

UBC-NLP at IEST 2018: Learning Implicit Emotion With an Ensemble of Language Models

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Abstract

We describe UBC-NLP contribution to IEST-2018, focused at learning implicit emotion in Twitter data. Among the 30 participating teams, our system ranked the 4th (with 69.3% *F*-score). Post competition, we were able to score slightly higher than the 3rd ranking system (reaching 70.7%). Our system is trained on top of a pre-trained language model (LM), fine-tuned on the data provided by the task organizers. Our best results are acquired by an average of an ensemble of language models. We also offer an analysis of system performance and the impact of training data size on the task. For example, we show that training our best model for only one epoch with < 40% of the data enables better performance than the baseline reported by [Klinger et al. \(2018\)](#) for the task.

1 Introduction

Emotion is essential in human experience and communication, lending special significance to natural language processing systems aimed at learning it. Emotion detection systems can be applied in a host of domains, including health and well-being, user profiling, education, and marketing. There is a small, yet growing, body of NLP literature on emotion. Early works focused on creating and manually labeling datasets. The SemEval 2007 Affective Text task [Strapparava and Mihalcea \(2007\)](#) and [Aman and Szpakowicz \(2007\)](#) are two examples that target the news and blog domains respectively. In these works, data were labeled for the 6 basic emotions of Ekman ([Ekman, 1972](#)). More recent works exploit *distastant supervision* ([Mintz et al., 2009](#)) to automatically acquire emotion data for training systems. More specifically, a number of works use hashtags like *#happy* and *#sad*, especially occurring finally in Twitter data, as a proxy of emotion [Wang](#)

[et al. \(2012\)](#); [Mohammad and Kiritchenko \(2015\)](#); [Volkova and Bachrach \(2016\)](#). [Abdul-Mageed and Ungar \(2017\)](#) report state-of-the-art results using a large dataset acquired with hashtags. Other works exploit emojis to capture emotion carrying data ([Felbo et al., 2017](#)). [Alhuzali et al. \(2018\)](#) introduce a third effective approach that leverages first-person seed phrases like “*I’m happy that*” to collect emotion data.

[Klinger et al. \(2018\)](#) propose yet a fourth method for collecting emotion data that depends on the existence of the expression “emotion-word + one of the following words (when, that or because)” in a tweet, regardless of the position of the emotion word. The “Implicit Emotion” shared task¹ participants were provided data representing the 6 emotions in the set (anger, disgust, fear, joy, sad, surprise). The trigger word was removed from each tweet. To illustrate, the task is to predict the emotion in a tweet like “Boys who like Starbucks make me [*#TRIGGERWORD#*] because we can go on cute coffee dates” (with the triggered word labeled as *joy*). In this paper, we describe our system submitted as part of the competition. Overall, our submission ranked the 4th out of the 30 participating teams. With further experiments, we were able to acquire better results, which would rank our model at top 3 (70.7% *F*-score).

The rest of the paper is organized as follows: Section 2 describes the data. Section 3 offers a description of the methods employed in our work. Section 3 is where we present our results, and we perform an analysis of these results in Section 5. We list negative experiments in Section 6 and conclude in Section 7.

¹<http://implicitemotions.wassa2018.com>

2 Data

We use the Twitter dataset released by the organizers of the “Implicit Emotion” task, as described in the previous section. The data are partitioned into 153,383 tweets for training, 9591 tweets for validation, and 28,757 data points for testing. The training and validation sets were provided early for system development, while the test set was released one week before the deadline of system submission. The full details of the dataset can be found in [Klinger et al. \(2018\)](#). We now describe our methods.

3 Methods

3.1 Pre-processing

We adopt a simple pre-processing scheme, similar to most of the pre-trained models we employ. This involves lowercasing all text and filter out punctuation, urls, and user mentions. We also split clusters of emojis into individual emojis, following [Duppada et al., 2018](#). For our vocabulary V , we retain the top $100k$ words and then remove all words occurring < 2 times, which leaves $V = 23,656$.

3.2 Models

We develop a host of models based on deep neural networks, using some of these models as our baseline models. In addition, as an additional baseline, we compare to [Klinger et al. \(2018\)](#) who propose a model based on Logistic Regression with a bag of word unigrams (BOW). All our deep learning models are based on variations of recurrent neural networks (RNNs), which have proved useful for several NLP tasks. RNNs are able to capture sequential dependencies in especially time series data, of which language can be seen as an example. One weakness of RNNs, however, lies in gradient either vanishing or exploding during training. Long-short term memory (LSTM) networks were developed to target this problem, and hence we employ these in our work. We also use a bidirectional version (BiLSTM) where the vector of representation is built as a concatenation of two vectors, one that runs from left-to-right and another running from right-to-left. Our systems can be categorized as follows: (1) Systems tuning simple pre-trained embeddings, (2) Systems tuning embeddings from language models, and (3) Systems directly tuning language models. We treat #1

and #2 as baseline systems, while our best models are based on #3.

3.2.1 Systems With Simple Embeddings

Character and/or Word embeddings ([Mikolov et al., 2013](#); [Pennington et al., 2014](#); [Bojanowski et al., 2016](#)) have boosted performance on a host of NLP tasks. Most state of the art systems now fine-tune these embeddings as a simple transfer learning technique targeting the first layer of a network ([McCann et al., 2017](#)). We make use of one such pre-trained embeddings (fastText) to identify the utility of tuning its learned weights on the task.

FastText: The first embedding model is fastText² ([Bojanowski et al., 2016](#)), which builds representations based on characters, rather than only words, thus alleviating issues of complex morphology characteristic of many languages like Arabic, Hebrew, and Swedish, but also enhancing representations for languages of simpler morphology like English. Additionally, fastText partially solves issues with out-of-vocabulary words since it exploits character sequences. FastText is trained on the Common Crawl dataset, consisting of 600B tokens.

For this and the next set of experiments (i.e., experiments in 3.2.2), we train both an LSTM and BiLSTM. Since we treat these as baseline systems, especially with our goal to report our experiments in available space for the competition³, we try a small set of hyper-parameters, identifying best settings on our validation set. We train each network for 4 epochs each. For optimization, we use *Adam* ([Kingma and Ba, 2014](#)). The model’s weights W are initialized from a normal distribution $W \sim N$ with a small standard deviation of $\sigma = 0.05$. We apply two sources of regularization: *dropout* : we apply a dropout rate of 0.5 on the input embeddings to prevent co-adaptation of hidden units’ activation and *L2 - norm* : we also apply an L2-norm regularization with a small value (0.0001) on the hidden units layer to prevent the network from over-fitting on training set. Each of the networks has a single hidden layer. Network architectures and hyper-parameters are listed in Table 1.

²<https://fasttext.cc/docs/en/english-vectors.html>

³Authors were encouraged to keep page limit to a maximum of 5 pages, with 4 pages preferred.

Hyper-Parameter	Value
Embed-dim-fastText	300
Embed-dim-ELMo	1024
layers	1
units	300
batch size	32
epochs	4
dropout	0.5

Table 1: Network architecture and hyper-parameters for experiments with simple pre-trained embeddings with fastText 3.2.1 and ELMo 3.2.2 across our LSTM and BiLSTM networks.

3.2.2 Embedding From LMs

Peters et al. (2018) build embeddings directly from language models, which they refer to as ELMo. ELMo is shown to capture both complex characteristics of words (as syntax and semantics) as well as the usage of these words across various linguistic contexts, thanks to its language modeling component. ELMo is trained on a dataset of Wikipedia and is publicly available⁴. We train with ELMo-acquired weights in our input layer using the same network architectures and hyper-parameters employed with fastText as we explain before.

3.2.3 Fine-Tuning LMs: ULMFiT

Another recent improvement in training NLP systems is related to the way these systems are fine-tuned, especially vis-a-vis how different layers in the network operate during training time. Howard and Ruder (2018) present ULMFiT⁵, an example such systems that is pre-trained on a language model exploiting Wikitext-103. Ultimately, ULMFiT employs a number of techniques for training. These include “gradual unfreezing”, which aims at fine-tuning each layer of the network independently and then fine-tuning all layers together. Gradual unfreezing proves useful for reducing the risk of overfitting as also found in Felbo et al. (2017). ULMFiT also uses “discriminative fine-tuning”, which tunes each layer with different learning rates, the idea being different layers capture different types of information (Howard and Ruder, 2018; Peters et al., 2018). Howard and Ruder (2018) also use different learning rates, which they refer to as “slanted triangular learning rates”, at different times of the training process.

⁴<https://github.com/allenai/bilm-tf>

⁵<http://nlp.fast.ai/category/classification.html>.

With ULMFiT, we experiment with different variations of LMs: forward (**Fwd**), backward (**Bwd**), and an average of these (**BiLM (Fwd+Bwd)**). We follow Howard and Ruder (2018) in training each of the Fwd and Bwd models independently, and then combining their predictions using an ensemble averaging. This is the setting we refer to as BiLM. As we show in Section 3, this is a beneficial measure (similar to what Howard and Ruder (2018) also found). For our hyper-parameters for this iteration of experiments, we identify them on our validation set. We list the network architectures and hyper-parameters for this set of experiments in Table 2.

Hyper-Parameter	Value
dim-size	400
vocab	23,656
batches	64
layers	3
units	1,150
epochs	19

Table 2: Hyper-parameters for our submitted system exploiting fine-tuned language models from Howard and Ruder (2018).

4 Results

Table 3 shows results of all our models in F -score. As the Table shows, all our models achieve sizeable gains over the logistic regression model introduced by (Klinger et al., 2018) as a baseline for the competition (F -score = 60%). Even though our models trained based on fastText and ELMo each has a single hidden layer, which is not that deep, these at least 1.5% higher than the logistic regression model. We also observe that ELMo embeddings, which are acquired from language models rather than optimized from sequences of tokens, achieves higher performance than FastText embeddings. This is not surprising, and aligns with the results reported by Peters et al. (2018).

For results with ULMFiT, as Table 3 shows, it acquires gains over all the other models. As mentioned earlier, we experiment with different variations of LMs (Fwd, Bwd, and BiLM). Results in our submitted system are based on the Fwd model, and are at 69.4%. After system submission, we also experimented with the Bwd and BiLM models and were able to acquire even higher gains, putting our best performance at 70.7% (which moves us to the top 3 position).

System	Dev	Test
<i>Baseline (Klinger et al., 2018)</i>		
BOW Log-Reg	0.601	0.601
<i>Embeddings</i>		
<i>FastText (Bojanowski et al., 2016)</i>		
LSTM	0.629	0.629
Bi-LSTM	0.628	0.626
<i>Embed. from LM (ELMo) (Peters et al., 2018)</i>		
LSTM	0.635	0.635
Bi-LSTM	0.615	0.614
<i>Fine-Tuned LM (Howard and Ruder, 2018)</i>		
Fwd LM (submitted system)	0.694	0.693
Bwd LM	0.686	0.693
BiLM	0.707	0.707

Table 3: Results: BiLM refers to an ensemble of both the Fwd and Bwd LMs.

5 Analysis

5.1 Error Analysis

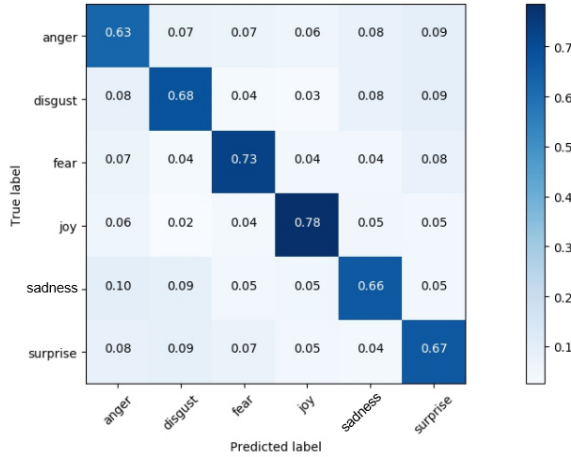


Figure 1: Confusion matrix of errors in F -score across the different emotion classes.

Using predictions from our best model (as described in Table 2), we investigate the extent with which each emotion is mislabeled and the categories with which it is confused. Figure 1 shows the confusion matrix of this analysis. As the Figure shows, *anger* is predicted with least F -score ($\% = 63$), followed by *sadness* ($\% = 66$). Figure 1 also shows that *anger* is most confused for *surprise* and *sadness* is most confused for *anger*. Additionally, *disgust* is the third most confused category ($\% = 66$), and is mislabeled as *surprise* 9% of the time. These results suggest overlap in

the ways each of the emotions is expressed in the training data.

To further investigate these observations, we measure the shared vocabulary between the different classes. Figure 2 shows percentages of lexical overlap in the data, and does confirm that some categories share unigram tokens to varying degrees. Lexical overlap between classes seem to align with the error matrix in Figure 1. For example, *anger* overlaps most with *surprise* ($\% = 9$) and *sadness* overlaps most with *anger* ($\% = 10$). These findings are not surprising, since our models are based on lexical input and do not involve other types of information (e.g., POS tags). Table 5.1 offers examples of overlap in the form of lexical sequences between test data and training data across a number of classes.

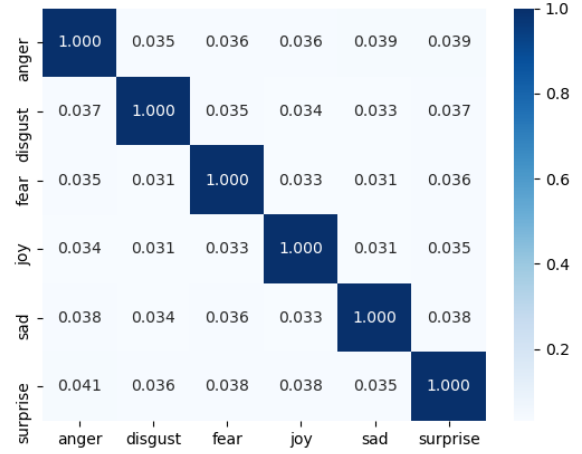


Figure 2: Heat Map for percentages of shared vocabulary between emotion classes.

5.2 Size of Training Data

We also investigate the impact of training data size on model accuracy. For this purpose, we train models with different data sizes with the best parameter settings shown in table 2⁶. Figure 3 shows the impact of different percentages of training examples on model performance. We test model performance for this analysis on our validation data.

⁶Due to the high computational cost of training these models, we only train each model with one epoch for this analysis.

Test Example	True	Predicted	Train Example	True
I'm [#TRIGGERWORD#] that like none of my friends at school have seen national lamoon's day	disgust	sad	[#TRIGGERWORD#] that like none of my videos from last night ..	sad
hey luke! I'm so [#TRIGGERWORD#] because you don't follow me, not lies, but please follow me	anger	sad	i'm so [#TRIGGERWORD#] because you don't follow me	sad

Table 4: Examples overlapping lexical sequences in test and training data.

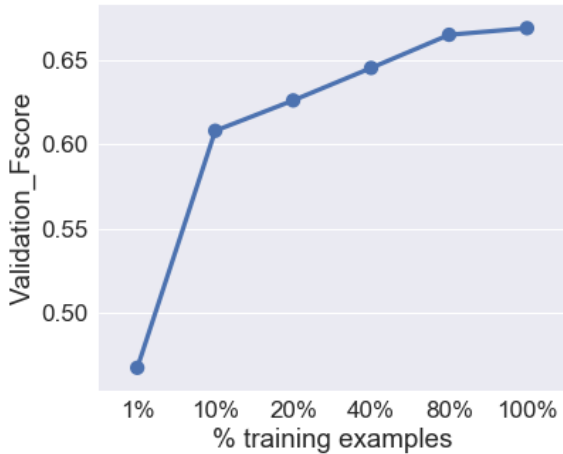


Figure 3: Impact of training data size on model performance, tested on our validation data. Results in F -score.

Interestingly, as figure 3 shows, the model exceeds the baseline model reported by the task organizers (Klinger et al., 2018) when trained on only 10% of the training data. Additionally, the model outperforms the fastText and ELMo models by only seeing 40% of the training data. Once the model has access to 80% of the training data, its gains start to increase relatively slowly.

6 Negative Experiments

We performed a number of negative experiments that we report briefly here. Our intuition is that training our models with Twitter-specific data should help classification. For this reason, we trained ULMFiT with 4.5 million tweets with the same settings reported in table 2. We did not find this set of experiments to yield gains over the results reported in Table 3, however. For example, an Fwd LM trained on Twitter domain data yields 67.9% F -score, which is 1.4% less than the F -

score obtained by the Wikipedia-trained Fwd LM in 3. The loss might be due to the smaller size of the Twitter data we train on, as compared to the Wikipedia data the ULMFiT is originally trained on (i.e., > 103 million tokens).

7 Conclusion

In this paper, we described our system submitted to IEST-2018 task, focused on learning implicit emotion from Twitter data. We explored the utility of tuning different word- and character-level pre-trained representations and language modeling methods to minimize training loss. We found that the method introduced by Howard and Ruder (2018) yields best performance on the task. We note that our baselines employing sub-word embeddings (fastText) and embeddings from language models (ELMo) can be improved by using deeper neural architectures with larger model capacity, which we cast for future work. We have also shown that the classifier confuses certain emotion classes with one another, possible due to overlap of lexical sequences between training and test data. This reflects the difficulty of the task.

8 Acknowledgement

We acknowledge the support of the Natural Sciences and Engineering Research Council of Canada (NSERC). This research was also supported by the Social Sciences and Humanities Research Council of Canada (SSHRC). The research was enabled in part by support provided by West-Grid (<https://www.westgrid.ca/>) and Compute Canada (www.computecanada.ca).

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