UNIFYING THE DISCRETE AND CONTINUOUS EMOTION LABELS FOR SPEECH EMOTION RECOGNITION

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ABSTRACT

Traditionally, in paralinguistic analysis for emotion detection from speech, emotions have been identified with discrete or dimensional (continuous-valued) labels. Accordingly, models that have been proposed for emotion detection use one or the other of these label types. However, psychologists like Russell and Plutchik have proposed theories and models that unite these views, maintaining that these representations have shared and complementary information. This paper is an attempt to validate these viewpoints computationally. To this end, we propose a model to jointly predict continuous and discrete emotional attributes and show how the relationship between these can be utilized to improve the robustness and performance of emotion recognition tasks. Our approach comprises multi-task and hierarchical multi-task learning frameworks that jointly model the relationships between continuous-valued and discrete emotion labels. Experimental results on two widely used datasets (IEMOCAP and MSPPodcast) for speech-based emotion recognition show that our model results in statistically significant improvements in performance over strong baselines with non-unified approaches. We also demonstrate that using one type of label (discrete or continuous-valued) for training improves recognition performance in tasks that use the other type of label. Experimental results and reasoning for this approach (called mis-matched training approach) are also presented.

Index Terms— speech emotion recognition, discrete and continuous labels, multi-task, hierarchical multi-task

1. INTRODUCTION

Emotion is a complex entity which can be modelled in different ways. When defined as a motor response to stimuli, it can be viewed as belonging to a discrete set; whereas when considered as a subjective feeling, it can be expressed as a continuous vector in multiple dimensions [1]. Though these two definitions of emotion appear to be different, they have shared and complementary information. Psychological models like Plutchik’s ‘wheel of emotions’ [2] or Russell’s ‘arousal-valence’ space [3] represent discrete emotions on and within a circle on a continuous “arousal-valence” plane, demonstrating that the values of “arousal” and “valence” are correlated to the perception of discrete emotion.

Speech Emotion Recognition (SER), which refers to the task of identifying the emotional state of the speaker using speech as input, can be used to predict both discrete or continuous emotions. The most commonly used continuous representation for this task comprises three attributes – Valence (V), Arousal (A), and Dominance (D) (from Russell [4]). Among these three dimensions, Valence represents the pleasantness of the emotion, Arousal denotes the intensity of it, and Dominance represents the degree of control over a social situation. Similarly, a number of discrete emotions have been identified – happy, sad, angry etc. Translating between these two forms of emotion representations has been of interest [5, 6, 7, 8], both with audio and textual input. However conflicting results have been found: while some studies [6] find that there is little correlation between continuous values and discrete labels, others [5] find correlations like ‘anger has higher arousal and lower valence’. Based on the notion that discrete and continuous emotion attributes are likely related, in this paper, we propose to examine such dependency relationships.

In order to investigate the relationship between continuous and discrete attributes, we develop neural network models that jointly predict continuous and discrete emotion labels. The motivation behind this is two-fold: (a) holistic models for automatic emotion recognition must be able to capture both generic and specific notions of emotion contained in the continuous and discrete emotion labels, and (b) since discrete and continuous emotion labels may be related to each other, robust and generalizable machine learning models can be built by leveraging this dependency. We propose a multi-task learning framework where continuous and discrete emotion labels are predicted together, but independently of each other. Next, we consider the possibility that knowledge of the discrete emotion might help predict more accurately the continuous emotion and vice versa and hence introduce hierarchical multi-task models that model such a relationship to jointly predict discrete and continuous emotion.

We further demonstrate that these continuous and discrete labels need not necessarily be manually annotated within the same corpus to be improve recognition performance. Of the prevailing annotated datasets for emotion recognition, very few are annotated for both continuous and discrete attributes such as MSPPodcast [9], and IEMOCAP [10] while others like MELD [11] are annotated for discrete attributes only. We demonstrate that even if the model is trained on continuous emotion labels from MSPPodcast and discrete labels from IEMOCAP, the proposed Hierarchical Multi-Task approach improves performance and generalizability. This implies that emotion recognition datasets can be trained jointly on multiple corpora with different labels. In summary, this paper makes the following contributions:

1. We propose a multi-task learning framework that jointly predicts the continuous and discrete labels from speech
2. We extend this framework to model hierarchical dependencies, where knowledge of discrete attributes aids continuous prediction and vice versa.
3. We demonstrate that the proposed approach can be used when the mis-matched labels (continuous and discrete) are drawn from different datasets.

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2. PROPOSED APPROACH

2.1. Encoder Decoder Architecture

To perform SER on input speech, we use an encoder-decoder architecture for the task. The encoder takes as input a sequence of N content-based speech features \( X = [x_1, x_2, \cdots x_N] \), and produces as its output a sequence of hidden representations \( H = [h_1, h_2, \cdots h_M] \). These hidden representations are the input to a decoder that either predicts continuous emotion \( \hat{c} \), discrete emotion \( \hat{y} \), or both.

The decoder comprises a temporal self-attentive pooling layer, followed by a Multi-layer Perceptron (MLP) that extracts task-specific embeddings, i.e., \( E_D \) for discrete prediction and \( E_C \) for continuous prediction. These embeddings are then passed through the final classification layer that maps to 3 dimensions for continuous prediction (corresponding to V,A,D), or 5 dimensions for discrete prediction (corresponding to the number of discrete emotion classes). The continuous and discrete baseline models use a similar neural network architecture, except for the number of output neurons.

Each of the models we describe below, baseline models that perform either continuous or discrete prediction, and multi-task or hierarchical multi-task models that predict both discrete and continuous emotion, share the same encoder structure but with slightly different decoder architectures.

2.2. Baseline Models

Baseline Discrete Model
To independently predict the discrete attributes from input \( X \), our encoder-decoder model termed as Baseline D uses a decoder with discrete self-attentive pooling, MLP which generates the discrete embedding \( E_D \), and a discrete classification layer that produces the discrete label \( \hat{y} \) as its output. The model is shown in Fig. 1 (top left).

Given the true discrete label \( y \), the model is optimized using the multi-class cross entropy criterion. For a dataset with \( A \) utterances, the cross-entropy loss is computed as:

\[
L_{\text{disc}} = - \sum_{i=1}^{A} \sum_{c=1}^{K} y_{i,c} \log(\hat{y}_{i,c})
\]  

(1)

Baseline Continuous Model
To predict the continuous attribute labels independently from the input speech, our encoder-decoder model, called Baseline C uses a continuous emotion pooling layer and MLP to predict the continuous emotion \( \hat{c} = [\hat{c}_{Val}, \hat{c}_{Aro}, \hat{c}_{Dom}] \).

The variables \( \hat{c}_{Val}, \hat{c}_{Aro}, \) and \( \hat{c}_{Dom} \) correspond to the valence, arousal and dominance predictions respectively.

This model is optimized using the Concordance Correlation Coefficient (CCC) Loss. Given the prediction \( \hat{c} \) and the ground truth \( c \), the CCC loss is defined as shown in Equation 2.

\[
L_{\text{ccc}} = 1 - \frac{2s_{\hat{c}c} s_{\hat{c}}}{s_{\hat{c}}^2 + s_{c}^2 + (\hat{c} - c)^2}
\]  

(2)

where \( s_{\hat{c}c}, s_{\hat{c}}^2, s_{c}^2, \hat{c}, c \) represent the covariance between the ground truth and prediction, variance of the ground truth, variance of the prediction, mean of the groundtruth and mean of the prediction respectively. The resulting loss for continuous emotion recognition can be written as the sum of the CCC losses for valence, arousal and dominance prediction.

2.3. Multi-Task Model

Since continuous and discrete representations carry information about the same emotion, we are interested in understanding if jointly predicting continuous and discrete attributes improves model performance. To do this, we use a multi-task architecture to predict both the discrete and continuous emotion attributes simultaneously. Since we seek to find the commonality between the discrete and continuous representations, in the multi-task architecture, we elect to utilize a shared speech encoder that transforms the input speech into hidden representations \( H \) that contains the information that pertains to both the continuous and discrete emotion attributes, i.e., the shared information.

The Multi-task C,D model predicts both discrete label \( \hat{y} \) and continuous vector \( \hat{c} = [\hat{c}_{Val}, \hat{c}_{Aro}, \hat{c}_{Dom}] \) for every utterance.

The architecture of the model is shown in Fig. 1 (left). The model uses a common encoder, but within the decoder, two parallel branches are used to learn task specific pooling and MLP parameters. The discrete branch (left) generates a discrete embedding \( E_{D} \), which is then used to predict the discrete emotion \( \hat{y} \). Similarly, the continuous branch predicts a continuous embedding \( E_{C} \), which is used to predict the continuous emotion \( \hat{c} \). The model is optimized with the total loss as shown in Equation 3.

\[
L_{\text{total}} = \alpha(L_{\text{ccc}}^{\text{Val}} + L_{\text{ccc}}^{\text{Aro}} + L_{\text{ccc}}^{\text{Dom}}) + \beta L_{\text{disc}}
\]  

(3)

where the values of \( \alpha \) and \( \beta \) are set to 1 empirically.

2.4. Hierarchical Multi-Task Model

Multi-task modelling described in the previous section seeks to utilize the shared information between discrete and dimensional attributes to predict them jointly. However, it doesn’t assume any...
direct dependency between the discrete and continuous emotion attributes. Based on the hypothesis that knowledge of discrete emotion attributes would help improve continuous attribute predictions and vice-versa, we develop hierarchical multi-task models.

In this model, the continuous and discrete emotion prediction branches in the decoder are used to generate the continuous and discrete embeddings $E_C$ and $E_D$ respectively, as in the multi-task formulation. However, here, the predicted continuous emotion, i.e., $\hat{c}$ is not computed solely based on $E_C$, but also on $E_D$. In other words, the discrete emotion embedding is used in conjunction with the continuous embedding to predict the continuous emotion. We term this our Hierarchical D-C model since the discrete embedding is used as auxiliary input to predict the continuous emotion. Similarly, one can define a Hierarchical C-D model where the continuous emotion embedding is used as auxiliary input to predict the discrete emotion.

The Hierarchical D-C model is shown in Fig. 1 (right). To perform continuous emotion prediction with the help of the discrete predictions, discrete emotion embedding $E_D$, (which is used to predict the discrete emotion $\hat{y}$) is concatenated with the continuous embedding $E_C$. This concatenated embedding $[E_D, E_C]$ is then used to predict the continuous emotion, $\hat{c}$. Similarly, in the Hierarchical C-D model, in order to utilize continuous attributes to predict discrete attributes, $E_C$ is concatenated with $E_D$ and used to predict $\hat{y}$.

### 3. EXPERIMENTS

#### 3.1. Data

Our experiments are conducted on the MSPPodcast[12] and IEMOCAP [13]. MSP Podcast is the largest human labelled emotion dataset with 29,965 training examples and 10,013 test utterances. It is comprised of segments of speech from podcasts, which means that the speech is expressive and the acoustic environment less constrained by background noise and other interference. The MSP-Podcast data has labels for three continuous dimensions - valence, arousal and dominance, and for multiple discrete emotions - of which we use five : neutral, angry, happy, sad, and disgust. In this work, we report our results on the balanced test1 evaluation set with 30 male and 30 female speakers. The second dataset we use is IEMOCAP which is a 20 hour dataset, with annotations on acted emotion. It comprises of 10 different speakers, 5 male and 5 female. It is labelled for three continuous dimensions - valence, arousal and dominance, and for 9 discrete emotions out of which we utilise the ones that overlap with our MSPPodcast set, i.e., neutral, angry, happy, sad, and disgust.

#### 3.2. Model Hyperparameters

All our models are built using the ESPNet[14] toolkit, and will be publicly released to encourage further research. We use HUBERT-large embeddings as the input features and a 4 layer conformer encoder with 64 hidden units for our models. We freeze the HUBERT-large frontend, and train the conformer and pooling decoder parameters. We employ separate self-attentive pooling[16] layers for continuous and discrete emotion prediction so the model can learn which frames to focus on in order to make emotion predictions. Our decoders consist of linear projections that map from the encoded output dimension of 768 to 64, 32 and consequently the output sizes of 3 for the continuous prediction and 5 for the discrete prediction. We use a ReLU activation to ensure that the predicted continuous attributes are strictly positive and use LeakyReLU elsewhere. We use a dropout of 0.2 in the decoder. Our models are trained with the Adam optimizer, and a peak learning rate of 1e-3 for 15,000 warmup steps.

#### 3.3. Evaluation Metrics

Discrete emotion recognition is evaluated using F1 or accuracy. For continuous prediction, we compute the Concordance Correlation Coefficient for each of the attributes arousal, valence and dominance, and consequently their mean. Equation (4) shows how the CCC is computed given prediction $\hat{c}$, and ground truth $c$, where $s_c$, $s_\hat{c}$, $s_{c,\hat{c}}$, $\bar{c}$, $\bar{\hat{c}}$ represent the covariance between the ground truth and prediction, variance of the ground truth, variance of the prediction, mean of the groundtruth and mean of the prediction respectively.

$$\text{CCC} = \frac{2s_{c,\hat{c}}}{s_c^2 + s_{\hat{c}}^2 + (\bar{c} - \bar{\hat{c}})^2}$$

**Table 1.** Emotion Recognition Results on IEMOCAP using 5-fold cross-validation: Concordance Correlation Coefficient- overall, Valence, Activation and Dominance is reported for continuous emotions, and Unweighted accuracy is reported for discrete emotion prediction.

| Model Description | CCC  | CCC-V | CCC-A | CCC-D | Acc  |
|-------------------|------|-------|-------|-------|------|
| Baseline C        | 0.580| 0.548 | 0.606 | 0.566 | -    |
| Baseline D        | -    | -     | -     | -     | 0.737|
| Multi-task C,D    | 0.603| 0.571 | 0.669 | 0.567 | 0.723|
| Hierarchical D-C  | 0.667| 0.660 | 0.717 | 0.625 | 0.744|
| Hierarchical C-D  | 0.648| 0.651 | 0.694 | 0.599 | 0.749|

#### 3.4. Results on IEMOCAP

Table [1] shows our experimental results on the IEMOCAP dataset, where all results are computed using standard 5-fold cross validation [17]. We observe that multi-task training improves CCC by 0.02 over the continuous baseline, however, it does not outperform the discrete baseline. We contend that this is because both of these predictions are being generated independent of the other. The proposed hierarchical models outperform the baselines and multi-task model on discrete and continuous emotion prediction. Specifically the hierarchical model that uses discrete attributes to aid the prediction of continuous attributes, i.e., Hierarchical D-C outperforms the multi-task model and the continuous baselines on CCC - gaining 0.087 absolute CCC. This is perhaps because knowledge of the discrete emotion aids in the prediction of dominance and arousal. We also observe an absolute 0.8% improvement on accuracy in Hierarchical D-C. The hierarchical model that uses continuous emotions to help predict discrete attributes, i.e., Hierarchical C-D outperforms the other 3 models on accuracy. This reaffirms our hypothesis that knowledge of discrete and continuous emotion attributes can be used to improve performance on continuous and discrete emotion prediction respectively. We note that the Hierarchical C-D model improves the recognition of discrete emotion attributes compared to the multi-task model and the continuous baseline.

#### 3.5. Results on MSPPodcast

Table [3] reports the results of experiments on MSPPodcast. The continuous and discrete emotion prediction baselines obtain comparable scores to state-of-the-art approaches[18].
Table 2. Results on MSPPodcast and IEMOCAP: The second two columns represent the attributes used in training from the IEMOCAP and MSPPodcast datasets respectively. CCC is reported on IEMOCAP Session05 and on the test1 evaluation sets for MSPPodcast respectively. F1 is reported on the test1 evaluation set for MSPPodcast and unweighted accuracy on Session05 for IEMOCAP (we use this because these are standard metrics reported for these datasets).

| ID | IEMOCAP Train | MSPPodcast Train | IEMOCAP CCC | IEMOCAP Acc | MSPPodcast CCC | MSPPodcast F1 |
|----|---------------|------------------|-------------|-------------|----------------|---------------|
| 1  | -             | Cont.            | 0.125       | -           | 0.524          | -             |
| 2  | Cont.         | -                | 0.327       | -           | 0.140          | -             |
| 3  | -             | Disc.            | 0.459       | 0.701       | -              | 0.266         |
| 4  | Disc.         | Cont.            | 0.586       | -           | 0.524          | -             |
| 5  | Cont.         | Disc.            | 0.695       | 0.470       | 0.189          | 0.302         |
| 6  | Disc.         | Disc.            | 0.625       | 0.705       | 0.497          | 0.283         |

Table 3. Results on MSPPodcast: Concordance Correlation Coefficient (CCC) - overall, Valence, Activation and Dominance is reported on the test1 evaluation set. For discrete emotions, unweighted F1 is reported.

| Model Description | CCC | CCC-V | CCC-A | CCC-D | F1  |
|-------------------|-----|-------|-------|-------|-----|
| Baseline C        | 0.593 | **0.597** | 0.646 | 0.538 | -   |
| Baseline D        | 0.587 | 0.591 | 0.637 | 0.533 | 0.368|
| Multi-task C,D    | 0.617 | 0.588 | 0.675 | **0.584** | 0.404|
| Hierarchical D-C  | 0.605 | 0.554 | 0.661 | 0.569 | **0.411**|

Multi-task training to jointly predict continuous and discrete attributes improves F1 score over the discrete baseline while slightly degrading continuous emotion prediction performance. As with the IEMOCAP dataset, the proposed hierarchical models outperform the baselines and multi-task prediction models. Specifically, the hierarchical D-C model improves CCC on continuous attribute prediction over the multi-task and baseline continuous models. Hierarchical multi-task learning helps learn useful intermediate representations [19]. Therefore in the hierarchical D-C model, the continuous prediction task helps learn better discrete emotion representations, thereby improving discrete prediction as well with respect to the baseline. The Hierarchical C-D model also improves prediction of discrete emotion over the other 3 models. This model also outperforms the baseline and multi-task models on continuous emotion prediction, with gains arising from improved prediction of arousal and dominance.

3.6. Combining IEMOCAP and MSPPodcast

In this section, we attempt to use discrete and continuous labels from different datasets and analyse gains when training models on multiple datasets with matched (e.g. discrete-discrete) and mis-matched (e.g. continuous-discrete) labels. We perform all experiments using a subset of the MSPPodcast data chosen randomly such that the resulting size is the same as that of the IEMOCAP training data. This is done in order to be able to make fair comparisons on transferrability of representations. Table 2 summarizes the results of our experiment on transferring labels across datasets.

IEMOCAP Discrete Prediction: Consider rows with ID 4, 6, 8 from Table 2, we observe that the best unweighted accuracy on the IEMOCAP test set is obtained when the model is trained on IEMOCAP discrete labels and MSPPodcast continuous labels.

IEMOCAP Continuous Prediction: Comparing rows 2, 5, 7 from Table 2, we observe that the best CCC on IEMOCAP is achieved when IEMOCAP continuous labels and MSPPodcast discrete labels are both included in the training.

MSPPodcast Discrete Prediction: From rows 3, 6, 7 in Table 2, we observe that the best F-1 score is obtained on MSPPodcast when discrete labels from both datasets are used, i.e., for row 6 model.

MSPPodcast Continuous Prediction: From the rows 1, 5, 8 from Table 2, we can conclude that when the MSPPodcast continuous labels are used alone, the best performance is achieved.

In conclusion, we observe that using mis-matched labels from the MSPPodcast data for training improves performance on discrete and continuous emotion prediction for IEMOCAP. We also note that though discrete labels from IEMOCAP are transferrable and improve performance on MSPPodcast, the continuous labels from IEMOCAP do not seem to provide gains on MSPPodcast.

Therefore MSPPodcast discrete and continuous representations help improve performance on the mismatched label of IEMOCAP, while such transferred representations from IEMOCAP do not significantly impact MSPPodcast predictions. We believe this is in part because of the difference in the nature of annotations across the IEMOCAP and MSPPodcast datasets. For example, from our analysis we observe that anger is assigned a lower arousal and higher valence than neutral in IEMOCAP while in MSPPodcast, anger is assigned a higher arousal and lower valence than neutral. Furthermore, the inter-annotator agreement for continuous values in MSPPodcast are much lower in the IEMOCAP, which makes it challenging to obtain gains in MSPPodcast continuous predictions using transferred representations from IEMOCAP.

4. CONCLUSION AND FUTURE WORK

Emotion Recognition remains a challenging task. Different datasets are labelled with varying annotation labels, making it challenging to train large scale emotion models utilising all the datasets. In this paper, we introduce hierarchical multi-task learning models that predict discrete or continuous labels by using continuous or discrete labels respectively.

With our method, we obtain absolute improvements of 1.2 % Accuracy and 4.3 points F-1 for discrete prediction on IEMOCAP and MSPPodcast respectively. On continuous labels, we improve 0.09 CCC for IEMOCAP, and 0.025 CCC in MSPPodcast. Furthermore, we also combine IEMOCAP and MSPPodcast with mis-matched emotion annotations, and show that mis-matched labels from MSPPodcast help performance on IEMOCAP.
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