Emoji Understanding and Applications in Social Media: Lay of the Land and Special Issue Introduction

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1 INTRODUCTION

Pictographs, commonly referred to as “emoji,” are a popular enhancement to electronic communication. Emoji are widely used to express sentiment, emotion, and sarcasm across all major social media platforms. In 2018, Facebook reported that people share over 700 million messages with emoji every day, and another 900 million daily emoji-only messages are sent on Facebook Messenger.¹ In the same year, Twitter reported processing 250 million emoji per month.² In 2015, Instagram reported that nearly half of the comments posted on photos contain emoji.³ Social media data have been used to study how emoji are used across different languages, cultures, and user communities and as features to train machine learning models to solve problems spanning many applications. However, the pictorial nature of emoji, that (the same) emoji may be used in different contexts to express different meanings, that the same emoji may be rendered differently

¹<https://blog.emojipedia.org/facebook-reveals-most-and-least-used-emojis/>.

²<https://memeburn.com/2018/07/twitter-most-tweeted-emoji/>.

³<http://instagram-engineering.tumblr.com/post/117889701472/emojiengineering-part-1-machine-learning-for-emoji>.

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across different devices and platforms, and that emoji are used in different cultures and communities over the world who interpret emoji differently, make it difficult to apply traditional Natural Language Processing techniques to analyze and understand them. This special issue explores computer and social science efforts to understand social, cultural, communicative, and linguistic roles of emoji and novel computational methods to understand, interpret, and exploit them.

1.1 Background

First introduced two decades ago, emoji become mainstream after their standardization by The Unicode Consortium in 2009, which enabled emoji adoption on mobile platforms. Early work on emoji interpretation focused on how the sentiment and semantics of emoji differ when the same emoji is displayed on multiple mobile platforms or operating systems [8]. Based on qualitative and quantitative research methods, Miller et al. exposed how the platform-specific differences in emoji renderings can lead to misinterpretation of emoji-rich communication. This finding also highlighted the fact that similar to words, emoji can take multiple meanings based on the context of their use. To address this problem, Wijeratne et al. created EmojiNet⁴ [11, 12], the largest machine-readable emoji sense inventory consisting of (i) 12,904 sense labels over 2,389 emoji, which were extracted from the web and linked to machine-readable sense definitions seen in BabelNet; (ii) context words associated with each emoji sense, which are inferred through word embedding models; and (iii) recognizing discrepancies in the presentation of emoji on different platforms and specification of the most likely platform-based emoji sense for a selected set of emoji. They also demonstrated that the emoji knowledge embedded in EmojiNet can be coupled with supervised and unsupervised learning approaches to achieve state-of-the-art performances in downstream emoji understanding tasks such as emoji sense disambiguation [11] and emoji similarity calculation [13].

To investigate to what extent the meaning of emojis is shared across languages and countries, Barbieri et al. [6] gathered a dataset of about 80 million tweets in English, Spanish, and Italian geo-localised in USA, UK, Spain, and Italy. Four skip-gram continuous vector models were created (one per country-language pair) using the retrieved tweets To model for each emoji its intended distributional “semantics” (i.e., word embedding vector). To assess the degree of similarity of a pair of emojis X and Y, a novel method was designed that consists of retrieving the lists of top-N most similar emojis for each emoji and distributional model. The lists for X and Y are then compared to check the number of common elements that is used as surrogate for the “semantic” similarity between X and Y. Several interesting observations are drawn, such as the fact of music 🎵, nature ☀️, or facial 😊 emojis have their meaning preserved across country-language pairs or that the clover 🍀 emoji means different things in different languages. Moreover, when the overall similarity across language-country is computed by comparing the 200 most frequent emojis, strong correlations are found, however, and more pronounced, but not surprisingly, for the pair USA–UK. A similar study is carried out comparing emoji’s semantics across seasons, taking advantage of the collected USA tweets.

Word prediction is a popular, widespread functionality found in several computer interfaces; however, emoji prediction software was not well developed until recently. Barbieri et al. [4] carried out one of the first studies to address the problem of predicting an emoji given a text input. Undertaken in a dataset of tweets each containing only one emoji, the research intended to guess the exact emoji used in the tweet given the text. A computational model based on Long Short-term Memory Networks was developed that relied on two different embedding models

⁴<http://emojinet.knoesis.org/>.

for representing the input sequence: words and character embedding, the latter to better model noisy social media text. Overall, the neural model outperforms competitive baselines based on word-level information. It is noticeable that the good behaviour of word-level information, since word-emoji associations are common in the dataset (e.g., word “love” and ❤️), however, considering word sequences offers competitive advantages. The work was extended to study the use of visual information (i.e., images) in combination with text to predict emojis in the Instagram social network [3]. The interest in the emoji prediction task is probably evidenced by the large number of research teams that took part on the first Multilingual Emoji Prediction challenge organized in the SemEval 2018 evaluation forum⁵ [5], where 49 and 22 teams took part in the English and Spanish emoji prediction tasks, respectively.

A plethora of studies have been undertaken to understand several aspects of emoji such as the popularity of emoji and its relation with ambiguity [1, 11, 12], the syntactic function of emoji in messages [9], their computational semantic representation in modern continuous lexical spaces [6, 7, 13], and the relation between tone modifiers and user identity [10]. Since space does not allow to further elaborate, we point the reader to a recent systematic review on the area [2].

1.2 Papers Presented in the Special Issue

We received 18 submissions for the special issue. After multiple rounds of extensive reviewing, six articles were selected for publication. The article that opens the special issue, titled “[Emote-Controlled: Obtaining Implicit Viewer Feedback through Emote based Sentiment Analysis on Comments of Popular Twitch.tv Channels](#),” by Konstantin Kobs, Albin Zehe, Armin Bernstetter, Julian Chibane, Jan Pfister, Julian Tritscher, and Andreas Hotho, addresses the problem of sentiment analysis of commentaries posted on Twitch. The authors first show that the language used in Twitch strongly differs from the language used in other social networks, thus requiring special attention. A main characteristic of Twitch’s posts is the use of emotes, the little pictures that are used to express users’ feelings and opinions. The study assembles a large dataset of Twitch commentaries that was partially annotated into positive, negative, and neutral categories to undertake sentiment analysis. Sentiment classification is addressed using different methods: lexicon-based including an available lexicon, an emoji lexicon, and a newly designed emote lexicon and machine learning (CNN). The lexicon-based method is unsupervised and includes a decision rule while the CNN learns from “auto-annotated” data. The article discusses two case studies with respect to sentiment trajectories automatically computed over Twitch commentaries. The article shows that auto-computed sentiment correlates well with “key” temporal aspects of the events.

The next article, titled “[New Emoji Requests from Twitter Users: When, Where, Why, and What We Can Do About Them](#),” by Yunhe Feng, Zheng Lu, Wenjun Zhou, Zhibo Wang, and Qing Cao, presents the first study on identifying the new emoji requests posted on Twitter. The authors collect 30 million tweets that mention the word “emoji” and filter them using a comprehensive set of well-defined linguistic patterns to identify new emoji requests. They propose a time-continuity sensitive ranking strategy to locate the most desired emojis and develop a web-based interactive emoji tracking system, which enables the analysis of the most-requested emoji in real time. The article also presents an approach to automatically categorize the new emoji requests into eight emoji categories identified by the Unicode Consortium. By analyzing the time, geographic location, and the message context in which the new emoji request appear, they try to explain what caused the emoji to be requested by Twitter users. The real-time new emoji tracking system can be accessed at <https://call4emoji.org/>.

⁵<https://competitions.codalab.org/competitions/17344>.

The third article of the special issue, titled “[No More One Liners: Bringing Context into Emoji Recommendations](#),” by Joon-Gyum Kim, Taesik Gong, Bogoan Kim, JaeYeon Park, WooJeong Kim, Evey Huang, Kyungsik Han, Juho Kim, JeongGil Ko, and Sung-Ju Lee, proposes a machine learning approach for emoji recommendation in a conversational environment. The novelty of the approach lies on the exploitation of the conversational context (i.e., previous sentences) and on Long Short Term Memory Networks to produce better recommendations. The investigation is grounded on a user study that assessed the usefulness of context to predict emojis. As for the recommendation system, it is trained on Twitter conversations with pre-computed word and emoji embeddings. The recommender system produces several emoji that are clustered (using k -means clustering) and presented to the user in a dynamic interface. A user-centred evaluation shows that the use of context is more effective (i.e., quicker and more accurate) than baseline conditions when recommending emoji.

The article “[Gender and Age Influences on Interpretation of Emoji Functions](#),” by Susan C. Herring and Ashley R. Dainas, presents a survey-based approach to analyze the pragmatic functions of emoji and the effects of age and gender on emoji interpretation. Based on a Facebook public comments dataset consisting of 45 messages with emoji, the authors set up a web-based survey and record responses received from 519 individuals to understand the pragmatic functions of emoji in Facebook messages. The authors report that emoji are frequently used as tone modifiers along with text, which aligns with the previous research on emoji pragmatics. The article also identifies the significant differences in age and gender of the surveyed users, providing additional dimensions to explore in emoji understanding tasks such as emoji recommendation.

Emoji skin tone is a unique feature that allows a user to change the color of an emoji from a predefined set of colors. Emoji skin tones are especially popular among darker-skinned users to represent their online identities on social media [10]. The article “[Emoji Skin Tone Modifiers: Analyzing Variation in Usage on Social Media](#),” by Alexander Robertson, Walid Magdy, and Sharon Goldwater, is an attempt to study how emoji skin tones resemble the identities of minority user groups on Twitter. By analyzing Tweets with tone-modified emoji posted by people living in multiple geographical locations that are known for human diversity, they show that skin tones are mainly used in positive message contexts, suggesting skin tones are not used as a tool to promote negative thoughts among diverse user groups. The authors also explain why certain skin tones are not adopted by social media users highlighting the need to carefully consider user diversity when designing emoji and skin tones.

Now expanding beyond digital communication in social media, emojis are finding usage in surveys of user satisfaction, pictorial pain scales, and other formal and informal questionnaires that might otherwise use a numerical Likert scale. How do survey participants experience and interpret emojis in this context? The article “[Exploring and Understanding Participants’ Perceptions of Facial Emoji Likert Scales in Online Surveys: A Qualitative Study](#),” by Sarah Alismail and Hengwei Zhang, reports on interviews with 42 participants interacting with an emoji scale survey, investigating how participants interpreted the facial emoji, including the subjectivity of facial expressions and comparisons with a numerical Likert scale.

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