Dual Student Training for Automatic Speech Recognition

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Abstract

Dual Student is a neural network learning algorithm that has recently been a breakthrough for semi-supervised image classification. Two networks are trained on both labeled and unlabeled data, and along with the training, the networks share only reliable knowledge to improve each other. This paper employs the experimental method to investigate the effectiveness of Dual Student training for sequential data, such as speech, adapting it for automatic speech recognition. Extensive experiments conducted on the TIMIT dataset show the benefits of this approach to leverage amounts of unlabeled data for frame-based phone classification. Dual Student significantly boosts the performance for training a network using only a small set of labeled utterances. Finally, an improvement is proposed by alternating learning from labeled data and knowledge exchange. The results show that the novel scheduled learning compared to the standard Dual Student allows achieving better accuracy.

1 Introduction

In recent years, several improvements have been made in Automatic Speech Recognition (ASR). The introduction of deep learning techniques has given a new light to the field, enhancing supervised tasks and revealing the power of semi-supervised models. In the context of phoneme-based classification, both supervised and Semi-Supervised Learning (SSL) can be used. According to nowadays demand and real-world scenarios, data is most commonly unlabeled, and only in rare cases a supervised approach can be beneficial. Hence, to exploit data in the best possible way, SSL models are required.

In the context of frame-based phone classification, a SSL solution comes with the work of Salvi et al. [1], which proposed a model based on sparse autoencoders with feed-forward networks and mini-batch stochastic gradient descent, leveraging both labeled and unlabeled data. Other research in the field was conducted with graph-based approaches [2], achieving, to the best of our knowledge, the current state-of-the-art frame-based phone recognition accuracy with the Prior-Regularised Measure Propagation (pMP) algorithm. However, the limitation of this method is its high computational cost.

Another interesting SSL approach employed for image classification is from Ke et al. [3], which aimed to improve consistency-based methods, such as VAT [4], Π [5] models, and Mean Teacher [6]. Consistency-based methods have achieved state-of-the-art results in SSL. According to the *smoothness assumption*, these methods involve two roles, a teacher and a student, and penalize different predictions under small perturbations. However, since the teacher is an exponential moving average (EMA) of the student, the two models are tightly correlated, resulting in a performance bottleneck over long training. Dual Student (DS) overcomes this problem by decoupling the two roles, replacing the teacher with another student.

DS's main idea is to share knowledge between two neural networks during the training. Sharing knowledge is not a novel concept, and previous work has already been done in this area, mainly for *knowledge distillation*. Caruana et al. [7] have shown a way to efficiently compress knowledge from a larger model to a smaller one, faster for inference. Hinton et al. [8] further developed this approach using a different compression technique. The effectiveness of knowledge distillation using teacher-student training for building accurate and compact neural networks was also investigated by Fukuda et al. [9]. Nowadays, the teacher-student paradigm has become even more popular for ASR [10, 11, 12, 13]. Sparta et al. [14] applied it using vast amounts of unlabeled data (1 Million hours of speech) and distributed training, reaching impressive results. They trained a very large and slow teacher, unusable in real-life applications due to its size, which was then used to generate labels for the student, a smaller and more efficient model. Lin et al. [15] further improved this approach by training the student with probabilistic labels created by the teacher. Unlike these methods, DS has two networks with the same size, the same capability, and both sharing knowledge.

2 Methods

2.1 Dual Student training

During DS training, two networks improve each other by sharing only reliable knowledge, thanks to the *stable sample* concept, a sample that should satisfy two conditions. First, a small perturbation should not affect the prediction of the sample. Second, the prediction of the sample has to be far from the decision boundary, meaning that the sample has a high probability for the predicted label; hence the model is sure about its prediction. It is noteworthy to specify that the notion of *stable sample* applies to the models and not to DS itself. Therefore, a sample can be stable for one student but may not be for the other. In this regard, the first student shares its knowledge about its *stable samples* to improve the other student. The two aforementioned conditions are encoded in Eq. 1. Given a sample x, a noisy augmentation $\bar{x}$, and θ^i the weights of student i, then the sample x is stable for student i according to:

$$\mathcal{R}_x^i = \{\mathcal{P}_x^i = \mathcal{P}_{\bar{x}}^i\}_{\mathbf{1}} \;\&\; (\{\mathcal{M}_x^i > \xi\}_{\mathbf{1}} \| \{\mathcal{M}_{\bar{x}}^i > \xi\}_{\mathbf{1}}) \tag{1}$$

where $\mathcal{P}_x^i$ and $\mathcal{P}_{\bar{x}}^i$ are the predicted labels of x and $\bar{x}$, respectively, by student i. $\mathcal{M}_x^i = \|f(\theta^i, x)\|_\infty$ is the probability of the predicted label, $\{condition\}_{\mathbf{1}}$ is a boolean function which returns 1 when the condition is true and 0 otherwise. The hyper-parameter ξ is a confidence threshold in the range $[0, 1)$ which defines the minimum probability of the predicted label for the sample to be considered stable. A lower threshold ξ implies a softer condition for a *stable sample*.

Whenever a sample is stable for both students, then the Euclidean distance is used to measure the prediction consistency. The stability of sample x for student i is defined by:

$$\mathcal{E}_x^i = \|f(\theta^i, x) - f(\theta^i, \bar{x})\|^2 \tag{2}$$

The smaller $\mathcal{E}_x^i$ is, the more stable sample x is for student i. If $\mathcal{E}_x^i < \mathcal{E}_x^j$, then student i will share its knowledge about sample x; otherwise, student i learns from student j about sample x. The distance between the predictions of the two students can be measured using the mean squared error (MSE) as:

$$\mathcal{L}_{mse}(x) = \|f(\theta^i, x) - f(\theta^j, x)\|^2 \tag{3}$$

The stabilization loss for student i on sample x is then given by:

$$\mathcal{L}_{sta}^i(x) = \begin{cases} \{\mathcal{E}_x^i > \mathcal{E}_x^j\}_{\mathbf{1}} \mathcal{L}_{mse}(x), & \text{if } \mathcal{R}_x^i = \mathcal{R}_x^j = 1 \\ \mathcal{R}_x^j \mathcal{L}_{mse}(x), & \text{otherwise} \end{cases} \tag{4}$$

Therefore, if x is not stable for student i, then x contributes to the stabilization loss for student i only if x is stable for student j. On the other hand, if x is stable for student i, then sample x contributes to the stabilization loss for student i only if x is even more stable for student j. The stabilization loss definition ensures that only reliable knowledge is shared between the students and the amount of shared knowledge is controlled by the threshold ξ.

Besides the stabilization loss, another important role is played by the consistency loss, commonly used in consistency-based methods and defined by:

$$\mathcal{L}_{con}^i(x) = \mathcal{R}(f(\theta^i, x), f(\theta^i, \bar{x})) \tag{5}$$

where $\mathcal{R}(\cdot, \cdot)$ is a distance measure that can be either MSE or KL divergence. The stabilization constraint drives the students to generalize better given small perturbations on sample x.

Finally, the overall training loss for student i can be summarized as follows:

$$\mathcal{L}^i = \mathcal{L}^i_{cls} + \lambda_1 \mathcal{L}^i_{con} + \lambda_2 \mathcal{L}^i_{sta} \tag{6}$$

where $\mathcal{L}^i_{cls}$ is the standard classification loss while λ_1 and λ_2 are hyper-parameters to balance the weight of each term. The blueprint of DS training is listed in Algorithm 1.

Algorithm 1: Training of Dual Student for Semi-Supervised Learning [3]

```
Require : Batch $\mathcal{B}$ containing labeled and unlabeled samples
Require : Two independent models $f(\theta^i)$ and $f(\theta^j)$
for each batch $\mathcal{B}$ do
    get $\mathcal{B}_1$,$\mathcal{B}_2$ from $\mathcal{B}$ by data augmentation;
    for model in { $f(\theta^i)$, $f(\theta^j)$ } do
        Calculate $\mathcal{L}_{cls}$ on labeled samples;
        Calculate $\mathcal{L}_{con}$ by Eq. 5 between $\mathcal{B}_1$ and $\mathcal{B}_2$;
    end
    for each unlabeled sample $x$ do
        for model in { $f(\theta^i)$, $f(\theta^j)$ } do
            Determine whether $x$ is stable by Eq. 1;
        end
        if both $f(\theta^i)$ and $f(\theta^j)$ are stable for $x$ then
            Calculate the stability of $x$ by Eq. 2;
        end
        Calculate $\mathcal{L}_{sta}$ for $f(\theta^i)$ and $f(\theta^j)$ by Eq. 4;
    end
    Update $f(\theta^i)$ and $f(\theta^j)$ by the loss in Eq. 6
end
```

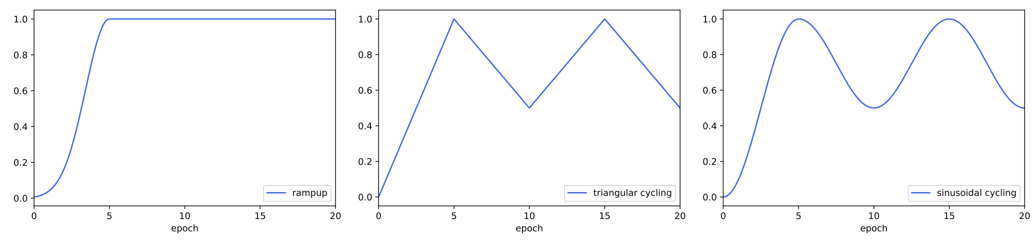
2.2 Data augmentation

One of DS's key features is to augment each batch $\mathcal{B}$ during the training to get $\mathcal{B}_1$ and $\mathcal{B}_2$. The students, then, aim to predict the same label y on both the augmented data. Usually, data augmentation for ASR is directly applied to the waveform [16, 17]. Recently, Park et al. [18] proposed SpecAugment, a data augmentation method instead applied to the filter bank coefficients. We decided to simply apply Gaussian noise over the 39 features, with zero-mean and standard deviation σ, appropriately tuned in the experiments. We are aware that this augmentation method may slightly break the temporal relation encoded in delta and delta-delta. However, data augmentation was out of this project's scope, and other augmentation methods can be explored as future work.

2.3 Scheduled learning

We improved DS training by introducing a novel idea: scheduled learning. Namely, learning mostly from the classification of labeled samples is interleaved with learning from knowledge exchange exploiting unlabeled samples. The reason that drives this variation is that once a student has learned from the other student, it may be better to exploit this newly acquired knowledge focusing more on the labeled samples. Lately, the model can exchange further (and better) knowledge with the other student, and so on. The modification was implemented by updating the values of λ_1 and λ_2 at each epoch according to a cyclical schedule with period T_{cycle}, while in [3] they follow a ramp-up only in the first 5 epochs and then they remain constant.

We proposed two new schedules: triangular cycling and sinusoidal cycling, both shown in Figure 1 and compared to the original ramp-up. The values on the y axis, in the range $[0, 1]$, must be multiplied by two scale factors, λ_1^{max} and λ_2^{max}, to get the correct λ_1 and λ_2 respectively along with the training. When λ_1 and λ_2 reach their minimum values, the students are optimized by minimizing mainly the classification loss. On the other hand, when λ_1 and λ_2 reach their peak, knowledge exchange comes into play. In the first period, every schedule starts from 0, since it is useless to share knowledge at the very beginning when both students still have not learned anything. Contrarily, for the remaining periods, the cyclical schedules have their minimum value set to 0.5 instead of 0 to avoid focusing exclusively on the labeled data, which would lead to overfitting, decreasing the overall performance.



(a) Ramp-up (b) Triangular (c) Sinusoidal

Figure 1: Learning schedules to control the values of λ_1 and λ_2. Triangular and sinusoidal cycling are the novel learning schedules proposed by us.

3 Experiments

3.1 Data

We performed our experiments on the TIMIT dataset [19], which contains utterances from native English speakers along with phonetic transcriptions. Following standard recipes [20, 21] and previous work [1], we excluded glottal stop segments and SA sentences (read by all the 630 speakers), and we used the core test set, consisting of 192 sentences. We drew out from the training set 184 sentences as the validation set for tuning hyper-parameters and monitoring the training. To achieve a less biased generalization assessment in the validation phase, the split was done guaranteeing that no speaker appears in both sets. The networks' inputs are 39-dimensional feature vectors, each containing 13 MFCCs, delta, and delta-delta features. The feature extraction was performed with a Hamming window of length 30 ms and a shift of 10 ms, resulting in 1049763 training frames, 54912 validation frames, and 56623 test frames. We used the standard set of 48 phones for training, while in the evaluation phase, we mapped them to 39 phones, as done in [1, 20, 15]. To experiment with the benefits of unlabeled data, we removed the targets to a percentage of frames. We varied the percentage of labeled samples to 1%, 3%, 5%, 10%, 20%, and 30%. Importantly, each utterance can only be either fully labeled or fully unlabeled. The whole procedure and the resulting numbers are in line with previous work [1, 15], and so a fair comparison can be made.

The features were then normalized. Three different normalization types were considered: over the whole training set, over each speaker separately, and each utterance individually. Some preliminary experiments on a 3-layer mono-directional Long Short Term Memory (LSTM) showed that speaker-dependent normalization significantly achieves better results; hence, we adopted this normalization for the rest of the experiments.

3.2 Architectures

We considered two architectures in the experiments, consisting of 3 LSTM layers of 96 units, followed by a fully connected layer. The only difference between the two used architectures is the type of LSTM employed. Indeed, one consists of mono-directional LSTM layers, whereas the other consists of bidirectional LSTM layers. The number of layers and the number of units were chosen for a fair comparison with the work by Lin et al. [15].

We tested all the combinations of the architectures for the two students. Therefore, one combination uses mono-directional LSTM layers in both students (mono-DS), while the other uses bidirectional LSTM layers (bi-DS). Finally, a third combination, called Imbalanced Student (IS), has one of each architecture.

Moreover, to analyze unlabeled data benefits, we set as baselines the single architectures with mono-directional LSTM layers (mono-LSTM) and bidirectional LSTM layers (bi-LSTM), trained in a fully-supervised way.

3.3 Hyper-parameters

In line with Lin et al. [15], the batch size was set to 100. The batch contains both labeled and unlabeled data proportionally to the composition of the training set. Consequently, in mono-LSTM

Table 1: Network architecture, where L represents the length (number of frames) of an utterance.

Layer (type)	Output Shape
Utterance $\mathbf{x}$	L$\times$ 39
LSTM	L$\times$ 96
LSTM	L$\times$ 96
LSTM	L$\times$ 96
Dense	L$\times$ 48

Table 2: Optimal hyper-parameters found for mono-DS with the percentage of labeled data equal to 30% on the TIMIT dataset.

schedule	σ	ξ	λ_1^{max}	λ_2^{max}	con. loss	val. accuracy (%)
ramp-up	0.5	0.3	10	100	MSE	73.32
triangular	0.3	0.3	10	100	MSE	72.83
sinusoidal	0.5	0.4	10	100	MSE	73.60

and bi-LSTM, which contain only labeled data, the number of samples actually considered in each batch was equal to $\%labeled \times 100$. In this way, the gradient updates for labeled samples were the same for both DS and supervised training.

We adopted Adam with weight decay, a well-known optimizer which performs better than the straightforward stochastic gradient descent. We selected learning rate $\eta = 0.01$ and weight decay $wd = 10^{-4}$ with preliminary experiments on mono-LSTM. For all the other hyper-parameters, default values were used. Finding optimal settings for the optimizer was out of scope since our goal was not to provide state-of-the-art SSL results on TIMIT but rather to show the benefits of DS training for sequential data.

DS algorithm introduces five additional hyper-parameters not used in standard supervised learning procedure: λ_1^{max}, λ_2^{max}, σ, ξ, and T_{cycle}. We performed an exhaustive grid search to tune them and select between MSE and KL as consistency loss for each of the three learning schedules. The grid search was only done for mono-DS with 30% of labeled data. Given the number of hyper-parameters and the project's time-scope, it was unfeasible to tune them also for bi-DS, IS and different percentages of labeled data. Moreover, we kept T_{cycle} fixed to 10 epochs, since in the standard DS the ramp-up was over the first 5 epochs. A tuning of this hyper-parameter is left for future work.

In the grid search, the training was run over 20 epochs. λ_1^{max} and λ_2^{max} were searched in log space, whereas σ and ξ in linear space. A summary of all the configurations tested in the grid search is shown in Figure 2. In total, over 1500 hyper-parameter settings were considered. It is important to mention that the most-right plots reveal the correlation between the two students, where it can be easily seen that each student learns as much as the other for most of the cases. The top 10 hyper-parameter settings are shown in Figure 3, and only triangular and sinusoidal cyclical schedules fall into this ranking. The 10 most promising configurations for each learning schedule were further tested over a more extended training of 100 epochs, and the final optimal hyper-parameters are shown in Table 2.

3.4 Practical setup

The work, accessible on GitHub[1], was implemented from scratch using TensorFlow, a powerful and open-source deep learning framework. The experiments were run on one GPU, using Google Colab and Google Cloud Platform.

[1]https://github.com/simone-porcu/DT2119-Final-Project

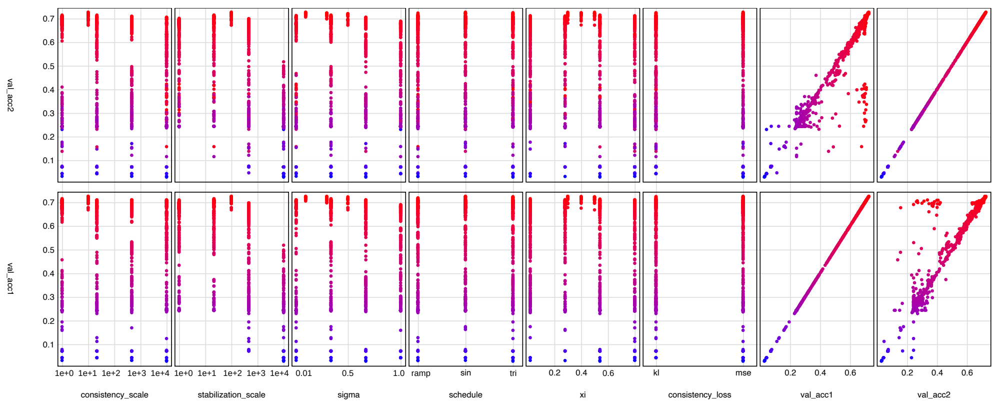


Figure 2: Scatter plot of more than 1.500 configurations tested in the grid search.

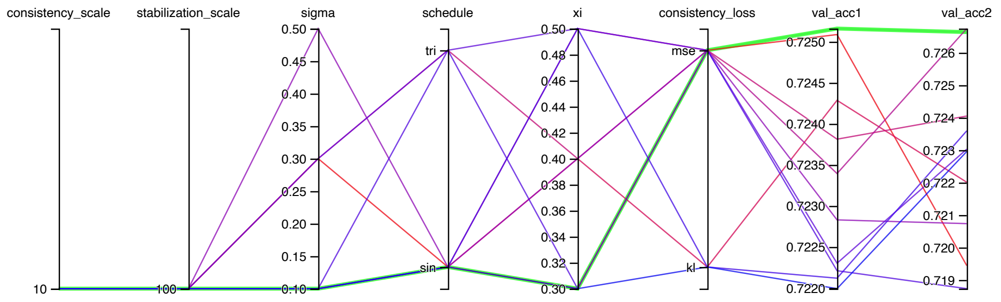


Figure 3: Parallel coordinate plot showing the top 10 configurations from the grid search, the one with the highest validation accuracy is highlighted in green.

4 Results

The optimal hyper-parameters previously found were used to train the models for 100 epochs with different percentages of labeled data. Table 3 shows a comparison between the baseline mono-LSTM and mono-DS. The comparison also takes into consideration the three different schedules investigated. Mono-DS with the triangular cyclical schedule is the best model in the less supervised experiments, i.e., with 1%, 3%, 5%, and 10% of labeled data, gaining $\approx$ 9% test accuracy against mono-LSTM. On the other hand, for 20% and 30% of labeled data, mono-DS with the ramp-up schedule is the best one, gaining 7.96% and 6.36%, respectively, over mono-LSTM.

Table 4 compares the baseline mono-LSTM and IS. It is noteworthy to highlight that the results for IS refer to the mono-directional student. Indeed, the imbalanced configuration goal is to improve an efficient small student (mono-directional) by training it with a larger and stronger one (bidirectional), similar to what happens in knowledge distillation, except that both students share knowledge. The conclusions are similar to mono-DS. IS with the triangular schedule outperforms all the other models, apart from 30% of labeled data where IS with the sinusoidal schedule achieved the highest accuracy. Moreover, we can observe that, even though the bidirectional student should pump up the mono-directional performance in the IS setup, this is not the case; indeed, there is no significant difference between the accuracy achieved by mono-DS and IS.

Furthermore, additional experiments compared bi-LSTM to bi-DS, as shown in Table 5. Also in this case, bi-DS outperforms bi-LSTM for all the percentages of labeled samples. Besides, as expected, bi-DS is better than mono-DS in terms of accuracy, given the relative capacity, at the cost of less scalability.

The results also point out that mono-DS with the triangular cyclical schedule outperforms bi-LSTM for small percentages of labeled data, i.e., 1%, 3%, and 5% (compare Table 3 and 5). On the other hand, considering the fully-supervised training, mono-LSTM is considerably worse than bi-LSTM.

This indicates that a network can beat a stronger one thanks to DS training by leveraging unlabeled data.

Finally, mono-DS and IS were compared to SSL renowned methods tested on the TIMIT dataset, as shown in Table 6. We can notice that both mono-DS and IS achieved better results than previous work [1, 15], including pMP [2], the current SSL state-of-the-art on TIMIT.

Table 3: Results on frame-based phone classification on the test and validation sets on the TIMIT dataset for mono-LSTM and mono-DS, for each learning schedule.

Labeled	mono-LSTM		mono-DS ramp-up		mono-DS tri		mono-DS sin	
Obs. (%)	**val. acc.**	**test acc.**	**val. acc.**	**test acc.**	**val. acc.**	**test acc.**	**val. acc.**	**test acc.**
1	50.81	51.59	56.34	56.20	56.66	**56.69**	55.77	55.63
3	57.13	56.73	62.27	61.99	63.14	**63.08**	62.59	61.93
5	59.74	59.65	65.00	64.27	65.34	**65.22**	64.68	64.62
10	62.84	61.86	68.15	67.07	68.33	**67.82**	67.81	67.29
20	66.83	65.39	71.39	**70.60**	71.03	70.12	70.91	70.46
30	69.21	67.91	73.32	**72.23**	72.83	71.62	73.60	72.20

Table 4: Results on frame-based phone classification on the test and validation sets on the TIMIT dataset for mono-LSTM and IS (the accuracy of the mono-directional student is shown), for each learning schedule.

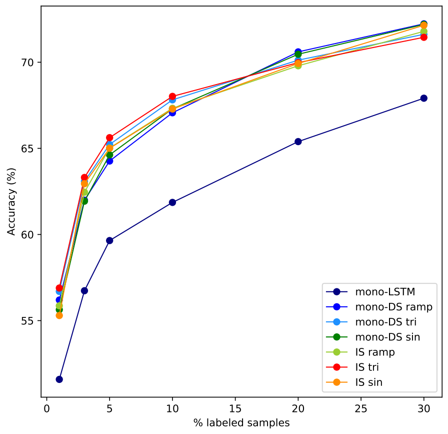
Labeled	mono-LSTM		IS ramp-up		IS tri		IS sin	
Obs. (%)	**val. acc.**	**test acc.**	**val. acc.**	**test acc.**	**val. acc.**	**test acc.**	**val. acc.**	**test acc.**
1	50.81	51.59	56.59	55.86	56.78	**56.89**	56.15	55.30
3	57.13	56.73	63.05	62.46	63.97	**63.31**	63.32	62.95
5	59.74	59.65	65.56	65.02	66.22	**65.62**	65.11	65.01
10	62.84	61.86	68.25	67.33	68.76	**68.02**	67.97	67.28
20	66.83	65.39	71.52	69.69	71.56	**69.98**	71.63	69.93
30	69.21	67.91	73.39	71.79	72.99	71.45	73.22	**72.15**

Table 5: Results on frame-based phone classification on the test and validation sets on the TIMIT dataset for bi-LSTM and bi-DS, for each learning schedule.

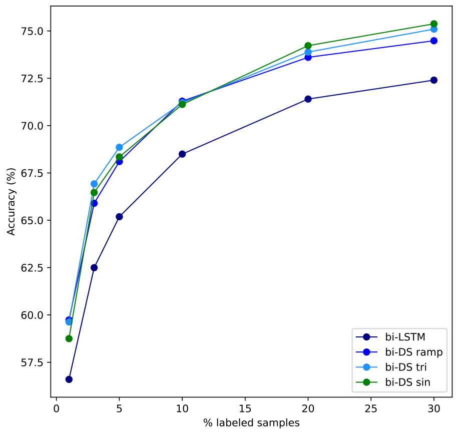
Labeled	bi-LSTM		bi-DS ramp-up		bi-DS tri		bi-DS sin	
Obs. (%)	**val. acc.**	**test acc.**	**val. acc.**	**test acc.**	**val. acc.**	**test acc.**	**val. acc.**	**test acc.**
1	56.48	56.60	59.70	**59.74**	59.65	59.63	58.80	58.75
3	63.99	62.50	67.16	65.90	67.29	**66.92**	67.14	66.47
5	66.28	65.19	69.22	68.10	69.28	**68.85**	69.34	68.35
10	69.40	68.50	72.21	**71.29**	72.40	71.21	72.77	71.12
20	72.97	71.40	75.39	73.61	74.72	73.88	75.37	**74.22**
30	73.57	72.40	75.90	74.48	76.21	75.09	76.74	**75.38**

Table 6: Accuracy rates (%) for frame-based phone classification on the TIMIT dataset for mono-LSTM, SSSAE [1], pMP [2], Teacher-Student [15], mono-DS and IS. The optimal learning schedule was chosen for each percentage of labeled samples according to the values in Table 3.

Method	Reference	10% labeled	30% labeled
		Test accuracy (%)	
mono-LSTM	this work	61.86	67.91
SSSAE	[1]	67.03	69.65
pMP	[2]	67.22	71.06
Teacher-Student	[15]	67.15	70.78
mono-DS	this work	67.82	**72.23**
IS	this work	**68.02**	72.15



(a) Mono-LSTM, mono-DS and IS.



(b) Bi-LSTM and bi-DS.

Figure 4: Frame-based phone recognition accuracy (%) for different percentages of labeled samples on the TIMIT dataset.

5 Conclusions

In this paper, we conducted a significant number of experiments to validate DS training benefits for sequential data. The results were consistent through all the experiments for different percentages of labeled data. DS always outperforms the standard fully-supervised learning procedure given the same architecture and hyper-parameters. Therefore, we can conclude that the DS approach is beneficial to exploit large amounts of unlabeled samples even for handling sequential data such as speech. We also introduced two novel scheduled learnings, employing triangular and sinusoidal cycling, which showed slightly better results than ramp-up.

Further experiments could be to tune the hyper-parameters for each percentage of labeled data, taking into consideration the learning rate and different optimizers. Future work may also focus on other data augmentation methods. Finally, experiments on the sinusoidal/triangular cycle period may investigate its influence on the performance, whose value was instead fixed in this project.

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