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# A Novel Approach for Effective Learning in Low Resourced Scenarios

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## Abstract

Deep learning based discriminative methods, being the state-of-the-art machine learning techniques, are ill-suited for learning from lower amounts of data. In this paper, we propose a novel framework, called simultaneous two sample learning (s2sL), to effectively learn the class discriminative characteristics, even from very low amount of data. In s2sL, more than one sample (here, two samples) are simultaneously considered to both, train and test the classifier. We demonstrate our approach for speech/music discrimination and emotion classification through experiments. Further, we also show the effectiveness of s2sL approach for classification in low-resource scenario, and for imbalanced data.

## 1 Introduction

Deep neural networks (DNNs), in particular convolutional and recurrent neural networks, with huge architectures have been proven successful in wide range of tasks including audio processing such as speech to text [1 - 4], emotion recognition [5 - 8], speech/non-speech (e.g., of non-speech include noise, music, etc.) classification [9 - 12], etc.

Training these deep architectures require large amount of annotated data, as a result, they cannot be used in low data resource scenarios which is common in speech-based applications [13 - 15]. Apart from collecting large data corpus, annotating the data is also very difficult, and requires manual supervision and efforts. Especially, annotation of speech for tasks like emotion recognition also suffer from lack of agreement among the annotators [16]. Hence, there is a need to build reliable systems that can work in low resource scenario.

In this work, we propose a novel approach to address the task of classification in low data resource scenarios. Our approach involves simultaneously considering more than one sample (in this work, two samples are considered) to train the classifier. We call this approach as simultaneous two sample learning (s2sL). The proposed approach is also applicable to low resource data suffering with data imbalance. The contributions of this paper are:

- Representation of the training data, where the feature vectors pertaining to two different samples are simultaneously considered to train the classifier.
- Introduce modifications to the multi-layer perceptron (MLP) architecture so that it can be trained using our proposed data representation.

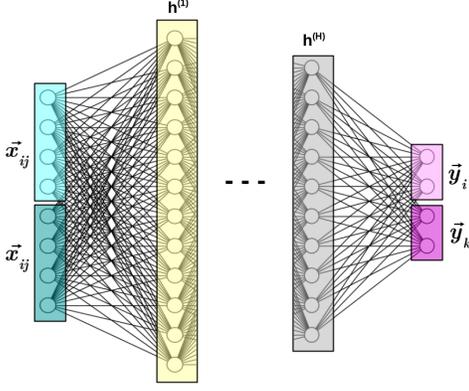


Figure 1: Training of s2s-MLP.

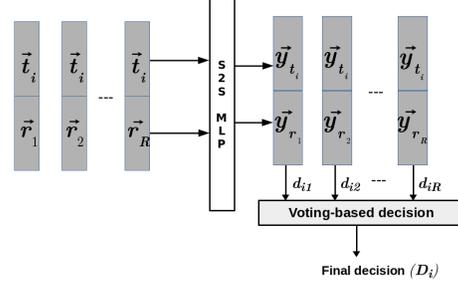


Figure 2: Testing of s2s-MLP.

- New decision mechanism to classify the test samples.

## 2 Proposed approach

The s2sL approach proposed to address low data resource problem is explained in this Section. In this work, we use MLP (modified to handle our data representation) as the base classifier. Here, we explain the s2sL approach by considering two-class classification task.

### 2.1 Data representation

Consider a two-class classification task with  $C = \{C_1, C_2\}$  denoting the set of class labels, and let  $N_1$  and  $N_2$  be the number of samples corresponding to  $C_1$  and  $C_2$ , respectively. In general, to train a classifier, the samples in the train set are provided as input-output pairs as follows.

$$(\vec{x}_{ij}, C_i), \quad i = 1, 2; \text{ and } j = 1, 2, \dots, N_i, \quad (1)$$

where  $\vec{x}_{ij} \in \mathbb{R}^{d \times 1}$  refers to the  $d$ -dimensional feature vector representing the  $j^{\text{th}}$  sample corresponding to  $i^{\text{th}}$  class label, and  $C_i \in C$ , refers to output label of  $i^{\text{th}}$  class. In the proposed data representation format, called simultaneous two sample (s2s) representation, we will simultaneously consider two samples as follows.

$$([\vec{x}_{ij}, \vec{x}_{kl}], [C_i, C_k]), \quad \forall i, k = 1, 2; j = 1, 2, \dots, N_i \quad \text{and } l = 1, 2, \dots, N_k, \quad (2)$$

where  $\vec{x}_{ij}, \vec{x}_{kl} \in \mathbb{R}^{d \times 1}$  are the  $d$ -dimensional feature vectors representing the  $j^{\text{th}}$  sample in  $i^{\text{th}}$  class and  $l^{\text{th}}$  sample in the  $k^{\text{th}}$  class, respectively; and  $(C_i, C_k) \in C$  refers to the output labels of  $i^{\text{th}}$  and  $k^{\text{th}}$  class, respectively.

Hence, in s2s data representation, we will have an input feature vector of length  $2d$  i.e.,  $[\vec{x}_{ij}, \vec{x}_{kl}] \in \mathbb{R}^{2d \times 1}$ , and output class labels as either  $[C_1, C_1], [C_1, C_2], [C_2, C_1]$  or  $[C_2, C_2]$ . Each sample can be combined with all the samples (i.e., with  $(N_1 + N_2)$  samples) in the dataset. Therefore, by representing the data in the s2s format, the number of samples in the train set increases to  $(N_1 + N_2)^2$  from  $(N_1 + N_2)$  samples. We hypothesize that the s2s format is expected to help the network not only to learn the characteristics of the two classes separately, but also the difference and similarity in characteristics of the two classes.

### 2.2 Classifier training

MLP, the most commonly used feed forward neural network, is considered as the base classifier to validate our proposed s2s framework. Generally, MLPs are trained using the data format given by eq. (1). But to train the MLP on our s2s based data representation (as in eq. (2)), the following modifications are made to the MLP architecture (refer to Figure 1).

- We have  $2 \times d$  units (instead of  $d$  units) in the input layer to accept the two samples i.e.,  $\vec{x}_{ij}$  and  $\vec{x}_{kl}$ , simultaneously.

- The structure of the hidden layer in this approach is similar to that of a regular MLP. The number of hidden layers and hidden units can be varied depending upon the complexity of the problem. The number of units in the hidden layer is selected empirically by varying the number of hidden units from 2 to twice the length of the input layer (i.e., 2 to  $4 \times d$ ) and the unit at which the highest performance is obtained are selected. In this paper, we considered only a single hidden layer. Rectified linear units (ReLU) are used for hidden layer.
- The output layer will consist of units equal to twice the considered number of classes in the classification task i.e, the output layer will have four units for two-class classification task. The sigmoid activation function (not softmax) is used on the output layer units. Unlike regular MLP, we use sigmoid activation units in the output layer, with binary cross-entropy as the cost function, because the output labels in the proposed s2s based data representation will have more than one unit active at a time (not one-hot encoded output) and this condition cannot be handled using softmax function.

As can be seen from Figure 1, the output layer in our proposed method has outputs  $\vec{y}_i$  and  $\vec{y}_k$  which corresponds to the outputs associated with the input feature vectors  $\vec{x}_{ij}$  and  $\vec{x}_{kl}$ , respectively. For a two-class classification problem, there will be four units in the output layer and the possible output labels are  $[0, 1, 0, 1]$ ,  $[0, 1, 1, 0]$ ,  $[1, 0, 0, 1]$ ,  $[1, 0, 1, 0]$  corresponding to the class labels  $[C_1, C_1]$ ,  $[C_1, C_2]$ ,  $[C_2, C_1]$  and  $[C_2, C_2]$ , respectively. This architecture is referred to as s2s-MLP. In s2sL, s2s-MLP is trained using the s2s data representation format. Further, the s2s-MLP is trained using adam optimizer.

### 2.3 Classifier testing

Generally, the feature vector corresponding to the test sample is provided as input to the trained MLP in the testing phase and the class label is decided based on the obtained output.

However, in s2sL method, the feature vector corresponding to the test sample should also be converted to the s2s data representation format to test the trained s2s-MLP. We propose a testing approach, where the given test sample is combined with a set of preselected reference samples, whose class label is known a priori, to generate multiple instances of the same test sample as follows.

$$[\vec{t}, \vec{r}_j], \quad j = 1, 2, \dots, R, \quad (3)$$

where  $\vec{t} \in \mathbb{R}^{d \times 1}$ ,  $\vec{r}_j \in \mathbb{R}^{d \times 1}$  refer to the  $d$ -dimensional feature vector corresponding to the test sample and the  $j^{th}$  reference sample, respectively.  $R$  refers to the considered number of reference samples. These reference samples can be selected from any of the two classes.

For testing the s2s-MLP (as shown in Figure 2), each test sample  $\vec{t}_i$  (same as 't' in (3)) is combined with all the  $R$  reference samples ( $\vec{r}_1, \vec{r}_2, \dots, \vec{r}_R$ ) to form  $R$  different instances of the same test sample  $\vec{t}_i$ . The corresponding outputs ( $d_{i1}, d_{i2}, \dots, d_{iR}$ ) obtained from s2s-MLP for the  $R$  generated instances of  $\vec{t}_i$  are combined by voting-based decision approach to obtain the final decision  $D_i$ . The class label that gets maximum votes is considered as the predicted output label.

## 3 Experiments

We validate the performance of the proposed s2sL by providing the preliminary results obtained on two different tasks namely, Speech/Music discrimination and emotion classification. We considered the GTZAN Music-Speech dataset [17], consisting of 120 audio files (60 speech and 60 music), for task of classifying speech and music. Each audio file (of 2 seconds duration) is represented using a 13-dimensional mel-frequency cepstral coefficient (MFCC) vector, where each MFCC vector is the average of all the frame level (frame size of 30 msec and an overlap of 10 msec) MFCC vectors. It is to be noted that our main intention for this task is not better feature selection, but to demonstrate the effectiveness of our approach, in particular for low data scenarios.

The standard Berlin speech emotion database (EMO-DB) [18] consisting of 535 utterances corresponding to 7 different emotions is considered for the task of emotion classification. Each utterance is represented by a 19-dimensional feature vector obtained by using the feature selection algorithm from WEKA toolkit [19] on the 384-dimensional utterance level feature vector obtained using openS-MILE toolkit [20]. For two class classification, we considered the two most confusing emotion

Table 1: Accuracies (in %) for balanced data classification.

Task		Data proportion			
		1/4	2/4	3/4	4/4
Speech/ Music	MLP	70.8	74.6	80.1	81.2
	<b>s2sL</b>	<b>75.2</b>	<b>79.3</b>	<b>82.7</b>	<b>85.1</b>
Neutral/ Sad	MLP	86.3	88.0	90.5	91.1
	<b>s2sL</b>	<b>90.4</b>	<b>91.2</b>	<b>92.1</b>	<b>92.9</b>

Table 2:  $F_1$  for imbalanced data classification. Note: EB is Eusboost and MM is MWMOTE.

Task		Data proportion			
		1/4	2/4	3/4	4/4
Anger/ Happy	MLP	.41	.49	.53	.56
	EB	.47	.54	.59	.64
	MM	.48	.55	.61	.66
	<b>s2sL</b>	<b>.54</b>	<b>.60</b>	<b>.64</b>	<b>.69</b>

pairs i.e., (Neutral,Sad) and (Anger, Happy). Data corresponding to Speech/Music classification (60 speech and 60 music samples) and Neutral/Sad classification (79 neutral and 62 sad utterances) is balanced whereas Anger/Happy classification task has data imbalance, with anger forming the majority class (127 samples) and happy forming the minority class (71 samples). Therefore, we show the performance of s2sL on both, balanced and imbalanced datasets.

All experimental results are validated using 5-fold cross validation (80% of data for training and 20% for testing in each fold). Further, to analyze the effectiveness of s2sL in low resource scenarios, different proportions of training data, within each fold, are considered to train the system. For this analysis, we considered 4 different proportions i.e.,  $(1/4)^{th}$ ,  $(2/4)^{th}$ ,  $(3/4)^{th}$  and  $(4/4)^{th}$  of the training data to train the classifier. For instance,  $(2/4)^{th}$  means considering only half of the original training data to train the classifier, and  $(4/4)^{th}$  means considering the complete training data. 5-fold cross validation is considered for all data proportions. Accuracy (in %) is used as a performance measure for balanced data classification tasks (i.e., Speech/Music classification and Neutral/Sad emotion classification), whereas the more preferred  $F_1$  measure [21] is used as a measure for imbalanced data classification task (i.e., Anger/Happy emotion classification).

Table 1 show the results obtained for proposed s2sL approach in comparison to that of MLP for the tasks of Speech/Music and Neutral/Sad classification, by considering different proportions of training data. The values in Table 1 are mean accuracies (in %) obtained by 5-fold cross validation. It can be observed from Table 1 that for both tasks, s2sL method outperforms MLP, especially at low resource conditions. s2sL shows an absolute improvement in accuracy of 4.4% and 4.1% over MLP for Speech/Music and Neutral/Sad classification tasks, respectively, when  $(1/4)^{th}$  of the original training data is used in experiments.

Table 2 show the results (in terms of  $F_1$  values) obtained for proposed s2sL approach in comparison to that of MLP for Anger/Happy classification (data imbalance problem). Here, state-of-the-art methods i.e., Eusboost [22] and MWMOTE [23] are also considered for comparison. It can be observed from Table 2 that the s2sL method outperforms MLP, and also performs better than Eusboost and MWMOTE techniques on imbalanced data (around 3 % absolute improvement in  $F_1$  value for s2sL compared to MWMOTE, when  $(4/4)^{th}$  of the training data is considered). In particular, at lower amounts of training data, s2sL outperforms all the other methods, illustrating its effectiveness even for low resourced data imbalance problems. s2sL method shows an absolute improvement of 6% (0.54 – 0.48) in  $F_1$  value over the second best (0.48 for MWMOTE), when only  $(1/4)^{th}$  of the training data is used.

## 4 Conclusions

In this paper, we introduced a novel s2s framework to effectively learn the class discriminative characteristics, even from low data resources. In this framework, more than one sample (here, two samples) are simultaneously considered to train the classifier. Further, this framework allows to generate multiple instances of the same test sample, by considering preselected reference samples, to achieve a more profound decision making. We illustrated the significance of our approach by providing the experimental results for two different tasks namely, speech/music discrimination and emotion classification. Further, we showed that the s2s framework can also handle the low resourced data imbalance problem.

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