WORD ORDER DOES NOT MATTER FOR SPEECH RECOGNITION

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ABSTRACT

In this paper, we study training of automatic speech recognition system in a weakly supervised setting where the order of words in transcript labels of the audio training data is not known. We train a word-level acoustic model which aggregates the distribution of all output frames using $LogSumExp$ operation and uses a cross-entropy loss to match with the ground-truth words distribution. Using the pseudo-labels generated from this model on the training set, we then train a letter-based acoustic model using Connectionist Temporal Classification loss. Our system achieves $2.3\%/4.6\%$ on *test-clean/test-other* subsets of LibriSpeech, which closely matches with the supervised baseline's performance.

1. INTRODUCTION

Transcribing speech, and generally labeling data, is an expensive process. Thus, it is relevant to study what level of supervision is needed in the first place. Indeed, sparse, crude annotations come cheaper, and can even sometimes be mined in the wild. Modern acoustic models (AMs) are able to classify so well that, we believe and particularly demonstrate in this paper, they can recover at least word order, and probably much more. This ability revolves around the fact that self-training (pseudo-labeling) [1] works even with models that are far from convergence and have only a weak performance [2]. Said differently, it is possible for the model to improve by training with *very noisy* labels. What other type of noise in the labels distribution can a model overcome, by recouping co-occurrences through statistic of a large enough training set?

We investigate if an automatic speech recognition (ASR) model can be trained with the sole annotations being the distribution of labels (bag of words), with a restricted (words) vocabulary. It turns out that combining this kind of model with self-training reaches the same performance as a fully supervised equivalent model. Thus, the word order has no importance (the title of this paper), as it can be easily recovered by the model and self-training: without a language model, with a simple training scheme, at least with enough data (960 hours of the LibriSpeech [3] benchmark).

2. RELATED WORK

Weakly supervised learning can be formulated in various ways depending on how the weakly supervised labels are defined. Several works study weakly supervised training with video data: either contextual metadata [4] or subtitles[1] presented as a part of a video frame [5]. Both works demonstrate that weakly supervised training in combination with supervised training improves ASR over standalone supervised training. In contrast, we use another source of weak supervision. *Bag-of-words* labels for each sample (hard labels) has been considered in [6] to classify words, while we use words distribution (soft labels). [7] also considers soft labels as we do, but these soft labels do not form a distribution over the words: image-to-words visual classifier tags images with soft textual multi-labels. Being similar to us in the weak supervision formulation, both [6, 7] are solving a (semantic) keyword spotting task, while we focus on more general ASR task. Related to the *bag-of-words* approaches, [8] introduces a system for weakly supervised temporal action segmentation and labeling given only unordered action sets for video.

Semi-supervised learning has been actively studied over last years in speech recognition community, primarily in the context of self-training, or pseudo-labeling, [9, 10, 11, 12, 2, 13, 14, 15]. All these approaches combine both labeled and unlabeled data with pseudo-labels (PLs), generated in one way or another. We use PLs in teacher-student manner to further improve weakly supervised model switching from word tokens to letter tokens.

Unsupervised pre-training on unlabeled data has also been used recently to improve ASR task with further fine-tuning on labeled data [16, 17, 18, 19, 20] or alternating supervised and unsupervised losses optimization [21]. Others focused on learning representations from unlabeled data which are useful for phoneme classification and speaker verification [22, 23, 19] (labeled data are still used to train a classifier on top of learned representations). Compared to these efforts we use only weak supervision.

Unsupervised learning for ASR is an ongoing research on methods with no supervision at all: they either learn how to align unlabeled text and unlabeled audio [24] or use adversarial training [25, 26, 27].

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[1]Authors design an algorithm to automatically recognize subtitles (can be viewed as "noisy" labels).
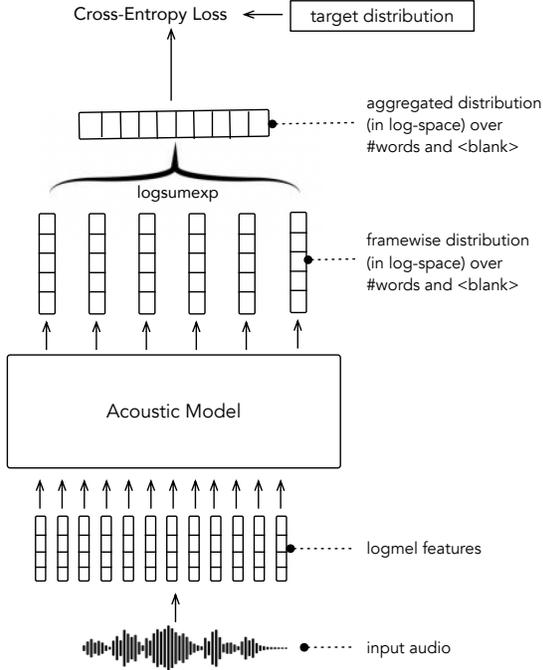
Fig. 1. Weakly supervised ASR training pipeline.

3. METHOD

3.1. Overview

We consider the problem of performing ASR in a weakly supervised manner where the order of words in the transcript labels of training data are not known. Traditionally, in a supervised setting for ASR, we are given a training set $\cup_{i=1}^{N}\{x_i, y_i\}$ comprising of N samples, where x_i is an input audio sequence and y_i is a sequence of words. In the weakly supervised setting that we consider, $y_i \in \mathbb{R}^{|V|+1}$ is a probability distribution over the word vocabulary V and a *<blank>* token which models all "garbage" frames that could occur between words. All out-of-vocabulary (OOV) words are mapped to a special *<unk>* word in the vocabulary. An overview of the full training pipeline used in our work is presented in Algorithm 1.

Algorithm 1: Full training pipeline.

Data: Audio samples $\{x_i\}$ and their bag-of-words labels $\{y_i\}$.
Result: Acoustic model g_θ.
1. Train a word-based weakly supervised model q_θ on $\{x_i, y_i\}$ with cross-entropy loss, Eq.(2), until convergence;
2. Apply greedy decoding on $\{x_i\}$ using q_θ to generate transcriptions $\{\tilde{y}_i\}$ as PLs, where $\tilde{y}_i = \text{argmax}_y q_\theta(y|x_i)$;
3. Replace *<unk>* word in PLs using an n-gram LM beam-search decoding with a constraint that the words to be replaced should belong to the corresponding transcription;
4. Train a letter-based ASR model g_θ with CTC loss using the PLs generated from Step 3.

3.2. Target labels as probability distribution

Let a target transcript in a supervised ASR setting is "$w_0\ w_1\ w_2\ w_1$", where w_0, w_1 are the words in the vocabulary V and w_2 is an OOV word. In our weakly supervised setting, we convert this into probability distribution by taking their count and normalizing the count by total number of words in the transcript. For example, the target for the above words sequence becomes $p =\{w_0: 0.25, w_1: 0.5, \textit{<unk>}: 0.25\}$. Further, we also introduce a new hyperparameter α which is the prior probability on the *<blank>* word and then re-normalize the probabilities of the words such that they sum to 1. For example, with $\alpha = 0.5$, the target label becomes $p =\{w_0: 0.125, w_1: 0.25, \textit{<unk>}: 0.125, \textit{<blank>}: 0.5\}$.

3.3. Weakly supervised word-level model training

Fig. 1 gives an overview of weakly supervised training. We use 80-dimensional log-mel spectrograms as input features. The AM architecture closely follows [28]: the encoder is composed of a convolutional frontend (1-D convolution with kernel-width 7 and stride 3 followed by GLU activation) followed by 36 4-heads Transformer blocks [29] with relative positional embedding. The self-attention dimension is 384 and the feed-forward network (FFN) dimension is 3072 in each Transformer block. The output of the encoder is followed by a linear layer to the output classes. For all Transformer layers, we use dropout on the self-attention and on the FFN, and layer drop [30], dropping entire layers at the FFN level.

We apply $LogSoftmax$ operation on each output frame to produce a probability distribution (in log-space) over output classes (vocabulary, V + *<blank>*). Then, all the output frames o are aggregated into a single probability distribution q by applying $LogSumExp$ operation with normalization by the number of output frames T, see Eq.(1). The loss function $\mathcal{L}$ is the cross-entropy loss between predicted output distribution q and the target distribution p, see Eq.(2).

$$q = LogSumExp\left(o_1, o_2, ...o_T\right) - log\,T \qquad (1)$$

$$\mathcal{L} = -\sum_{i=1}^{|V|+1} p_i\, log\, q_i \qquad (2)$$

3.4. Inference using greedy decoding

To perform inference using the weakly supervised model, we adopt a simple greedy decoding strategy. This is very similar to the greedy decoding procedure for Connectionist Temporal Classification (CTC) [31]. First, we pass the input utterance through the AM and get framewise emissions over the vocabulary V and *<blank>* token. We then consider the word with max score at each time step, collapse the repeated tokens and remove *<blank>* token to get the final prediction.

3.5. From word-based to letter-based acoustic model

The number of words in the vocabulary V impacts both the training convergence and word error rate (WER) performance of our word-level AM. First, rare words appear only a couple of times in the training dataset[2], and thus the word-level AMs will not be able to generalize well on these words. Techniques to alleviate this issue have been explored in [32, 33]. However, we found in practice that with $|V| > 15,000$ the weakly supervised problem (2) is becoming very difficult, and with larger vocabularies the approach would fail to converge. We thus propose here to train a *word*-based AM on a limited vocabulary in a *weakly supervised* fashion, and then to "distill" its knowledge into a *letter*-based AM, which has the potential to address any word in the dictionary. Distillation is performed by running the word-based AM inference over the training utterances. We then train a letter-based AM on the corresponding generated PLs, via a regular CTC approach. We use the same Transformer-based encoder consisting of 270M parameters from [28] for the AM.

3.6. Uncovering *<unk>* in pseudo-labels (PLs)

As the word-level AM is trained on a limited vocabulary V, corresponding PLs generated by this model may contain *<unk>* words. While we can train the letter-based model by simply removing *<unk>*, we will show that refining PLs by uncovering unknown words leads to better performing letter-based AMs. For that matter, we consider a language model (LM) $p^{LM}(\cdot)$ trained on a separate text-only training corpus[3], with a large vocabulary V^{LM}. Then, considering a PL sequence $\pi = \{\pi_1, \pi_2, \ldots, \pi_L\}$ with L words, we denote $\mathcal{U}(\pi)$ the set of positions where an *<unk>* was produced. We then aim at replacing these unknown words in the PL sequence by finding the most appropriate words according to the LM likelihood:

$$\max_{\forall i \in \mathcal{U}(\pi), \pi_i \in V^{LM}} p^{LM}(\pi) \tag{3}$$

For efficiency, maximizing this likelihood is performed with a beam-search procedure. It is possible to further constrain this search for unknown words replacement, by enforcing new words π_i to belong to the original bag-of-word acoustic transcription, instead of the full vocabulary $\pi_i \in V^{LM}$ in (3).

4. EXPERIMENTS AND RESULTS

All the models are trained using wav2letter++ [34] framework. The experiments are run on Nvidia Volta 32GB GPUs and we use 16 GPUs for weakly supervised experiments and 64 GPUs for running CTC experiments. We use SpecAugment [35] as the data augmentation to augment the input data

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[2]In the LibriSpeech training corpus, the 10,000 most frequent word appears 51 times.

[3]To ensure acoustic training transcriptions word order is not used, the language model training data should not include any acoustic transcriptions.

for both weakly supervised, CTC model training. We use LibriSpeech [3] dataset for our study which consists of 960h of read speech and report numbers on the standard dev/test sets. We use 5-gram LM for beam-search decoding of models trained with CTC and Transformer LM for rescoring the top hypothesis from beam-search to further improve WER performance. All the LMs are trained on the official LM training data provided with LibriSpeech. For details on beam-search decoding and Transformer LM rescoring used in our work, we refer the reader to [36].

4.1. Tuning *<blank>* prior probability, α

We performed a grid search over *<blank>* token prior probability, α values from 0 to 0.9 in steps of 0.1. We use a vocabulary size of 10K, which consists of top 10K words from the training set sorted by their frequency. Fig. 2 shows the word error rate (WER) with greedy decoding (no LM) on clean/other dev subsets of LibriSpeech with varying hyperparameter α: the best performance is achieved for $\alpha = 0.9$. It is interesting to note that $\alpha = 0.9$ roughly corresponds to predicting each word for one output frame and predicting *<blank>* for all other frames. This follows from the fact that the AM outputs an average of 33.33 frames per second when using stride 3 in the convolution layer and 10ms hop length for Short Time Fourier Transform (STFT) computation. Also, the samples in LibriSpeech have an average speaking rate of 2.7 words per second. Thus, predicting each word for one output frame and *<blank>* for all other output frames amounts to $\alpha = 1.0 - 2.7/33.33 = 0.91$.
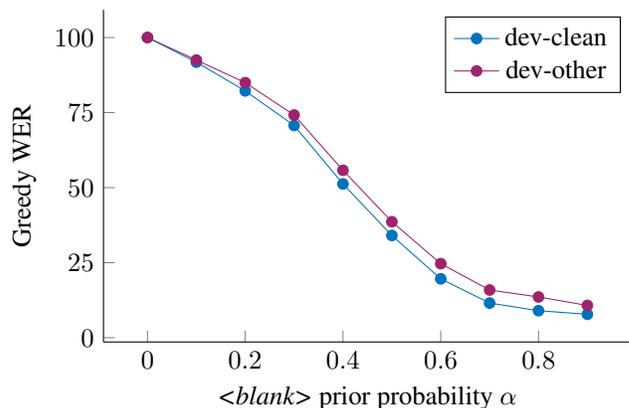

Fig. 2. Dependence between WER (no LM) and α hyperparameter on *dev-clean* and *dev-other* subsets of LibriSpeech.

4.2. Weakly Supervised ASR

For weakly supervised training, we use top 10k words (based on the frequency) from the training set as the vocabulary. Table 1 shows results of weakly supervised ASR model which achieves $8.2\%/11.3\%$ WER (no LM) on the clean/other test subsets, respectively. Since the model is trained only to infer 10k words, it is not a fair comparison to compare the WER numbers to supervised baseline model.

Table 1. WER comparison for supervised and weakly supervised models on LibriSpeech.

Method	LM	Dev WER		Test WER	
		clean	other	clean	other
Supervised [14] (SOTA)	-	1.9	4.4	2.1	4.3
	Transformer			1.9	3.9
Supervised (baseline)	-	2.5	5.9	2.7	6.1
	word 5-gram	1.9	4.7	2.4	5.3
	Transformer	1.6	4.0	2.1	4.5
Weakly supervised (word-based)	-	7.8	10.7	8.2	11.3
+ PL (letter-based)	-	2.9	6.4	3.0	6.5
	word 5-gram	2.3	5.2	2.6	5.5
	Transformer	1.9	4.3	2.3	4.6

Table 2. WER for PLs generated with 3 different strategies to deal with *<unk>*: (1) remove *<unk>* word in PLs; (2) and (3) replace *<unk>* in PLs with beam-search procedure using 5-gram LM over full train vocabulary or transcript vocabulary of the corresponding sample.

Strategy	Train WER	Dev WER	
		clean	other
1. Remove *<unk>*	6.2	7.5	9.9
2. Replace *<unk>*; train vocab.	3.7	5.1	8.7
3. Replace *<unk>*; transcript vocab.	1.6	2.9	6.4

To get a sense of how good the weakly supervised model is performing, we have trained 4 different models with vocabulary sizes of 100, 1K, 5K and 10K words with $\alpha = 0.9$. We compare their performance with WER of our supervised baseline model where the output vocabulary is restricted to the same vocabulary. We also measure the WER of oracle model which always outputs correct predictions and is restricted to the output vocabulary, serving as a lower bound for the WER. Fig. 3 shows the WER comparison for different vocabulary sizes on the dev sets. It can be seen that the the weakly supervised model can achieve a performance competitive with the supervised model (after restricting the output vocabulary).

In order to understand if the model is able to localise word predictions [6], we perform inference on the audio file taking the output tokens with highest score at each output frame. We map the output frames corresponding to the inferred sequence back to input audio to see where the words are produced. A few examples are shown in Fig. 4. It can be seen the model tends to output a word at the onset of the word in the audio.

4.3. Pseudo-Labeling

We use the weakly supervised model trained on 10K vocabulary to generate PLs on training set. As we discussed in Section 3.6, we consider 3 possible ways to deal with *<unk>* word in PLs and the WER on training set is shown in Table 2. We can see that replacing *<unk>* in the PLs with beam-search
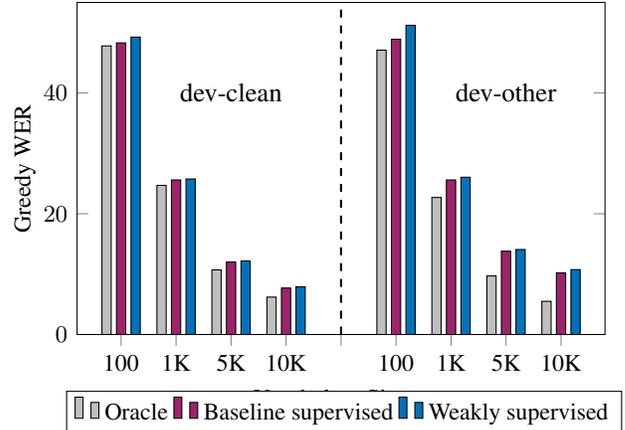

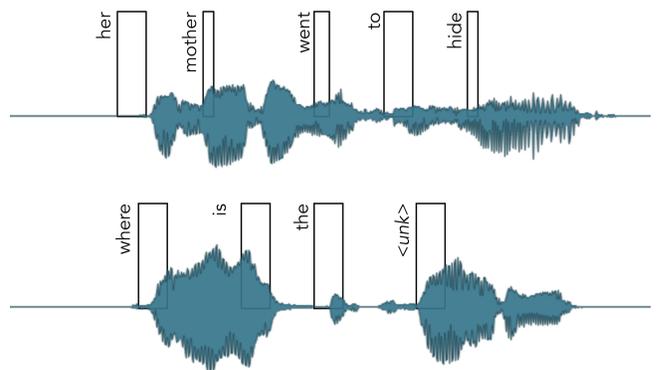**Fig. 3**. WER comparison for different constrained lexicon sizes on dev sets

Fig. 4. Word localisation for the weakly supervised model.

using 5-gram LM and restricting vocabulary to the original bag-of-word acoustic transcriptions gives the best performance. We train letter-based CTC models on these PLs and the performance on dev sets is shown in Table 2: the better WER on the training set translates to the better WER on dev sets.

And finally, we perform beam-search decoding using 5-gram LM for the best model which uses PLs from strategy (3): it gives a WER of $2.6\%/5.5\%$ on clean/other test sets, respectively. Rescoring with a Transformer LM further improves the WER to $2.3\%/4.6\%$ on clean/other test sets and is competitive with the supervised baseline.

5. CONCLUSION

We demonstrated that speech recognition models can be developed without any knowledge of the words order or their counts in the transcript, and words distribution is enough. Moreover, weakly supervised learning can be successfully combined together with pseudo-labeling to achieve the same performance as supervised learning. This result shows that state-of-the-art speech recognition models can be developed with much less supervision than what is traditionally being used.

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