SocialNLP EmotionGIF 2020 Challenge Overview: Predicting Reaction GIF Categories on Social Media

Boaz Shmueli\textsuperscript{1,2,3,*}, Lun-Wei Ku\textsuperscript{2} and Soumya Ray\textsuperscript{3}
\textsuperscript{1}Social Networks and Human-Centered Computing, Taiwan International Graduate Program
\textsuperscript{2}Institute of Information Science, Academia Sinica
\textsuperscript{3}Institute of Service Science, National Tsing Hua University

Abstract

We present an overview of the EmotionGIF 2020 Challenge, held at the 8th International Workshop on Natural Language Processing for Social Media (SocialNLP), in conjunction with ACL 2020. The challenge required predicting affective reactions to online texts, and includes the EmotionGIF dataset, with tweets labeled for the reaction categories. The novel dataset included 40K tweets with their reaction GIFs. Due to the special circumstances of year 2020, two rounds of the competition were conducted. A total of 84 teams registered for the task. Of these, 25 teams successfully submitted entries to the evaluation phase in the first round, while 13 teams participated successfully in the second round. Of the top participants, five teams presented a technical report and shared their code. The top score of the winning team using the Recall@K metric was 62.47%.

1 Introduction

Emotions, moods, and other affective states are an essential part of the human experience. The detection of affective states in texts is an increasingly important area of research in NLP, with important applications in dialogue systems, psychology, marketing, and other fields (Yadollahi et al., 2017). Recent approaches have taken advantage of progress in machine learning, and specifically deep neural networks (LeCun et al., 2015), for building models that classify sentiments and emotions in text. Training these models often requires large amounts of high-quality labeled data.

Two main approaches have been used for collection and labeling emotion data: manual annotation and distance supervision. With manual annotation, humans are presented with a text, and are requested to annotate the text. When using this approach, several emotional models can be used for labeling. The two most common models are the discrete emotional model (Ekman and Friesen, 1971), where the user needs to select among a few categorical emotions (e.g., disgust, joy, fear), and the dimensional emotion model (Mehrabian, 1996), which uses three numerical dimensions (valence, arousal, dominance) to represent all emotions.

With the help of crowd-sourcing platforms such as Amazon Mechanical Turk (Buhrmester et al., 2016), human annotation can be quickly scaled up to produce large datasets. However, to achieve large, high-quality datasets, the cost incurred is usually high. In addition, misinterpretations of text due to cultural differences or contextual gaps are common, resulting in unreliable, low-quality labels. It should be noted that the annotators detect the perceived emotions, i.e., the emotions that are recognized in the text.

\*Corresponding author: shmueli@iis.sinica.edu.tw
Another method for data collection is distant supervision, often using emojis or hashtags (e.g., Go et al. (2009), Mohammad and Kiritchenko (2015)). This method provides high-volume, automatic collection of data, albeit with some limitations such as noisy labels (hashtags might not be related to the emotions conveyed in the text). It should be noted that the data collected in this case corresponds to the intended emotions by the text’s author. Distant supervision can also be used to label reactions to text. For example Pool and Nissim (2016) use the Facebook feature that allows users to respond with one of six emojis (Like, Love, Haha, Wow, Sad and Angry) to collect posts and their readers’ reactions. These reactions are a proxy to the readers’ induced emotions – the emotions they felt when reading the text. This method is limited by the narrow emotional range of labeling.

To improve research on fine-grained emotional reaction and open up new research possibilities, we conducted the ReactionGIF 2020 shared task. The challenge offered a new dataset of 40K tweets with their fine-grained reaction category (or categories). The task challenge was to predict each tweet’s reactions in an unlabeled evaluation dataset. In the following sections, we describe and discuss the dataset, the competition, and the results.

2 EmotionGIF Dataset

Twitter is a popular micro-blogging site, where users create short text posts known as tweets. In most languages, including English, tweets are limited to 280 characters (the limit is 140 characters in Japanese, Chinese, and Korean). As part of the post, users can also mention other users (@user), and use hashtags (#hashtag). Additionally, posts can include images videos, or animated GIFs. Animated GIFs are short animations that are commonly used on the internet. One of the most popular uses of animated GIFs is as reactions in online conversations, such as social media interactions. These GIFs, known as reaction GIFs, are able to convey emotions in an expressive and accurate way (Bakhshi et al., 2016), and have become very popular in online conversations. Figure 1 shows a typical interaction on Twitter: User_1 posted a tweet (“I just won first place!”), and User_2 replied with a tweet that includes an “applause”-category reaction GIF, and some text (“Congratulations dear!”).

| GIF Category | Description | Example |
|--------------|-------------|---------|
| happy_dance  | Happy dance | 😃 |
| hearts       | Hearts     | ❤️    |
| slow_clap    | Slow clap  | 🙌    |
| oops         | Oops       | 🙄    |
| thank_you    | Thank you  | 😊    |
| thumbs_down  | Thumbs down| 👏    |
| thumbs_up    | Thumbs up  | 👏    |
| want         | Want       | 🙏    |
| win          | Win        | 🎉    |
| wink         | Wink       | 😌    |
| yawn         | Yawn       | 😦    |
| omg          | OMG        | 😱    |
| smh          | SMH        | 😞    |
| you_got_this | You got this| 🤦    |

Table 1: GIF categories

For the challenge, we collected similar 2-turn interactions. Each sample in the dataset contains the text of the original tweet, the text of the reply tweet, and the video file of the reaction GIF. The label for each tweet is the reaction category (or categories) of the GIF. Because some replies only contain a reaction GIF, the reply text is optionally empty. We use a list of 43 reaction categories, pre-defined by the Twitter platform, and used when a user needs to insert a GIF into a tweet (see Figure 2). The list is shown in Table 1, and covers a wide range of emotions, including love, empathy, disgust, anger, happiness, disappointment, approval, regret, etc. There is an overlap between the reaction categories in terms of the GIFs they contain and thus some GIFs can belong to more than one category. Consequently, the label may contain more than one reaction category. For example, GIFs that are categorized with “shocked” might also be categorized in “omg”. Table 2 shows a few samples from the training dataset. Note that replies can be optionally empty. The GIF MP4 files are included in the

1i don’t know
2you only leave once
3shake my head
4oh my god
We collected the EmotionGIF dataset during April 2020, and it includes 40,000 English-language tweets and their GIF reactions. The dataset is divided 80%/10%/10% into training (32,000 samples), development (4,000 samples), and evaluation (4,000 samples) datasets.

Categories per sample Figure 3 shows the distribution of the number of categories per sample. The majority of samples (73.1%) in the training dataset are labeled with a single category. An additional 17.7% of samples have two labels, and 5.1% have three categories. The remaining samples are labeled with 3 to 6 labels.

Category Distribution Figure 4 shows the category distribution. The categories suffer from uneven distribution; a few of the categories (“applause”, “hug”, “agree”, “yes”, “no”) label between 5% to 10% of the samples, while most of them label 2% or less of the samples.

Category Co-occurrence The categories are semantically overlapping, and thus some category pairs co-occur more often than others. Figure 5 shows the co-occurrence heat map. For example, GIFs that are labelled with “facepalm” tend to also be labeled with “seriously”, “sigh”, and “smh” (Shake My Head), as these four categories are all expressions related to disappointment. “shocked” and “omg” (Oh My God) co-occur frequently, both indicating surprise, etc.

3 Shared Task
Due to year 2020’s extraordinary circumstances, the competition had two rounds: Round One and Round Two. A shared task website was set up, which included general information, dates, file format, frequently-asked questions, registration form, etc. In addition, two competition websites (Round One, Round Two) were set up on the Codalab platform, where participants could download the datasets and upload their submissions.

For the shared task, we provided the training dataset (32K each) with labels, and two datasets (development and evaluation, 4K samples each), without labels. Additionally, the development and evaluation datasets did not contain the video files. The task was to predict six labels for every sample, with the metric being Mean Recall at 6, or $MR@6$.

To compute $MR@6$, we first define the per-sample recall at 6 for sample $i$, $R@6_i$, which is the ratio:

$$R@6_i = \frac{|G_i \cap P_i|}{|G_i|}$$

where $G_i$ is the set of true (“gold”) reaction categories for sample $i$, and $P_i$ is the set of six predicted reaction categories for sample $i$. $R@6_i$ is the fraction of reaction categories correctly predicted for sample $i$. Because each sample is labeled with a maximum of six categories, $R@6$ is always a value between 0 and 1. We then average over all samples to arrive at $MR@6$:

$$R = MR@6 = \frac{1}{N} \sum_{i=1}^{N} R@6_i$$

We also calculated $R_1$ and $R_2$, which are the Recall at 6 values for the samples with a non-empty reply (i.e., the reply tweet included both a GIF and text), and with an empty reply (the reply tweet only include a GIF).

Each round of the competition had two phases: practice, and evaluation. During the practice phase, participants uploaded predictions for the development dataset and were able to instantly check the performance. In the evaluation phase, which determined the competition winners, participants uploaded predictions for the evaluation datasets. Results were hidden until the end of the Round to prevent overfitting to the data.

4 Submissions
A total of 84 people registered for the shared task. 25 teams successfully submitted entries to the evaluation phase in Round One, while 13 teams participated successfully in Round Two. Of the top

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5https://sites.google.com/view/emotiongif-2020/

6https://competitions.codalab.org/
Original tweet | Reply tweet | Reaction GIF | Reaction Categories
---|---|---|---
Why don’t you interact with me? | d74d...a34e.mp4 | oops |
someone give me a hug (from 2 metres away) | 2be1...5fc0.mp4 | want, hug |
So disappointed in the DaBaby | bb2d...cfcf.mp4 | smh |
Bonus stream tonight anyone? | e91e...49af.mp4 | win, ok, thumbs_up |
Camila Cabello and You | a9fc....b139a.mp4 | shrug, oops, idk |

Table 2: Dataset samples
participants, five teams presented a technical report and shared their code, as was required by the competition rules.

We provided a simple majority baseline that predicts the 6 most common labels for all samples (applause, hug, agree, yes, no, seriously). $MR@6$ for the majority baseline is 40.0%.

The highlights of these submissions are summarized below. More details are available in the relevant reports.

**Team Mojitok (Jeong et al., 2020)** This top submission used a combination of methods to attack the challenging aspects of the tasks. Four models were used: three transformer-based models, RoBERTa (Liu et al., 2019), DialoGPT (Zhang et al., 2019) and XLNet (Yang et al., 2019). The fourth was a RoBERTa model in combination with a label embedding using CGN (Chen et al., 2019) that captures category dependency was also employed. This model were fine-tuned, using the “large” variant of the pretrained models. 5-fold cross validation was used within each model to produce a total of 20 estimators. Soft-voting ensembles of these estimators were tested in various combinations. In addition, mixconnect (Lee et al., 2019) was used for regularization in some of the models. Reduction of the multi-label problem Pick-All-Labels Normalised (PAL-N) (Menon et al., 2019) multi-class formulation was found to optimize the $R@6$ metric.

**Team Whisky (Phen et al., 2020)** RoBERTa and BERT models were evaluated using different hyperparameters, and with different handling of emojis. The superiority of large RoBERTa model with long sequences was demonstrated.

**Team Yankee (Wang et al., 2020)** Elaborate preprocessing was used to increase token coverage. RoBERTa and two BERT models (case and uncased) were fine-tuned and then ensembled using power-weighted sum. The pretrained models are of the “base” variant. Binary cross entropy followed a sigmoid activation layer for prediction.

**Team Crius (Bi et al., 2020)** This method obtained features by fine-tuned pairwise and pointwise BERT, along with statistical semantic features and similarity-related features. These were concatenated and fed into a LightGBM classifier (Ke et al., 2017).

**Team IITP (Ghosh et al., 2020)** Preprocessing included removal of Twitter mentions and replacing emoticons with words. An ensemble of 5 models was used. The first model used two 2D CNN with attention networks, one for the original tweet and one of the reply tweet, using pre-trained GloVe embeddings. The outputs of the two CNN networks were concatenated and fed into a fully-connected layer followed by sigmoid activation layer and binary cross-entropy. Dropout layers were used at various stages for regularization. Four additional models with similar top architecture were trained using two instances each of 1D CNN+BiLSTM, Stacked BiGRU, BiLSTM, BiGRU. The outputs from these five models were majority-voted to produce the predictions.

### 5 Evaluation & Discussion

A summary of the submissions and their challenge scores is available in Table 3. Presented are the teams that submitted detailed technical reports and their code for verification. A full leaderboard that includes all the teams is available on the shared task website. This section highlights some observations related to the challenge.

**Unbalanced Labels.** Emotion detection in text often suffers from a data imbalance problem. Similarly our dataset (which supervised reactions, not emotions) has a similar phenomenon. This would be emphasized if we used a metric that is sensitive to class imbalances (e.g., Macro-F1). Our metric is less sensitive to these kind of problem. None of the teams decided to take any measures in that regard.

### Table 3: Recall at 6 scores for EmotionGIF

| Rank | Team     | Approach                                                                 | $R$ | $R_1$ | $R_2$ |
|------|----------|--------------------------------------------------------------------------|-----|-------|-------|
| 1    | Mojitok  | Ensemble of transformers (large), label embedding, mixconnect, PAL-N    | 62.47| 61.35 | 63.21 |
| 2    | Whisky   | RoBERTa                                                                  | 57.31| 55.22 | 58.70 |
| 3    | Yankee   | Preprocessing, ensemble of transformers (base)                           | 56.62| 52.82 | 59.15 |
| 4    | Crius    | Statistical features, similarity features, BERT, LightGBM                | 53.94| 50.05 | 56.54 |
| 5    | IITP     | Ensemble of RNNs (CNN, BiLSTM, GRU)                                      | 53.80| 50.06 | 56.29 |
Label dependency Multi-label datasets (Tsoumakas and Katakis, 2007), (Zhang and Zhou, 2013) introduce challenging classifications tasks. As we can see from Figure 5, in our dataset the categories are highly dependent. (Jeong et al., 2020) used a new approach to represent this correlation. Classification of multilabel datasets is a developing area that requires further research.

Models All of the submissions used deep learning models. Four of the models were transformer-based architectures, with most using pre-trained transformers (BERT or its variants). Some of the submissions enhanced these model in various ways, e.g. using k-fold CV ensembles (Jeong et al., 2020). The use of “large” vs “base” models explained some of the performance differential.

6 Conclusion
We summarized the results of the EmotionGIF 2020 challenge, which was part of the SocialNLP Workshop at ACL 2020. The challenge presented a new task that entailed the prediction of affective reactions to text, using the categories of reaction GIFs as proxies to affective states. The data included tweets and their GIF reactions. We provided brief summaries of each of the eligible participants’ entries. Most submissions used transformer-based architectures (BERT, RoBERTa, XL-Net) etc, reflecting their increasing use in NLP classification tasks, due to their superior performance but also the availability of easy-to-use programming libraries. The top system employed the use of various methods, including ensemble, regularization, and GCN to to achieve the top score.

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