Efficient Active Learning for Automatic Speech Recognition via Augmented Consistency Regularization

Jihwan Bang\textsuperscript{2*}, Heesu Kim\textsuperscript{1,3*}, YoungJoon Yoo\textsuperscript{1}, Jung-Woo Ha\textsuperscript{1}

\textsuperscript{1}Clova AI Research, NAVER Corp.
\textsuperscript{2}Search Solution Inc.
\textsuperscript{3}Dept. of Electrical and Computer Engineering, Seoul National University.

\{jihwan.bang,heesu.kim89,youngjoon.yoo,jungwoo.ha\}@navercorp.com

Abstract

The cost of labeling transcriptions for large speech corpora becomes a bottleneck to maximally enjoy the potential capacity of deep neural network-based automatic speech recognition (ASR) models. Therefore, in this paper, we present a new training scheme that minimizes the labeling cost by adopting the concepts of semi-supervised learning (SSL) and active learning (AL) approaches and making a synergy from them. While AL studies only focus on selecting minimized the number of samples to be labeled with a criterion and taking advantage of such samples, we show that the training efficiency can be further improved by utilizing the unlabeled samples by sophisticatedly designing unsupervised loss that complements the unwanted behavior of supervised loss effectively. Our unsupervised loss is built on Consistency-Regularization (CR) approach, and we propose appropriate augmentation techniques to adopt CR in ASR field successfully. From the qualitative and quantitative experiments on the real-world dataset from deployed end-user voice assistant services, we show that the proposed methods can handle a large number of unlabeled speech data to achieve competitive model performance, with a sustainable amount of human labeling cost.

Index Terms: speech recognition, active learning, semi-supervised learning, labeling cost

1. Introduction

End-to-End Automatic Speech Recognition (E2E-ASR) models \cite{1, 2, 3} have achieved an impressive improvement in Large Vocabulary Automatic Speech Recognition (LVASR) area. The state-of-the-art E2E-ASR models integrate Acoustic Model (AM) and Language Model (LM) as a jointly trainable single model \cite{4, 5}. Given more training data, thus, the performance of the E2E-ASR models can continue to be improved by benefiting from large-scale data while avoiding overfitting. However, these models require large-scale speech corpora with ground truth transcription for training \cite{1}. Furthermore, the cost to collect the ground truth labels might be more troublesome in ASR because the cost to transcribe speech utterances is more expensive due to its difficulty and time-consuming property compared to single labeling for image classification. Therefore, selecting the utterances to be annotated is necessary in reducing the labeling cost up to a sustainable level while providing competitive quality of services.

*Authors contributed equally to this research. The authors are sorted by alphabetical order.

This work is done while Heesu Kim did internship at Clova AI Research, NAVER Corp.

Many studies have been explored to choose the candidates for annotation, thus reducing the labeling costs. They can be categorized into two streams; Active Learning (AL) and Semi-Supervised Learning (SSL). AL reduces the labeling cost by selecting useful samples annotated by human experts (i.e., HLS), which are the most effective for model training. Meanwhile, SSL utilizes a large number of unlabeled samples by generating pseudo labels for them (i.e., MLS), then training the model using the generated pseudo labels with a small amount of human-labeled samples (i.e., HLS) as shown in Figure 1.

HLS, which are unfamiliar to the current model, might be informative to enhance the performance. However, on the contrary, they also have a potential to lose or corrupt the already trained information of the model. Therefore, we should be careful to alleviate such a potential problem, when adopting AL in model training. Also, the pseudo-labeling techniques in SSL do not always effectively or positively affect the model training. If we only use samples as MLS on which the current model’s is quite confident, they would not give practical benefit to model training. Moreover, if the confidence of the pseudo-label is falsely high on unlabeled samples, the falsely selected MLS would provide erroneous information to the model, incurring model to be corrupted.

In this paper, we first analyze the effect of precise discrimination of samples, to be human-labeled or not, and pseudo-labeling (SSL) for ASR performance. Second, we show that the mentioned problems of using the biased HLS and falsely selected MLS can be mitigated by applying sample augmentation. The sample augmentation approaches typically used in computer vision field \cite{6, 7, 8} has not been actively considered and applied in ASR field because of the inherent fragility of speech samples to distortions by such augmentation. Instead, we show that appropriate augmentations enable to get positive effects of the augmentation without corrupting essential linguistic information for ASR. By introducing Consistency Regularization (CR) loss to training objective with the carefully designed data augmentation, our method restore the degradation of performance caused by few labeled samples (HLS), thus achieving significant reduction of the labeling cost for transcriptions.
To validate the proposed method, we conduct extensive experiments on the real-world dataset acquired from CLOVA [9], which provides voice search and AI assistant services to end-users, such as Map Navigation, Set-top box control, and etc. The acquired dataset consists of totally about 550 hours of speech utterances recorded from various devices and users. Comparing with the upper-bound case where all unsupervised samples are annotated by human experts, our method shows only 0.26% degradation in Character-level Error Rate (CER) with about 1/3 of HLS and 1.08% decrease with about 1/7 of HLS.

In summary, our contributions to achieve such objective can be summarized as threefold: 1) this work introduces and adapts the consistency regularization on label-efficient E2E-ASR model training to alleviate problem caused by erroneously pseudo-labeled samples, 2) we design the feasible augmentations enabling to apply consistency regularization on speech utterances for ASR, and 3) we verify the efficacy of consistency regularization for speech utterances on extensive real-world data under a realistic scenario by analyzing the dynamic changes of usage and accuracy of pseudo labels during training iterations.

2. Related works

**Active Learning:** Studies on AL can be categorized into three major approaches in how they select the samples to be annotated by human experts: uncertainty-based approach [10, 11, 12, 13, 14, 15], diversity-based approach [16, 17], and expected-model-change approach [18, 19]. The uncertainty approach shows the substantial reduction in labeling cost, although it simply computes uncertainty as top-1 class posterior probability in single-label classification problems. The diversity approach takes account of diversity of the selected samples to represent the whole dataset distribution and the expected-model-change computes expected parameter changes of model for each sample, then selecting the samples incurring largest changes of model parameters.

**Active Learning for ASR:** In ASR, predicting the uncertainty or diversity is much difficult than visual data, because the transcription is configured as a label sequence. [20] demonstrates that length-normalized path-probability from the beam-search decoder can successfully represent the uncertainty of label sequence (i.e., transcription). The works [18, 19] propose the alternative metrics that based on the expected-model-change approach. They calculate expected gradient lengths, which is the norm of gradient of model parameters. Then, they select samples that show the largest expected gradient length, as expecting they change the model substantially in promising direction. However, computing expected gradient lengths over all model parameters requires a lot of computing time, thus it being impractical to large models.

**Semi-supervised Learning and Consistency Regularization:** Semi-supervised Learning (SSL) [8, 21, 22, 23, 24, 25, 26, 27, 28, 29] provides a way to improve model performance using lots of unlabeled samples. One of their main approaches is generating pseudo labels [21, 22] for unlabeled samples and utilizes them as like labeled samples. The works [24, 25, 29] have been studied to apply the pseudo-labeling approach for ASR, and they present that it is also effective in ASR and achieves competitive results with well designed training algorithms. Recently, Consistency Regularization (CR) [8, 23, 26, 27, 28] has been actively studied. It achieves the state-of-the-art results in situation of extremely small ratio of dataset are HLS and the other samples remains in unlabeled. Because it regularizes model to keep their prediction even with distortions on samples, it introduces objective (i.e., loss) complementary to the supervised loss acting as a regularization term. Still, the study of consistency regularization has not been popular in the ASR field because of the inherent fragility of the speech data on distortions. To resolve such problems, we introduce the appropriate augmentations which distort speech characteristics of samples without corrupting their linguistic features so that ASR model achieves better generalization performance under the problems caused during applying AL and SSL to model training.

3. Methodology

3.1. Uncertainty Sampling – Normalized Path-probability

To select the most informative samples from a given unlabeled sample pool, which is gathered by end-users of the deployed services to be human-labeled, we adopt the uncertainty-based AL approach. However, unlike single-label tasks where the uncertainty can be calculated easily with the top-1 class posterior probability, speech recognition requires to consider the joint probability of a label sequence.

We use the path-probability computed in the decoder part of E2E-ASR model during decoding a transcription since it represents the joint probability of decoded text. Moreover, we normalize the path-probability with the length of a decoded text to avoid underestimating longer text same as [20]. The most probable decoded text ($\hat{y}$) and their normalized path-probability (NP) can be calculated as equation 1 and equation 2, respectively.

The confidence ($\delta$) on a sample by model is also defined in equation 3 using NP.

$$\hat{y} = \arg \max_y \exp \left( \log P(y|x) / L \right)$$  \hspace{1cm} (1)

$$NP = \exp \left( \log P(\hat{y}|x) / L \right)$$  \hspace{1cm} (2)

$$\delta = 1 - NP$$  \hspace{1cm} (3)

Here, $x = (x_1, x_2, ..., x_T)$ is input audio feature sequence. The log joint probability $\log P(y|x)$ is divided by the length of transcription ($L$) for length-normalization.

In our method, we calculate NPs over all unlabeled samples, then selecting the samples with the lowest NP values as many as a budget, and annotate them by a human expert (HLS). To verify the superiority of NP as an uncertainty metric, we compares NP with the oracle uncertainty metrics (Loss, CER) exploiting human-labeled labels for calculating themselves and

![Figure 2: Character-Level Error Rate (CER) of model trained with subset split equally to have same hours (386.5/5 = 77.3 hours) after sorted by each uncertainty metric. set15 of each metric consists of the most uncertain (informative) samples.](image-url)
random sampling (RND) as bottom baseline. Figure 2 illustrates the CERs on the test set of the models trained from unlabeled sample subsets, which are divided in the descending order of uncertainty for each metric. That is, \( s \in \{1, 2, 3\} \) contains the most uncertain samples. Each subset consists of same amount of speeches. The CERs at \( s \in \{1, 2, 3\} \) represent the achievable performance with minimal (77.3h) samples separated by each metric. NP shows the best CER at \( s \in \{1, 2, 3\} \) and it also shows disable CER changes across five sets that CER almost monotonically increases as a set has less uncertain samples. In contrast to NP, the other oracle metrics show unexpected changes between the subsets since it might not measure directly a joint probability of predicted labels, instead just measuring the discrepancy of predictions w.r.t ground-truth without considering the dependency between labels in a sequence. Therefore, we decide to use NP and \( \tilde{y} \) as our uncertainty metric and pseudo-labels.

### 3.2. Consistency Regularization on ASR

In the proposed method, we do not discard the remaining samples in unlabeled sample pool after selecting HLS. Instead, we utilize them to assist HLS in training the ASR models by generating pseudo-labels and using unsupervised training approaches.

The pseudo-labels are likely to be not only less informative but noisy compared to that of HLS, so treating MLS as does for HLS would not notably contribute to model training, or it even hinders model performance by giving incorrect information to the model. Therefore, we introduce a new approach incorporating Consistency Regularization (CR) to the MLS when they participate in model training inspired by FixMatch [26], which is validated in image classification tasks and does not verified in field of ASR. CR practically imposes a loss on model training inspired by FixMatch [26], which is validated in image classification tasks and does not verified in field of ASR. CR practically imposes a loss on model training to regulate the model to predict consistent labels in a way to alleviate the mentioned problems in use of MLS. However, it is not trivial to adapt CR to ASR due to the difference characteristics between image and speech.

Basically, the sample augmentation improves the robustness of the model on a variety of conditions, by adding distortions to the samples while maintaining the essential semantics of samples that determining their labels. However, contrary to images, linguistic information contained in speech is much vulnerable to distortions and the sample semantics are easily corrupted by the distortions. Furthermore, the fault at any label in a sequence incurs subsequent faults in the character sequence generation task. For that reason, augmentations for a speech should be carefully designed to get benefits from applying an augmentation. Our candidates for an augmentation are changing playing speed (SPEED), pitch-shifting (PITCH) [30], and Adding White Gaussian Noise (AWGN).

Now, we use both of HLS and MLS for training, our loss consists of two terms: a supervised loss \( l_s \) on HLS and an unsupervised loss \( l_u \) on MLS. The supervised loss is defined as equation 4 following the standard cross-entropy loss [1].

\[
l_s = \frac{1}{|B|} \sum_{n=1}^{B} \sum_{l=1}^{L_n} H(\hat{y}_{n,l}, P(\hat{y}_{n,l}|x_n)) ),
\]

where \( B \) is the size of mini-batch, and \( L_n \) is the length of \( n \)-th sample of HLS. \( \hat{y}_{n,l} \) represents ground-truth labels and \( \hat{y}_{n,l} \) stands for the labels predicted by the model.

Our unsupervised loss is also defined as equation 5. To implement CR, we augment input feature \( x_n \) with augmentation function \( (A) \), then define the loss as cross-entropy between their predictions \( \hat{y}_{n,l} \) and pseudo-labels \( \hat{y}_{n,l} \).

\[
l_u = \frac{1}{\sum_{n=1}^{B} \sum_{l=1}^{L_n} L_n} \sum_{n=1}^{B} \sum_{l=1}^{L_n} H(\hat{y}_{n,l}, P(\hat{y}_{n,l}|A(x_n)))
\]

The labels \( \hat{y}_{n,l} \) used in equation 5 denote pseudo-labels generated from the original version of input \( x_n \). To prevent a problem caused by erroneous pseudo-labels on strongly unreliable samples, we use the unlabeled data whose confidence \( \delta \) exceeds the pre-defined threshold \( \tau \). By generating the pseudo-labels at each iteration, we can expect the correctness of pseudo-labels are continuously improved as the model training proceeds.

By integrating the supervised loss and the unsupervised loss, the total loss is defined as in equation 6

\[
l_{total} = l_s + \lambda \times l_u.
\]

### 4. Evaluation

#### 4.1. Experiment Setup

**Dataset:** We split and denote the samples acquired from CLOVA [9] according to the order of acquisition date, to an initial dataset \( (A) \) and an incoming dataset \( (B) \), each of which consists of 110 hours samples \( (A) \) and 386 hours samples \( (B) \), respectively. The initial dataset \( (A) \) is used to train a initial model. The incoming dataset \( (B) \) denotes the samples acquired during the services operating with the initial model. Such configurations reflect the real-world scenario where a size of incoming samples is normally bigger than that of initial samples, and acquired date of the samples in \( (A) \) is prior to that of the samples in \( (B) \). Additionally, we hold out 56 hours samples, which acquired later than the samples in both of \( (A) \) and \( (B) \) for test.

We extract spectrograms from the samples using the hamming window with 200 ms window-length, 100 ms stride-length, then use them as input features for E2E-ASR model training.

**Training and Model Details:** Our E2E-ASR model is built based on LAS [1]. We stacked three layers of bidirectional-LSTM for an encoder, two layers of bidirectional-LSTM for a decoder with attention module. The hidden and output size of all bidirectional-LSTM were set to 512, and the pyramidal structure in the encoder of original LAS [1] was replaced with two convolutional layers with batch-normalization and hard tangent activation function, which reduce the time and frequency dimensions of spectrogram to \( 4 \times 2 \times \), respectively. For model.
training, we utilized ADAM optimizer with learning rate 0.003 for HLS only training and 0.001 when we include MLS for the training and we construct a mini-batch with 512 samples. The learning rate was divided by 1.1 for every epoch over 30 epochs and the norm of gradients was clipped to 400 for training stability. Throughout the entire experiments, we set the threshold $\tau = 0.9$, which corresponds to average confidence ($\delta$) over $(B)$, and the scaling constant to $\lambda = 1$. Those hyperparameters are selected to highlight the impact of MLS in training. When using CR, we use three augmentation techniques designed in subsection 3.2; SPEED, AWGN, and PITCH, which modifies the samples by fast-forwarding 1.5 times, adds the noise up to $SNR=5$, and shifts two half-steps when an octave is divided in eight bins, respectively. All the experiments were performed using NAVER Smart Machine Learning (NSML) [31, 32].

4.2. Experiment Results

**Comparison:** We compared the two baselines: HLS-only case (Sup) and the case also using pseudo-labeled samples (NoCR and CR={S, A, P}) with various splits having different HLS:MLS ratios of $(B)$: LU12, LU14, LU16, and LU19 in Table 1. For example, LU12 means it consists of HLS and MLS in 1:2 ratio. NoCR means incorporating MLS in training without CR, so it imposes $l_\text{S}$ loss on MLS by providing pseudo-labels as ground-truth. Note that the abbreviations {S, A, P} each represents {SPEED, AWGN, PITCH} augmentations for CR.

Table 1 and Figure 3 show that the proposed CR variants outperform NoCR on every LU splits except CR-S at LU14 and CR-P achieves the best CERs on every splits including baselines and the other CR variants. NoCR shows worse CER than that of Sup even NoCR sees more samples in training with aggressive hyperparameters; relatively high $\lambda$ and low $\tau$. It explains our hypothesis mentioned in subsection 3.2 that wrong pseudo-labeled samples are able to hinder the model performance. The gains of CR variants over the baselines are more impressive when the amount of HLS is small (i.e., LU16 and LU19) where the labeling cost is fairly saved and the degradation by MLS is emphasized. For example, at the LU19, CR variants reduce 1.26%p and 1.60%p compared to Sup and NoCR, respectively. Otherwise, the gain from CR on splits having abundant HLS seems relatively marginal, but it also means they have already enjoyed enough benefit from AL. Therefore, further improvement from exploiting SSL with CR appears marginal.

**Discussion:** We hypothesize that the model trained by unsupervised loss without CR is likely to be degraded by the samples with wrong but highly confident pseudo-labels [33, 34]. To verify the hypothesis and clarify the source of improvement of the proposed CR variants, we analyze the usage of unlabeled samples in training and accuracy of their pseudo-labeled between the baselines and CR variants.

Firstly, we measure the usage of unlabeled samples in training and Figure 4a shows such tendency of usage-progression over training epochs for LU12 and LU16. From the result, we can see that NoCR shows the relatively more usage than that of CR variants over entire epochs. At the same time, we measure the CER between pseudo-labels and ground-truth labels of human experts. According to Figure 4b, NoCR presents the worse CERs than those of CR variants. From the above measurements, we can derive the conclusion that NoCR suffers from inaccurate pseudo-labels and the CR loss ($l_\text{i}_{\text{CR}}$) alleviates such an issue by regulating overconfidence from model, thus resulting in superior model performance while utilizing MLS in training.

5. Conclusions

In this study, we study a method integrating AL and SSL to handle the labeling cost by reducing the human annotation on uninformative samples and further utilizing the unlabeled samples in training. For achieving this, we propose to use Consistency Regularization with well-designed augmentations that alleviates the potential problems incurred from using inaccurate pseudo labels in training, thus increasing the gain from using pseudo-labeled samples. Finally, we can reduce about 2/3 of labeling cost with only 0.26%p degradation in Character-level Error Rate (CER) and 6/7 of it with 1.08%p degradation. This is the first work incorporating the Consistency Regularization into AL-SSL training pipeline for ASR, and presents the potential to remarkably reduce the human-labeling cost with negligible performance loss.
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