DATA2VEC-AQC: SEARCH FOR THE RIGHT TEACHING ASSISTANT IN THE TEACHER- STUDENT TRAINING SETUP

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ABSTRACT

In this paper, we propose a new Self-Supervised Learning (SSL) algorithm called data2vec-aqc, for speech representation learning from unlabeled speech data. Our goal is to improve SSL for speech in domains where both unlabeled and labeled data are limited. Building on the recently introduced data2vec \cite{1}, we introduce additional modules to the data2vec framework that leverage the benefit of data augmentations, quantized representations, and clustering. The interaction between these modules helps solve the cross-contrastive loss as an additional self-supervised objective. data2vec-aqc achieves up to 14.1\% and 20.9\% relative WER improvement over the existing state-of-the-art data2vec system over the test-clean and test-other sets, respectively of LibriSpeech, without the use of any language model (LM). Our proposed model also achieves up to 17.8\% relative WER gains over the baseline data2vec when fine-tuned on a subset of the Switchboard dataset. Code: https://github.com/Speech-Lab-IITM/data2vec-aqc.

Index Terms— self-supervised learning, automatic speech recognition, low-resource, domain adaptation

1. INTRODUCTION

SSL for speech representation learning from unlabeled data has been an active area of research over the past few years \cite{2, 3, 4}. All of these proposed systems try to solve a Masked Acoustic Modeling (MAM) task in some form. data2vec \cite{1} was one of the first works to show that learning from latent targets is possible for SSL-based speech representation learning.

While it is common knowledge that SSL benefits from scale \cite{5}, systems that can learn speech representations with limited amount of unlabeled data is the need of the hour \cite{5}. Given that the amount of unlabeled data in most languages is quite limited, SSL methods that can learn meaningful representations even in low-resource regimes (both data and compute) can help in the universal adoption of such systems. Moreover, to date, SSL in speech fails to perform well in instances of domain shift between the unlabeled source and labeled target \cite{6, 7}. Data augmentation is often considered to be an effective strategy in the supervised setting, specially in cases of limited access to labeled data \cite{8}. Previous to its adoption in Speech as MAM, SSL in Computer Vision (CV) existed as a task that focuses on learning to identify randomly augmented versions of the same image. Inspired by this, recent works in speech \cite{9, 10} exploit data augmentations to improve the performance and generalizability of SSL models. We adopt this simple yet powerful idea to learn useful speech representations efficiently when unlabeled data for a domain is scarce.

Main Contributions: In this paper, we propose data2vec-aqc, a novel SSL-based pre-training methodology for learning speech representations from low-resource unlabeled speech. We build on data2vec and achieve this by proposing several improvements to it. First, we make data2vec concurrently solve a MAM-based cross-contrastive task between the student and teacher networks by passing randomly augmented versions of the same audio sample passed through each network. We add a quantizer module similar to \cite{2}, as sampling negatives from the quantized representations has been proven to be effective. Additionally, we introduce a clustering module \cite{10}, to cluster the quantized representations and control the effect of those negatives in the contrastive loss computation, that share the same cluster as the positive. Our proposed data2vec-aqc achieves significant improvements over the standard data2vec framework when working with a limited amount of pre-training data. Additionally, when pre-trained on large-scale unlabeled speech (960 hours of unlabeled LibriSpeech data), our model performs significantly better than the baseline data2vec model over the several downstream tasks presented over SUPERB \cite{11}.

2. METHODOLOGY

The standard data2vec architecture involves a student and teacher network, both of which see raw speech as the input, and the teacher’s parameters are updated based on an exponential moving average of the student’s (a momentum en-
A simple $L_2$-loss is computed between the student embedding (after a linear projection) and the average of the embeddings from the top 8 layers of the teacher network. Though there is an option to switch to $L_1$-loss in the data2vec setup, the authors of [1] find that a simple $L_2$-loss works well for speech processing. Following the solid lines and entities in solid borders in Fig.1 would illustrate the standard data2vec architecture described above.

While the data2vec framework has shown remarkable results across a variety of SLP tasks [11], in this paper, we take a step further and focus on finding the right “teaching assistant” for the existing data2vec student-teacher learning framework. To achieve this, we introduce 3 additional components to the existing data2vec setup, which are: augmentation(s), a quantizer module, and a clustering module. We call our approach data2vec-aqc and highlight these components in the dashed borders of Fig.1. The following subsections elaborate on each of these components, and how each of them independently and jointly leads to the success of data2vec-aqc.

### 2.1. Augmentations (data2vec-a)

The primary focus of data2vec-a is to apply augmentation(s) to the raw audio in the standard data2vec framework before the feature extraction stage. Table 1 demonstrates the effect of the different augmentations applied. The augmentation choices and their effects have been described in Section 4. Adding this component to the data2vec setup leads to no change in the loss computation and we still use the standard data2vec loss given by,$ L_{\text{con}} = -\log \frac{\exp(sim(s_t, y_t)/\kappa)}{\sum_{\tilde{y} \sim Y_t} \exp(sim(s_t, \tilde{y})/\kappa)} \quad (1)  
$ 

where $s_t \in S_t$, $y_t \in Y_t$ and $sim(a, b) = a^T b / \|a\|\|b\|$ computes the cosine similarity between the student and teacher representations. The temperature parameter is represented by $\kappa$. For the rest of the paper, we denote the standard data2vec with augmentation(s) as data2vec-a, the standard network trained with $L_2 + L_{\text{con}}$ as data2vec + $L_{\text{con}}$, and finally, the standard network trained with $L_2 + L_{\text{con}}$ and input augmentation(s) as data2vec-a + $L_{\text{con}}$.

### 2.2. Quantized Representations (data2vec-aq)

Sampling positive and negative examples from discrete quantized representations for contrastive loss calculation on speech representations have proven to be effective in [2] over the originally proposed [16] which calculates the same over latent network representations. The quantizer module integrated into data2vec-aq borrows its design from [2]. Formally put, let $X^s$ and $X^t$ represent the features extracted from the inputs to the student and teacher, respectively. Passing these embeddings through the quantizer yields the discrete representations $Q^s$ and $Q^t$, respectively. Findings from [10]...
establish the benefit of using a cross-contrastive loss when using augmentations. As data2vec-aqc makes use of augmentation(s), we now plug in the cross-contrastive loss \( L_{cc} \) to the data2vec framework. Thus, if \( S_t \) represents the student embeddings and \( Y_t \) represents the embeddings from the teacher, over all the masked time-steps, we define the following loss terms over each masked time-step \( t \) as:

\[
L_{k\text{-cross}} = -\log \frac{\exp(\text{sim}(s_t, q_t^k)/\kappa)}{\sum_{q \sim Q_t^k} \exp(\text{sim}(s_t, q)/\kappa)} \tag{2}
\]

\[
L_{t\text{-cross}} = -\log \frac{\exp(\text{sim}(y_t, q_t^i)/\kappa)}{\sum_{q \sim Q_t^i} \exp(\text{sim}(y_t, q)/\kappa)} \tag{3}
\]

where, \( s_t \in S_t, y_t \in Y_t \). Equations 2 and 3 compute the contrastive loss between the student embeddings and the quantized representations of the teacher’s input and vice-versa for the masked time steps. We now define the overall cross-contrastive loss \( L_{cc} \) as, \( L_{cc} = \alpha L_{k\text{-cross}} + \beta L_{t\text{-cross}} \). The overall loss function for data2vec-aqc is \( L_2 + L_{cc} \), with \( \alpha = \beta = 0.5 \). The diversity loss from [2] is also a part of the final loss computation as we have a quantizer in place.

### 2.3. Clustering of Negatives (data2vec-aqc)

As suggested by [10], using a k-means clustering module to segregate negative examples and controlling the effect of weak non-informative negative examples helps the overall contrastive learning task. We make use of the same clustering module [10] which has cluster factor (CF) and scale factor (SF) as its hyper-parameters. If \( NF \) is the number of frames per speech sample in a mini-batch of audios, then the number of clusters per each audio in this mini-batch would be \( \text{ceil}(NF/CF) \). Upon clustering \( Q_t \), we identify the cluster to which the positive sample \( q_t \) belongs. If \( q_t \) belongs to the cluster \( R \), our objective would then be to control the “influence” of those negatives that share the same cluster \( R \). As suggested in [10], we scale down the cosine similarity values of the negative examples from \( R \) with the anchor \( c_t \) by a scaling factor \( SF \). Let \( Q^* \) denote the sampled set of negative examples. i.e., \( Q^* = \{q \sim Q_t \} \) and let the samples in \( Q^* \) be represented by \( q \). The formula for contrastive loss with an integrated clustering module would then be:

\[
L_c = -\log \frac{e^{(\text{sim}(c_t, q)/\kappa)}}{\sum_{q \in R} e^{(\text{sim}(c_t, q)/\kappa)} + \sum_{q \notin R} e^{(\text{sim}(c_t, q)/\kappa)}} \tag{4}
\]

In equation 4 we demonstrate that the influence of negative examples sharing the same cluster as the positive is guided by the scalar \( SF \). The overall loss function for data2vec-aqc would still be \( L_2 + L_{cc} \), but with each of the contrastive loss terms in \( L_{cc} \) taking the form of equation 4. We choose \( CF = 16 \) and \( SF = 0.3 \) in the pooled setting as the hyper-parameters for the clustering module after observing the results in [10].

### 3. EXPERIMENTAL SETUP

#### 3.1. Pre-training

In Tables 1 and 2, we present results for the data2vec BASE architecture (12 layers) pre-trained over the 360-hour split of the LibriSpeech dataset [17]. We have based our experiments on the 360-hour split, with a focus on developing SSL models using limited amounts of unlabeled data. All models have been pre-trained for 88750 updates (or 250 epochs) over LibriSpeech-360h on 4 A-100 GPUs, with the maximum number of tokens per GPU being 3.8 million. All other hyper-parameters were borrowed from the original setting in [1, 18]. We evaluate the proposed data2vec-aqc BASE model pre-trained on 960h of LibriSpeech, over the array of downstream tasks presented by SUPERB [11].

#### 3.2. Fine-tuning

For fine-tuning the pre-trained data2vec models, we drop all the added pre-training modules and just add a linear output layer on top of the encoder stack to solve the CTC task [2]. The pre-trained models presented in Tables 1 and 2 were fine-tuned for 36400 updates on the 100h split of the LibriSpeech dataset. To demonstrate the robustness of data2vec-aqc’s pre-training approach, we also fine-tune these pre-trained models for 11000 updates, on the 30-hour split of the Switchboard dataset [19]. Switchboard data being telephonic and conversational, these results showcase the generalization capabilities of the proposed approach.

| Table 1. Effect of different augmentations and \( L_{con} \) |
|-------------|------------|------------|------------|------------|
| Model       | clean      | other      | clean      | other      |
| Baseline data2vec | 6.4        | 17.5       | 6.4        | 17.7       |
| data2vec + \( L_{con} \) | 9.3        | 23.4       | 9.6        | 23.9       |
| data2vec-a (I) | 6.4        | 16.5       | 6.6        | 16.8       |
| data2vec-a (II) | 6.1        | 15.5       | 6.2        | 16.0       |
| data2vec-a + \( L_{con} \) | 6.6        | 17.2       | 6.8        | 17.5       |

### 4. RESULTS AND ANALYSIS

Results from Tables 1 and 2, are without the use of any LM.

**data2vec-a and \( L_{con} \):** Results from Table 1 indicate that adding an additional contrastive loss, degrades the performance of data2vec. However, introducing augmentations to the data2vec framework helps improve the performance over the baseline. The augmentation applied in data2vec-a (II) is an amalgamation of 3 different augmentation strategies. The audio sample is augmented with additive noise at a random signal-to-noise ratio (SNR) between 3dB and 15dB, with a probability of 0.6. With a probability of 0.7, the speech sample is the convolved with a random Reverberation Impulse Response (RIR). Eventually, with a probability of 0.8, at a
Table 2. data2vec-aqc performance (% WER) over different test sets without use of a language model.

| Model                        | dev clean | dev other | test clean | test other | WSJ dev93 | WSJ eval93 | Switchboard Dev |
|------------------------------|-----------|-----------|------------|------------|-----------|-------------|-----------------|
| **960h Pretraining for 400K updates** |           |           |            |            |           |             |                 |
| data2vec BASE [1]            | 4.2       | 9.6       | 4.2        | 9.7        | 20.4      | 20.0        |                 |
| wav2vec 2.0 BASE [2]         | 6.1       | 13.8      | 6.1        | 13.5       | 22.8      | 22.3        |                 |
| **360h Pretraining for 88750 updates** |           |           |            |            |           |             |                 |
| Baseline data2vec            | 6.4       | 17.5      | 6.4        | 17.7       | 23.1      | 22.3        | 21.3           |
| data2vec-a                   | 6.1       | 15.5      | 6.2        | 16.0       | 23.1      | 22.8        | 18.9           |
| data2vec-aq                  | 5.7       | 15.0      | 6.0        | 15.2       | 22.7      | 22.7        | 18.2           |
| data2vec-aq (Dual Augmentation) | 7.0     | 17.7      | 7.1        | 18.4       | 24.6      | 23.7        | 21.4           |
| data2vec-aqc                 | 5.3       | 13.9      | 5.5        | 14.0       | 22.0      | 21.7        | 17.5           |

signal-to-noise ratio (SNR) between 0dB and 15dB, background noise has been added from random noise samples of the noise set from the MUSAN corpus [20]. The reason behind this specific set of augmentations for data2vec-a (II) arises from the work of [21], which uses augmentations in a supervised setting and [10], which makes use of the same in a self-supervised setting. data2vec-a (I) on the other hand, makes use of the same set of augmentations but with no probability associated with any of the augmentations involved. In other words, additive noise, reverberation, and random noise samples are always applied in the case of data2vec-a (I). It is to be noted that, in the case of data2vec-a (I) and data2vec-a (II), the augmentations are applied only to the input to the student, and the teacher network gets the original sample as its input. Since data2vec-a (II) has the better performing augmentation, for ease of reference, when we refer to data2vec-a further, it indicates data2vec-a (II). We notice in data2vec-a + L Con, that the gains obtained from data2vec-a are offset when we add an additional contrastive loss. This again indicates that sampling negatives from latent representations might not be the best choice when implementing a contrastive loss and provides the motivation to integrate a quantization module.

data2vec-aq and data2vec-aqc: From the results in Table 2, we notice that with the help of a quantization module and a cross-contrastive loss ($L_{cc}$), data2vec-aq outperforms data2vec-a. This re-emphasizes the need to sample negative examples from quantized representations and also demonstrates the effectiveness of the cross-contrastive loss. To observe the effect of passing an augmented input to the teacher network, we pass the augmentation from data2vec-a (I) to the teacher and the augmentation from data2vec-a (II) to the student. However, we notice that data2vec-aq (Dual Augmentation) under-performs data2vec-a. Results from [22] suggest that using a weak-augmentation strategy for teacher is beneficial. The augmentation from data2vec-a (I) not being a weak augmentation explains this observation. Gains from efficient negative sampling through a clustering module can be observed with data2vec-aqc outperforming data2vec-aq. The proposed data2vec-aqc achieves up to 14.1% and 20.9% relative WER improvement compared to the Baseline data2vec over the test-clean and test-other sets, respectively of LibriSpeech, when fine-tuned on LibriSpeech-100h split.

Comparison with the 960h pre-trained models: Table 2 also presents the results of wav2vec 2.0 BASE and data2vec BASE that have been pre-trained on LibriSpeech-960h for 400K updates and fine-tuned on LibriSpeech-100h for 80K updates. These fine-tuned models have been sourced from the corresponding repositories of fairseq [18]. Though data2vec-aq has been pre-trained only on the 360h split for 88750 updates and fine-tuned on LibriSpeech-100h for 36400 updates, it competes in terms of performance with wav2vec 2.0 BASE. These results have been presented to demonstrate the effectiveness of data2vec-aqc’s pre-training approach.

Adaptation and SUPERB: data2vec-aqc model fine-tuned on LibriSpeech-100h outperforms the baseline data2vec model over the dev93 and eval93 sets of the WSJ dataset [23]. It is to be noted that the data from the WSJ dataset was not used in the pre-training or the fine-tuning stages. When fine-tuned on the 30-hour subset of the Switchboard data, data2vec-aqc outperforms the baseline data2vec model by 17.8% relative WER, thereby demonstrating its domain adaptation capabilities. data2vec-aq BASE pre-trained on LibriSpeech-960h has been evaluated over SUPERB [11] and is ranked 5th over the Challenge public set, significantly outperforming the data2vec BASE model which is ranked 13th in the same leaderboard. Also, data2vec-aq is among the best performing models for the Speech Enhancement task.

5. CONCLUSION

In this paper, we present data2vec-aqc, a novel SSL-based pre-training approach based on data2vec that improves speech representation learning with limited amounts of unlabeled data. As a part of our future work, we would like to explore and enhance data2vec-aqc’s performance on various other downstream tasks.
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