<u>List of Accepted Papers at Emoji2018 Workshop with Abstracts</u>

Paper #4 - “**Exploring Emoji Usage and Prediction Through a Temporal Variation Lens**”, Francesco Barbieri, Luis Marujo, William Brendel, Pradeep Karuturi and Horacio Saggion.
The frequent use of Emojis on social media platforms has created a new form of multimodal social interaction. Developing methods for the study and representation of emoji semantics helps to improve future multimodal communication systems. In this paper we explore the usage and semantics of emojis over time. We compare emoji embeddings trained on a corpus of different seasons and show that some emojis are used differently depending on the time of the year. Moreover, we propose a method to take into account the time information for emoji prediction systems, outperforming state-of-the-art systems. We show that, using the time information, the accuracy of some emojis can be significantly improved.

Paper #6 - “**Multi-task Emoji Learning**”, Francesco Barbieri, Luis Marujo, Pradeep Karuturi and William Brendel.
Emojis are very common in social media and understanding their underlying semantics is of great interest from a Natural Language Processing point of view. In this work, we investigate emoji prediction in short text messages using a multi-task pipeline that simultaneously predicts emojis, their categories and sub-categories. The categories are either manually predefined in the unicode standard or automatically obtained by clustering over word embeddings. We show that using this categorical information adds meaningful information, thus improving the performance of emoji prediction task. We systematically analyze the performance of the emoji prediction task by varying the number of training samples. We also do a qualitative analysis by using attention weights from the prediction task.

Paper #7 - “**I Stand With You: Using Emojis to Study Solidarity in Crisis Events**”, Sashank Santhanam, Vidhushini Srinivasan, Shaina Glass and Samira Shaikh.
We study how emojis are used to express solidarity in social media in the context of two major crisis events - a natural disaster, Hurricane Irma in 2017 and terrorist attacks that occurred in November 2015 in Paris. Using annotated corpora, we first train a recurrent neural network model to classify expressions of solidarity in text. Next, we use these expressions of solidarity to characterize human behavior in online social networks, through the temporal and geospatial diffusion of emojis as the crisis events unfold.

Paper #8 - “**Methodology to detect and improve emoji lexica with low quality manual annotations**”, Milagros Fernández-Gavilanes, Jonathan Juncal-Martínez, Silvia García-Méndez, Enrique Costa-Montenegro and Francisco Javier González-Castaño.

Sentiment analysis aims at detecting sentiment polarities in unstructured Internet information. However, only recently a relevant part of this information, emojis, has been considered. Their use in Twitter has grown considerably in recent years. Every time a new version of Unicode is released, finding out the sentiment users express by a new emoji is challenging. In [KNSSM15], the authors created an Emoji Sentiment Ranking lexicon from manual annotations of messages containing emojis. The quality of these annotations affects directly the quality of the generated emoji sentiment lexicon (high quality corresponds to high self-agreement and inter-agreement). In addition, in many cases, these measures are not provided by the creators of the datasets, so it is necessary to use another strategy to detect this problem. Therefore, we propose an automatic approach to identify and manage low-quality annotations. We compare emoji sentiment lexica resulting from two variants of a new approach and with lexica created from manually annotated datasets with poor and high qualities.

Paper #12 - “**Learning Emoji Embeddings using Emoji Co-occurrence Network Graph**”, Anurag Illendula and Manish Yedulla.
Usage of emoji in social media platforms has seen a rapid increase over the last few years. Majority of the social media posts are laden with emoji and users often use more than one emoji in a single social media post to express their emotions and to emphasize certain words in a message. Utilizing the emoji co-occurrence can be helpful to understand how emoji are used in social media posts and their meanings in the context of social media posts.In this paper, we investigate whether emoji co-occurrences can be used as a feature to learn emoji embeddings which can be used in many downstream applications such sentiment analysis and emotion identification in social media text. We retrieve 147 million tweets which have emojis in them and build an emoji co-occurrence network. Then we learn a network embedding model to embed emojis into a low dimensional vector space. We evaluate our embeddings using sentiment analysis and emoji similarity experiments, and experimental results show that our embeddings outperform the current state-of-the-art results for sentiment analysis tasks.

Paper #13 - “**Emoji Grammar as Beat Gestures**”, Gretchen Mcculloch and Lauren Gawne.
Emoji are popularly characterized as a "language", but languages have grammar. What does an emoji grammar look like? Drawing from sequences of the most common two, three, and four emoji in a large corpus of real emoji use, we find that top emoji sequences have a high level of repetition (~50%), whereas the equivalent top sequences of words from a large corpus have zero repetition. We argue that emoji are best analogized to "beat" gestures, a well-established type of co-speech gesture characterized by its high level of repetition.

Paper #16 - “**Distant Supervision for Emotion Classification Task using emoji2emotion**”, Aisulu Rakhmetullina, Dietrich Trautmann and Georg Groh.
Increasing number of research in the area of distant supervision for emotion detection task requires a reliable mapping between noisy labels and emotion classes. We propose a method

for an experimental creation of such a reliable mapping based on manually annotated data and quantitative relations between labels and classes. As an example, we apply the method on emoji-emotion pair in a form of emoji2emotion mapping.

Paper #18 - "**Receiver Interpretations of Emoji Functions: A Gender Perspective**", Susan C Herring and Ashley R Dainas.
Previous studies have reported gender differences in emoji use and attitudes toward emoji. Here we ask whether, and if so, to what extent, females and males also interpret emoji use differently. We conducted an online survey to assess how different genders interpret the pragmatic functions of emoji in their local discourse contexts, based on [Aut17's] taxonomy of functions. Responses (N=523; 352 females, 121 males, 50 'other') showed few overall differences in how females and males interpreted emoji functions, but the 'other' gender differed from the females and males. Based on responses to demographic and social media use questions, these differences appear related to platform norms (specifically, Facebook vs. Tumblr). We conclude by discussing the implications of these findings for automating emoji interpretation.