants were told which emojis were system-generated and which were the existing ones and then asked to answer which depicted the emotion more effectively. There were slight changes in the results with more responses for Emojinator, suggesting possible bias from respondents to indicate their preference for system-generated emojis (Figure 11).

However, the overall trend remained the same. Since participants could give feedback in this section, several interesting insights emerged. The impact of eyebrows on how well an emoji depicted an emotion could be seen in the happy

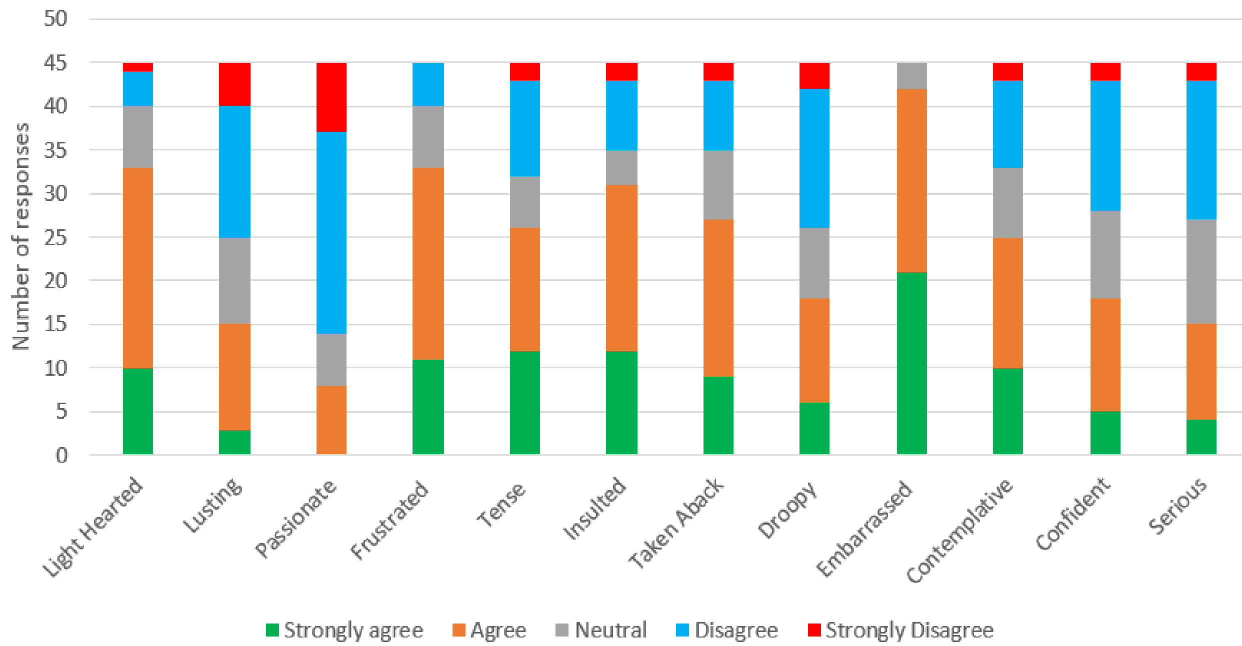

Figure 9: Section 1 Responses. The emoji for *embarrassed* was the best representation, while *passionate* had the worst

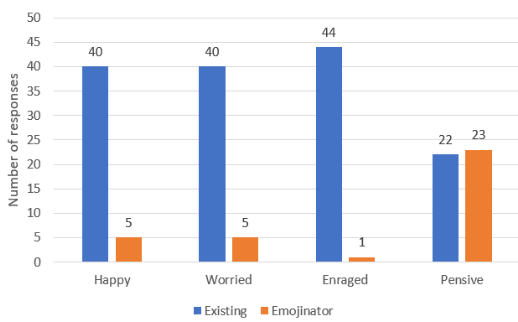

Figure 10: Section 2 Responses. *Pensive* was the only emoji with higher ratings for Emojinator output

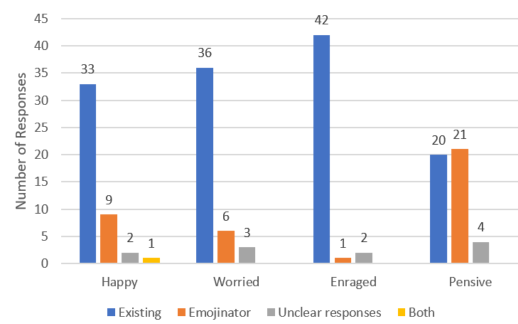

Figure 11: Section 3 Responses

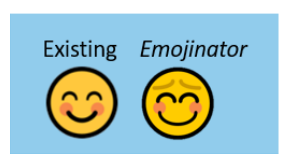

Figure 12: The *Happy* emoji

and enraged emojis. For the former, the addition of eyebrows resulted in comments such as how the smile seems 'strained' and how the existing emoji seems simpler in comparison since it does not have eyebrows (Figure 12). Similarly, the shape of the eyebrows in the enraged emoji led to comments such as how it looks sad because of the orientation of the eyebrows (Figure 13).

Results for the *pensive* emoji were better than the existing emoji since the existing one looks sadder according to the overall feedback. The Emojinator generated *pensive* emoji therefore also performed best in the final section.

Summary of Results To summarize the findings, more than half of the participants agreed or strongly agreed that 7 out of 12 emojis effectively depicted the stated emotion. When comparing system-generated to existing emojis, they rated the existing emojis higher for 3 out of 4 emojis. While these results offer insights into how well participants interpreted the system-generated emojis, interpretation may always be subjective. For instance, participants said they liked the Emojinator-generated emojis more once they found out which ones are system-generated. Besides this, participants could have been more used to emoji renderings on different operating systems, such as Apple and Google smartphones, which have been found to affect how people interpret the same emoji (Miller et al. 2017). A person's interpretation of emojis is also impacted by age (Koch, Romero, and Stachl 2022; Jaeger et al. 2018). Individuals above the age of 30

Figure 13: The *Enraged* emoji

tend to interpret emojis more literally, compared to younger people who interpret them more customarily (Herring and Dainas 2020). Therefore, evaluating creativity, in this case, emoji interpretation is a subjective area. However, trends in the above data do indicate that some form of consensus does exist among participants which will be useful in future work.

Evaluation

Evaluating creativity of Emojinator Evaluating creativity of a creative system can be complex due to the varying definitions of creativity. We used the creative tripod approach (Colton 2008), evaluating systems not just on output but also how they produce artefacts, using three principles:

- **Skillful:** The system is skillful since it can generate emojis. However, defining the level of skillfulness is difficult. Based on the way emojis are generated, the system is currently limited to just features such as eyes, eyebrows etc that have been written in code. Skillfulness can perhaps be enhanced by automating this process.
- **Appreciative:** At this stage, Emojinator has to be told what emotion to represent in an emoji. This can be achieved by a user entering a specific word or inputting valence and arousal values. Therefore, the software knows it has to generate an emoji based on the emotion or valence and arousal values it receives. However, the system does not fully know the value of its artwork. This is something which can be improved upon.
- **Imaginative:** The system is also imaginative in the sense that it makes every emoji unique by altering its features based on the arousal value which in turn determines the weight value. By doing this, it is generating unique and novel emojis. A limitation is that some of the emojis, however, look very similar (see Figure 7). By using fuzzy logic, the system has some autonomy in its decision-making. However, the software is still generating emojis based on rules that use the emotional state value – it is essentially *taught* how to be imaginative. Moreover, it could be more imaginative by adding a machine vision component, that could perhaps detect emotions that a person expresses and generate them in the form of an emoji.

User study and Results A limitation of the user study is that only four emojis were chosen to compare with existing emojis in sections 2 and 3. To better represent the diverse emotions in the circumplex model, more emojis could have been added. However, as it was an online survey, adding more emojis would have made the survey longer. This could have led to a decrease in the respondents' attention and response quality, as online survey respondents generally have shorter attention spans (Fricker and Schonlau 2002).

While 50 percent of participants agreed about representation for 7 emojis, the remainder did not fully associate the emojis with the stated emotions. A ranking approach that would have helped the user identify the second or third best emotion for a particular emoji would have been better. The distance between two emotions on the circumplex model then could have been used as a metric for evaluation.

Conclusion and Future Work

While there is room for improvement in this system, Emojinator was successful in meeting the objectives of generating emojis to represent emotions, making decisions on its own through AI and also being creative to some extent. Considering that not a lot of computational creativity work focuses on emoji generation, this system makes a unique contribution to existing research in this area. By incorporating soft computing techniques such as fuzzy logic, the system is also tolerant of approximations and imprecisions.

Overall, the emojis generated show potential for being used in computer-mediated communication. However, some parts of the software can be improved upon to make Emojinator more creative as a system.

In the future, the system can be further improved upon by making it more appreciative. This can be achieved by giving the system feedback on the emojis generated. This has also been done in previous works on emoji generation (Cunha et al. 2019) by making use of interactive evolutionary algorithms. This will also make the system more appreciative since it will know what the user likes and what the user does not like. This could result in the software becoming more creative, in line with the creative tripod approach.

Currently, the system also makes use of rules which define what kind of features it should have. This can be improved upon by training the system to identify on its own what kind of features an emoji should have. Actual human expressions can also be used to further enhance the system's understanding of emotions so that they reflect emotions better. The result of this would be greater autonomy for the system.

Research has also shown that a link exists between how personality, age and gender impact how emojis are interpreted. This is an interesting area to explore, and future user studies can also try to understand the relationship between emojis generated and the above-mentioned factors.

Link The source code for this system, along with the user study results and emojis generated can be found here: https://github.com/marziabil/emojis.

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