Multi-Label Emotion Classification

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I. ABSTRACT

Emotion Recognition is an important area of research to enable effective human-computer interaction. Human emotions can be detected using speech signal, facial expressions, body language, and electroencephalography(EEG). It is an important task in Natural Language processing, because of it's high impact in real world applications, ranging from health and well being to author profiling, consumer analysis and security. The works done so far in this field, focuses majorly on classifying emotions independently, without considering that emotions can co-exist. We present a model for multi-label emotion classification that uses span-prediction to help Emotion Recognition models learn relationships between labels and words in a sentence. Later, we present a loss function for modelling multiple co-existing emotions in an input sentence.

II. INTRODUCTION

Emotion recognition (ER) is an important task in Natural Language Processing (NLP), due to its high impact in real-world applications from health and well-being to author profiling, consumer analysis and security. Standard approaches in emotion classification treat individual emotion independently. However, emotions are not independent; a specific emotive expression can be associated with multiple emotions. The existence of association/correlation among emotions has been well-studied in psychological theories of emotions, such as Plutchik's wheels of emotion (Plutchik, 1984 [1]) that introduces the notion of mixed and contrastive emotions. For example, "joy" is close to "love" and "optimism", instead of "anger" and "sadness". The model we have implemented is summarised as follows:
I. The framework is casting the task of multi-label emotion classification as a span-prediction problem. We trained the model to take into consideration both the input sentence and a label set (i.e., emotion classes) for selecting a span of emotion classes in the label set as the output. The objective of the model is to predict emotion classes directly from the label set and capture associations corresponding to each emotion.
II. We make use of the label-correlation aware loss (LCA) (Yeh et al.,2017 [2]), originally introduced by Zhang and Zhou (2006)[3]. The objective of this loss function is to maximise the distance between positive and negative labels, which is learned directly from the multilabel emotion data set. Thus, a loss function is modelling multiple co-existing emotions for each input sentence.

III. DATASET DETAILS

We are using the SemEval-2018 Affect in Tweets (AIT) Dataset [4]. AIT was partitioned into training, development, and test sets for machine learning experiments. This dataset has data in 3 languages English, Spanish and Arabic. We will be performing only on English Language.

A. Fields of Data

There are a total of 13 fields in the dataset, out of which 11 are the classes and the other two are **ID** and **Tweets**. Number of the tweets in each emotion classes is mentioned in the Table:I.

Class name	Number of tweets
Anger	2544
Anticipation	978
Disgust	2602
Fear	1242
Joy	2477
Love	700
Optimism	1984
Pessimism	795
Sadness	2008
Surprise	261
Trust	357

TABLE I: No. of tweets per classes

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	ID	Tweet	anger	anticipation	disgust	fear	joy	love	optimism	pessimism	sadness	surprise	trust
0	2017-En-21441	"Worry is a down payment on a problem you may ...	0	1	0	0	0	0	1	0	0	0	1
1	2017-En-31535	Whatever you decide to do make sure it makes y...	0	0	0	0	1	1	1	0	0	0	0
2	2017-En-21068	@Max_Kellerman it also helps that the majorit...	1	0	1	0	1	0	1	0	0	0	0
3	2017-En-31436	Accept the challenges so that you can literall...	0	0	0	0	1	0	1	0	0	0	0
4	2017-En-22195	My roommate: it's okay that we can't spell bec...	1	0	1	0	0	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
6833	2017-En-21383	@nicky57672 Hi! We are working towards your hi...	0	0	0	0	0	0	0	0	0	0	0
6834	2017-En-41441	@andreamitchell said @berniesanders not only d...	0	1	0	0	0	0	0	0	0	1	0
6835	2017-En-10886	@isthataspider @dhodgs i will fight this guy! ...	1	0	1	0	0	0	0	1	0	0	0
6836	2017-En-40662	i wonder how a guy can broke his penis while h...	0	0	0	0	0	0	0	0	0	1	0
6837	2017-En-31003	I'm highly animated even though I'm decomposing.	0	0	0	0	0	0	0	1	0	0	0

6838 rows × 13 columns

FIG. 1: Snapshot of the Data-set

B. Data Visualisation

The Snapshot of Data-set using DataFrame of python is shown in Fig.1. The column following the tweet are the classes, these are binary value, i.e. the value is 1 if that emotion is present in the given tweet, else 0. We sought to visualise the association between the emotion classes to better understand the model's essence.

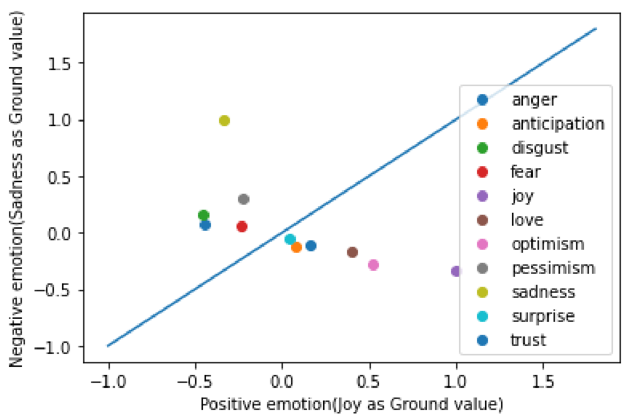

FIG. 2: Emotion representation on a 2-D plot

Emotions like anger, disgust, sadness, etc are modelled as negative emotions, while joy, optimism, love etc are modelled as positive emotions. Considering joy as ground value for positive emotion and sadness as ground value for negative emotion, we have plotted the above Fig. 2. From Fig. 2 we can observe that, above the line are the negative emotions like anger, disgust, fear, pessimism and sadness. While the positive emotions like joy, optimism, love, trust, anticipation and surprise lie below the line.

C. Data Pre-processing

For the pre-proceesing, we have performed normalization, lower-case conversion, hashtag unpacking, contraction unpacking, tokenization, etc.

IV. METHODOLOGY

We referred the paper (Alhuzali et al.,2021)[5] which describes the framework called SpanEmo for multi-label emotion classification. We have implemented that framework which is available at this github link.

A. Framework

Given an input sentence and a set of classes, a BERT-base encoder is employed to learn contextualised word representations. Next, a feed forward network(FFN) is used to project the learned representations into a single score for each token. We then used the scores for the label tokens as predictions for the corresponding emotion label. The green boxes at the top of the FFN illustrate the positive label set, while the red ones illustrate the negative label set for multi-label emotion classification. The same is illustrated by Fig.3 as well.

B. Working of the model

Let f$\{(s_i, y_i)\}_{i=1}^{N}$ be a set of N examples with the corresponding emotion labels of C classes, where s_i denotes the input sentence and $y_i \in \{0,1\}^m$ represents the label set for s_i. As shown in Fig. 3, both the label set and the input sentence were passed into the encoder BERT (Devlin et al., 2018) [6]. The hidden representations $(H_i \in R^{T\times D})^2$ for each input sentence and the label set were obtained as follows:

$$H_i = Encoder([CLS] + |C| + [SEP] + s_i), \quad (1)$$

where $\{[CLS], [SEP]\}$ are special tokens, $|C|$ denotes the size of emotion classes. We further used a feed-forward network(FFN) consisting of a non-linear hidden layer with a $Tanh$ activation $(f_i(H_i))$ as well as a position vector $p_i \in R^D$, which was used to compute a dot product between the output of f_i and p_i. In the end, We added a sigmoid activation to determine whether $class_i$ was the correct emotion label or not.

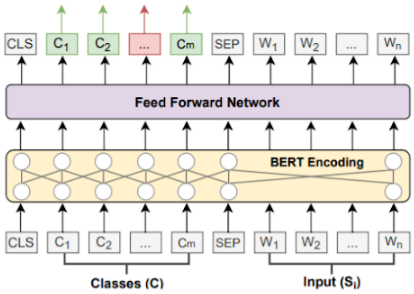

FIG. 3: Framework of the Model

C. Loss Function

To maximise the distance between positive and negative labels, we have used the label correlation aware loss(shown in equation (2)), which takes a vector of true binary labels (y), as well as a vector of probabilities ($\hat{y}$), as input.

$$\mathcal{L}_{LCA}(y, \hat{y}) = \frac{1}{|y^0||y^1|} \sum_{(p,q)\in y^0 \times y^1} exp(\hat{y}_p - \hat{y}_q) \quad (2)$$

where y^0: the set of negative label,
y^1: the set of positive labels,
$\hat{y}_p$: the p_{th} element of vector $\hat{y}$,
$\hat{y}_q$: the q_{th} element of vector $\hat{y}$.

To model label-correlation, we combined LCA loss with binary cross-entropy (BCE) and trained them jointly. The overall training objective was computed as follows:

$$\mathcal{L} = (1 - \alpha)\mathcal{L}_{BCE} + \alpha \sum_{i=1}^{M} \mathcal{L}_{LCA} \quad (3)$$

where $\alpha \in [0, 1]$: the weight used to control the individual contribution of LCA and BCE to the overall loss.

V. RESULTS

The paper we referred compares the scores of different models. The scores of all the models were less than the model that has been considered here. We also went through several other papers and found that the scores of our paper is the best amongst all. We have implemented

The BaseLine results of the Model: F1-macro score: 0.5456, F1-micro score: 0.7001, Jacard index score: 0.5738

	macro-F1	micro-F1	jacS
≥ 1 co.emo	0.5819	0.7207	0.6097
≥ 2 co.emo	0.5618	0.7195	0.6101
≥ 3 co.emo	0.5507	0.7089	0.5979

TABLE II: Results of multiple co-existing emotions

We validated the effectiveness of our method for learning the multiple co-existing emotions on english tweets. From the Table:II As the number of co-existing emotions increases, the results are decreasing. This can be because of the high percentage of single-label data present in the english tweet dataset.

Model/Metric	microF1	macroF1	jacS
JBNN	0.632	0.528	-
RERc	0.651	0.539	-
DATN	-	0.551	0.583
NTUA	0.701	0.528	0.588
$BERT_{base}$	0.695	0.520	0.570
$BERT_{base}$ + DK	0.713	0.549	0.591
$BERT_{base}$ - GCN	0.707	0.563	0.589
LEM	0.675	0.567	-
Our model	0.7001	0.5456	0.5738

TABLE III: Results of multiple co-existing emotions

As shown in Table:III, we additionally compared the performance of the model to other seven different English models which includes JBNN (He and Xia,2018 [7]), DATN (Yu et al., 2018 [8]), NTUA (Baziotis et al., 2018 [9]), RERc (Zhou et al., 2018 [10]), $BERT_{BASE}$+DK (Ying et al., 2019 [11]), $BERT_{BASE}$-GCN (Xu et al., 2020 [12]), LEM and (Fei et al., 2020 [13]).

VI. CONTRIBUTION

1. Srishti: Literature survey, Code: Data-loading, Pre-processing, Model, slides and report

2. Shruti: Literature survey, Code: Model, Data visualization, slides and report

3. Ritika: Literature survey, Code: Learning, Encoding, slides and report

4. Nishtha: Literature survey, Code: Training, Dataset creation, slides and report

5. Kartavi: Literature survey, Code: Testing, Debugging, Data visualisation, slides and report

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