



Investigating Methods to Improve Language Model Integration for Attention-based Encoder-Decoder ASR Models

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Abstract

Attention-based encoder-decoder (AED) models learn an implicit internal language model (ILM) from the training transcriptions. The integration with an external LM trained on much more unpaired text usually leads to better performance. A Bayesian interpretation as in the hybrid autoregressive transducer (HAT) suggests dividing by the prior of the discriminative acoustic model, which corresponds to this implicit LM, similarly as in the hybrid hidden Markov model approach. The implicit LM cannot be calculated efficiently in general and it is yet unclear what are the best methods to estimate it. In this work, we compare different approaches from the literature and propose several novel methods to estimate the ILM directly from the AED model. Our proposed methods outperform all previous approaches. We also investigate other methods to suppress the ILM mainly by decreasing the capacity of the AED model, limiting the label context, and also by training the AED model together with a pre-existing LM.

Index Terms: speech recognition, language model integration, attention-based encoder-decoder

1. Introduction & Related Work

End-to-end automatic speech recognition (ASR) models have shown competitive results on a variety of tasks [1, 2]. One of the most popular models is the attention-based encoder-decoder (AED) model [3]. This model can learn a direct mapping from input features to output labels by jointly learning the acoustic model (AM), pronunciation model, and language model (LM). The encoder maps the input features into some high-level representations. The decoder acts as a language model which uses attention to summarize the encoder's representations to produce output labels.

Monolingual or unpaired text data is usually much larger in magnitude than transcribed paired data. Therefore, using an external LM trained on monolingual text data in combination with the ASR model often yields better performance. There have been many studies on how to integrate the ASR model with an external LM. Shallow fusion [4] is often used which is simply a log-linear interpolation of the ASR and LM scores during inference. Other, more sophisticated approaches including Cold Fusion [5], Deep Fusion [6], Simple Fusion [7], and Component Fusion [8] fuse the LM into the ASR model by combining their hidden states during training. There also have been studies to include the LM into the training criterion in a log-linear fashion [9]. Among these studies, shallow fusion seems to be the most dominantly used approach.

Because of the discriminative ASR model, a Bayes interpretation suggests dividing by the prior of the ASR model when

combining with an external LM. During inference, the log-domain score of this prior model is subtracted from the log-linear combination of both ASR model and external LM scores. Due to the context-dependency on previous labels, the ASR model has implicitly learned an *internal LM* (ILM), which corresponds to this prior model. The internal LM can not be calculated exactly but there are various ways how to approximate it. In case of AED or RNN-T [10], the internal LM is assumed to be mostly learned by the decoder or prediction network, and various simple ways exist for its estimation by masking out the encoder. This was first suggested as part of the hybrid autoregressive transducer (HAT) [11]. The Density Ratio (DR) approach [12] is similar. It does not estimate the internal LM directly but instead estimates the prior as a separate LM trained on the training transcriptions only. Subtracting the internal LM during inference can be seen as removing the prior or bias of the training text data.

The authors of [13] also proposed a simple way to estimate the internal LM for AED models inspired by HAT, which is masking out the attention context vector. We call this zero approach. We argue that this was applied under a strong assumption that the AED decoder modeling also follows the proof proposed by HAT ([11] Appendix A). Instead, we believe that other ILM estimation methods can be more accurate when considering the encoder bias information as input instead of just zero.

Furthermore, it was observed that the effect of an external LM can be smaller if the decoder is over-parameterized [14]. This motivated us to study different ways of suppressing the ILM of the decoder. For AED models, this can be done by weakening the decoder by decreasing its number of parameters or accessible label context or by including an LM in the training process.

In this work, we present several novel methods to estimate the ILM directly from the AED model. We propose methods that use the averaged encoder states or averaged attention context vectors over all training data instead of zero input. We also introduce a new method called Mini-LSTM, which is trained to minimize directly the perplexity of the ILM and achieved the best results. We show that all our methods outperform the previously proposed methods namely Shallow Fusion, Density Ratio, and ILM estimation with zero encoder [13]. Moreover, we show that it is possible to train an AED model with a limited context decoder and still achieve comparable results with an LSTM decoder on some tasks.

2. Model

Our model follows the attention-based encoder-decoder model [15, 16]. The encoder maps the input sequence x_1^T into a

sequence of hidden states h_1^T where $T' \geq T$ due to down-sampling, and $h_t \in \mathbb{R}^{D_{\text{enc}}}$. For each decoder step i , the attention mechanism is used to calculate attention weights $\alpha_{i,t}$ as:

$$\alpha_{i,t} := \text{Softmax}(\text{Attention}(s_i, \beta_{i,t}, h_1^T)) \quad (1)$$

where $\beta_{i,t}$ is attention location-awareness feedback. The attention context vector $c_i \in \mathbb{R}^{D_{\text{enc}}}$ is then computed as a weighted sum over the encoder hidden states h_1^T as

$$c_i := \sum_{t=1}^T \alpha_{i,t} h_t, \quad c_0 := 0. \quad (2)$$

The decoder state is modeled as a recurrent function using LSTM:

$$s_i := \text{LSTM}(s_{i-1}, y_{i-1}, c_{i-1}) \quad (3)$$

Finally, the output probability for some label y_i is computed as:

$$p(y_i | y_{i-1}, x_1^T) = \text{Softmax}(\text{MLP}_{\text{readout}}(s_i, y_{i-1}, c_i)) \quad (4)$$

where $\text{MLP}_{\text{readout}} = \text{linear} \circ \text{maxout} \circ \text{linear}$.

2.1. Feed-forward (FF) Decoder

The decoder state is usually recurrent and modeled by an LSTM allowing full label context feedback. However, we can also limit the label context by modeling the decoder state using feed-forward (FF) layers. The computation of the decoder state is then defined as:

$$s_i = \text{FF}(y_{i-k}^{i-1}, c_{i-1}) \quad (5)$$

where k is the context size. The decoder state s_i has no explicit dependency on the previous state s_{i-1} but an implicit one via the attention mechanism in Equation (1) and Equation (2).

3. Internal LM Estimation

During inference, the search algorithm searches for the best word sequence w_1^N that maximizes:

$$\hat{w}_1^N = \arg \max_{N, w_1^N} \left\{ \log P(w_1^N | x_1^T) \right\}$$

In principle, the sentence posterior probability can be modeled directly by the AED model. In practice, however, significant improvement can be obtained by including an external LM via log-linear model combination (*shallow fusion*) [4]. During training, the AED model learns an internal LM (ILM) from the training data. It has been shown that additional benefit can be obtained when the ILM sequence prior information can be removed [11, 13].

Hence our probability is modeled by a combination of the three models

$$P(w_1^N | x_1^T) \propto P_{\text{AED}}(w_1^N | x_1^T) \cdot P_{\text{LM}}^{\lambda_1}(w_1^N) \cdot P_{\text{ILM}}^{-\lambda_2}(w_1^N)$$

where P_{AED} is the AED model probability, P_{LM} and P_{ILM} are the external LM and ILM respectively and λ_1 and λ_2 are scalar model scales.

The estimation of the ILM is not straightforward as it is implicitly modeled in the decoder. The ILM is defined as:

$$P_{\text{ILM}}(w_1^N) = \sum_{T, x_1^T} P_{\text{AED}}(w_1^N | x_1^T) \cdot P(x_1^T) \quad (6)$$

However, the summation is intractable. In the following, we will propose different estimation methods by modifying the attention context vector c_i since it represents the input to the decoder in our case, as an approximation to estimate P_{ILM} .

$$P_{\text{ILM}}(w_1^N) \approx \hat{P}_{\text{ILM}}(w_1^N) := P_{\text{AED}}(w_1^N | c_i = \hat{c}_i) \quad (7)$$

3.1. Zero-Attention ILM Estimation

We set the context vector to zero as proposed by [11, 13]. $\hat{P}_{\text{ILM}_{\text{zero}}}$ is defined by

$$\hat{c}_i^{\text{zero}} := 0 \quad \forall i.$$

3.2. Average-Attention ILM Estimation

The zero ILM estimation removes all encoder bias from the decoder. However, if this bias appears consistently in the encoder information, it can be considered part of the ILM and should also be accounted for during inference. To also capture this bias, we use the average encoder state instead of zero. There are several ways to estimate the average

Global Attention Context Average ($\mathbb{E}_{\mathcal{D}}[c]$). In this approach we average the attention context vectors c over all examples of our training data $(x, y) \in \mathcal{D}$ with $c_j(x, y)$:

$$\hat{c}_i^{\mathbb{E}_{\mathcal{D}}[c]} := \frac{1}{J_{\text{tot}}} \sum_{(x, y_1^J) \in \mathcal{D}} \sum_{j=1}^J c_j(x, y) \quad \forall i \geq 1, \quad \hat{c}_0^{\mathbb{E}_{\mathcal{D}}[c]} := 0,$$

and $J_{\text{tot}} := \sum_{(x, y_1^J) \in \mathcal{D}} J$.

Note that we also tested not using the special case for $i = 0$. This performed slightly worse in some cases, as it becomes slightly more inconsistent because $c_0 := 0$ is exactly what we defined for the AED model (Equation (2)).

Global Encoder Average ($\mathbb{E}_{\mathcal{D}}[h]$). Instead of taking the average context vector we can also directly average the encoder output h over the entire training data.

$$\hat{c}_i^{\mathbb{E}_{\mathcal{D}}[h]} := \frac{1}{T_{\text{tot}}} \sum_{(x_1^{T_x}, y) \in \mathcal{D}} \sum_{t=1}^{T_x} h_t(x) \quad \forall i \geq 1, \quad \hat{c}_0^{\mathbb{E}_{\mathcal{D}}[h]} := 0$$

and $T_{\text{tot}} := \sum_{(x_1^{T_x}, y) \in \mathcal{D}} T_x$.

Sequence-Level Encoder Average ($\mathbb{E}_x[h]$). To capture gradual shifts in the encoder imposed bias we restricted the average to the current utterance (x, y) .

$$\hat{c}_i^{\mathbb{E}_x[h]} := \frac{1}{T} \sum_{t=1}^T h_t(x) \quad \forall i \geq 1, \quad \hat{c}_0^{\mathbb{E}_x[h]} := 0$$

Note that this is not a proper ILM estimation as it makes use of the input x .

3.3. Trained Context ILM Estimation

In this approach, we define \hat{c} by a mini model which is trained to minimize the perplexity of the ILM, while keeping all other ASR model parameters fixed.

Mini-LSTM. We can use a mini LSTM defined as

$$\hat{c}_i^{\text{Mini-LSTM}} := \text{linear} \circ \text{LSTM}(y_1^{i-1}, \theta_{\text{Mini-LSTM}}) \quad \forall i$$

with trainable parameters $\theta_{\text{Mini-LSTM}}$. Specifically, we use the same decoder embedding for y as input to the LSTM consisting of 50 hidden units and then projected to $\mathbb{R}^{D_{\text{enc}}}$. The training steps are summarized as follows: (1) freeze trained θ_{AED} , (2) replace c_i with $\hat{c}_i^{\text{Mini-LSTM}}$, (3) retrain the AED model by only updating the linear and Mini-LSTM parameters.

This uses only a small amount of parameters to avoid any potential overfitting and to avoid learning another internal LM on its own. We train the parameters only on a subset of the training data. This estimation is just as efficient as calculating the average statistics above. Loading the dataset from disk is our bottleneck.

3.4. Decoder-Like LM

All the above methods try to estimate an LM from the AED model contrary to the fact that the AED model was never explicitly trained to be an LM. A more direct approach to model the LM probability that can *in principle* be learned by the AED is to train a proxy model.

We propose to train a dedicated LM that has the same topology as the AED decoder and is trained on the training transcriptions. This is closely related to the density ratio approach [12] where only source and target domain are matched in our case,

but the capacity (# of params) of the source and target LM are differing.

$$P_{\text{ILM}}(w_1^N) \approx P_{\text{train-LM}}(w_1^N) := P_{\text{decoder-like}}(w_1^N)$$

This method only models the theoretical LM capacity of the decoder and does not take any specific AED model into account.

3.5. ILM Suppression

Instead of estimating the ILM of an existing AED model we can also try to proactively suppress the formation of an ILM during the training such that no or fewer corrections are necessary at decoding time. In this work, we propose the following measures to suppress the ILM.

Under-Parameterized Decoder To limit the capacity of the AED decoder we reduce the number of hidden units in the decoder layer. The intuition is that with reduced capacity the model has to put more emphasis on the acoustic part to remain a viable AM and will reduce the effort put into language modeling. This is compensated in decoding by the strong external LM.

Limited Context Decoder The power of LSTM and Transformer LMs comes from the fact that these models have unlimited history and can effectively model the long semantic contexts of natural languages.

We propose to replace the recurrent decoder (Equation 3) with a limited context FF model (Equation (5)). We argue that limiting the visible context will not reduce the acoustic modeling capacity of the decoder while it can strongly reduce the effectiveness as a language model.

Train AED together with LM (train w. LM) Usually, the AED model and the LM are trained independently. There are approaches to include an external LM in the training of AMs via sequence training or local log-linear combination [9]. We argue that when an LM is present during training the AM learns to rely on the LM for language modeling and focuses more on acoustic modeling. Thereby, the ILM should be much weaker.

4. Experiments

We use RETURNN [17] for training and inference. All LM scales λ_1 and λ_2 are tuned using grid search. The LMs trained for Density Ratio have the same topology as the AED LSTM-based decoder. All our config files and code to reproduce these experiments can be found online¹.

4.1. Switchboard 300h

We conduct experiments on the Switchboard 300 hours dataset which consists of English telephone conversations [18]. We use Hub5'00 as development set which consists of Switchboard and CallHome. We use Hub5'01 and RT03 as test sets.

We use 40-dimensional Gammatone features [19]. Our encoder consists of 2 convolutional layers followed by 6 bidirectional LSTM layers with 1024 dimensions in each direction. The decoder consists of a Zoneout LSTM [20] layer with 1000 dimensions. We apply dropout of 30% and weight decay [21] of value $1e-4$ for further regularization. We also use SpecAugment [1] for data augmentation. We use byte-pair-encoding (BPE) [22] as output labels with a vocabulary size of 534. All models are trained for 33 epochs. The LM scales are tuned on Hub5'00 set and we use a beam size of 12 for inference. The external LM is a 6-layer Transformer model based on [23] and trained on both transcription and Fisher data.

¹<https://github.com/rwth-i6/returnn-experiments/tree/master/2021-internal-lm-attention>

4.2. LibriSpeech 960h

We also conduct experiments on the LibriSpeech 960h corpus [24]. The model architecture is similar to the one used for Switchboard, except that we use a standard LSTM in the decoder. We use 40-dimensional MFCC as input features and BPE as output labels with a vocabulary size of 10k. All models are trained for 15 epochs. The LM scales are tuned on dev-other set and we use a beam size of 32 for inference. We use a 24-layer Transformer model following [23] as an external LM.

4.3. ILM Estimation Methods

We evaluate our AED model with different LM integration methods on both Switchboard and LibriSpeech datasets. The results are shown in Tables 1 and 2. We observe that our proposed ILM estimation methods consistently outperform all of the previous approaches namely Shallow Fusion, Density Ratio, and ILM estimation with zero encoder. On Switchboard, Mini-LSTM and $\mathbb{E}_{\mathcal{D}}[c]$ methods perform the best on Hub5'00. With Mini-LSTM method, we achieve 3.7%, 6.15%, and 5.7% relative improvement in WER on Hub5'00, Hub5'01, and RT03 sets respectively compared to Shallow Fusion. On LibriSpeech, we observe even more improvement using the Mini-LSTM method yielding 15.3% and 14.0% relative reduction in WER on dev-other and test-other respectively. Moreover, we compute the ILM perplexities (PPLs) on the dev sets and we notice that better methods have better PPLs. The dev perplexity for $\mathbb{E}_x[h]$ is low which might be because we use the dev set input information during inference for the ILM. We can also see that zero is not the best estimation method which means that using encoder information bias is helpful.

Cross-domain inference We also conduct experiments on a cross-domain target dataset. We use the AED model trained on LibriSpeech as a source-domain model and chose TED-LIUM-V2 [25] to be the target-domain dataset. TED-LIUM-V2 consists of Ted talks speech. We trained an LSTM LM with 255M words of external target-domain text data. We use a beam size of 12. Results are shown in Table 3. We can observe again that Mini-LSTM method performs the best. It achieves 13.0% and 12.4% relative improvement in WER on both dev and test sets respectively compared to Shallow Fusion.

Table 1: WERs [%] on Switchboard 300h of AED model with Shallow Fusion (SF), Density Ratio (DR), and the proposed ILM estimation methods. ILM BPE-level perplexity (PPL) is reported on Hub5'00.

Method	λ_1 (LM)	λ_2 (ILM)	Hub5'00	Hub5'01	RT03	ILM PPL
None	0.0	0.0	13.8	13.4	16.3	-
SF	0.08	0.0	13.5	13.0	15.7	-
DR	0.14	0.12	13.2	12.7	15.3	-
zero	0.10	0.02	13.5	12.9	15.6	114.2
$\mathbb{E}_{\mathcal{D}}[h]$	0.22	0.20	13.1	12.3	15.0	65.1
$\mathbb{E}_{\mathcal{D}}[c]$	0.26	0.22	13.0	12.4	14.9	39.1
$\mathbb{E}_x[h]$	0.15	0.18	13.2	12.6	15.2	28.4
Mini-LSTM	0.22	0.20	13.0	12.2	14.8	25.6

4.4. Training with External LM

We include our result for the AED model trained together with an external LM in Table 2 with the ILM estimation methods. We observe that we achieve similar WER as the average-based ILM estimation methods without further prior correction. Also, the optimal LM-scale is higher compared to Shallow Fusion and more in line with the correction-based methods.

Table 2: WERs [%] on LibriSpeech 960h of AED model with Shallow Fusion (SF), Density Ratio (DR), and the proposed ILM estimation methods. ILM BPE-level perplexity (PPL) is reported on dev-other.

Method	λ_1 (LM)	λ_2 (ILM)	dev- clean	dev- other	test- clean	test- other	ILM PPL
None	0.0	0.0	3.77	10.37	4.10	10.88	-
SF	0.35	0.0	2.68	6.80	2.90	7.59	-
DR	0.40	0.20	2.40	6.68	2.56	7.22	-
train w. LM	0.54	0.0	2.36	6.19	2.58	6.81	-
zero	0.52	0.28	2.61	6.43	2.88	6.96	741
$\mathbb{E}_D[h]$	0.50	0.30	2.35	6.19	2.71	6.76	543
$\mathbb{E}_D[c]$	0.46		2.33	6.19	2.63	6.74	662
$\mathbb{E}_x[h]$	0.48		2.44	6.34	2.78	7.01	274
Mini-LSTM	0.64	0.42	2.37	5.76	2.64	6.53	311

Table 3: WERs [%] on LibriSpeech 960h of AED model evaluated on out-of-domain TED-LIUM-V2 dev and test sets. Results are with Shallow Fusion (SF), Density Ratio (DR), and the proposed ILM estimation methods.

Method	λ_1 (LM)	λ_2 (ILM)	TLv2-dev	TLv2-test
None	0.0	0.0	22.0	22.9
SF	0.50	0.0	18.5	19.3
DR	0.62	0.48	16.6	17.8
zero	0.54	0.36	17.3	18.3
$\mathbb{E}_D[h]$	0.56	0.68	16.7	17.5
$\mathbb{E}_D[c]$	0.46	0.58	16.8	18.0
$\mathbb{E}_x[h]$	0.52	0.60	16.7	18.0
Mini-LSTM	0.68	0.58	16.1	16.9

4.5. Under-parameterized Decoder

In Table 4, we show results for models trained with under-parameterized decoders by reducing the LSTM dimension on both Switchboard and LibriSpeech datasets. We can observe that the relative improvement after adding an external LM is increased when the decoder contains fewer parameters. However, the final WER is still worse than the baseline with 1000 LSTM units.

Table 4: WERs [%] of different decoder LSTM dimensions on Switchboard 300h and LibriSpeech 960h. Shallow Fusion is used.

LSTM Dim.	LM	SWB Hub5'00	LibriSpeech	
			dev-clean	dev-other
1000	No	13.8	3.77	10.37
	Yes	13.5	2.68	6.81
500	No	14.2	4.10	11.28
	Yes	13.7	2.65	7.48
300	No	14.3	4.06	11.07
	Yes	13.8	2.69	7.29
100	No	14.8	4.28	11.66
	Yes	14.3	2.73	7.57

4.6. Limited Context Decoder

We replace the recurrent LSTM decoder from Equation (3) with a FF decoder in Equation (5). The motivations behind this are: (1) AED model might not need the full label context, (2) limiting the label context can reduce the decoder LM effectiveness. We use 1 linear projection layer with bias followed by tanh activation function. We notice that, under this configuration, a context size of 3 is optimal ($k = 3$ in Equation (5)). Experiments on Switchboard and LibriSpeech datasets are shown in Tables 5 and 6. We observe that LM integration is needed oth-

Table 5: WERs [%] on Switchboard 300h using FF decoder AED model with Shallow Fusion (SF), Density Ratio (DR), and the proposed ILM estimation methods. ILM BPE-level perplexity (PPL) is reported on Hub5'00.

Method	λ_1 (LM)	λ_2 (ILM)	Hub5'00	Hub5'01	RT03	ILM PPL
None	0.0	0.0	14.6	14.0	16.8	-
SF	0.22	0.0	13.8	13.2	15.6	-
DR	0.21	0.04	13.7	13.2	15.6	-
zero	0.29	0.25	13.2	12.6	15.0	68
$\mathbb{E}_D[h]$		0.23	13.0	12.4	14.8	47
$\mathbb{E}_D[c]$	0.27	0.25	13.2		14.9	58
$\mathbb{E}_x[h]$			13.3	12.5		28
Mini-LSTM	0.29	0.29	13.1	12.6		

Table 6: WERs [%] on LibriSpeech 960h using FF decoder AED model with Shallow Fusion (SF), Density Ratio (DR), and the proposed ILM estimation methods. ILM BPE-level perplexity (PPL) is reported on dev-other.

Method	λ_1 (LM)	λ_2 (ILM)	dev- clean	dev- other	test- clean	test- other	ILM PPL
None	0.0	0.0	4.21	11.66	4.30	12.25	-
SF	0.35	0.0	2.77	7.94	3.05	8.04	-
DR	0.58	0.30	3.14	7.18	3.30	8.31	-
zero	0.43	0.28	2.81	7.31	3.01	8.06	795
$\mathbb{E}_D[h]$	0.44	0.42	2.54	6.73	2.81	7.21	462
$\mathbb{E}_D[c]$	0.50		2.96	7.16	3.25	7.93	921
$\mathbb{E}_x[h]$	0.48	0.46	2.74	6.60	2.87	7.10	267
Mini-LSTM	0.64	0.52	2.80	6.58	3.07	7.36	196

erwise the model is worse and that the relative improvement is stronger compared to the LSTM decoder. On Switchboard, after we applied our ILM estimation methods, the results became quite comparable to using the LSTM decoder. On LibriSpeech, with LSTM decoder the performance is still better but we argue that there is a possibility for more improvement with careful training and tuning.

5. Conclusion

In this work, we evaluated different methods to estimate the internal language model (ILM) from the decoder of attention-based encoder-decoder (AED) models. We proposed several new methods that outperformed all of the existing approaches. We presented a simple method for ILM estimation, called Mini-LSTM, that achieved the best results on both intra-domain and cross-domain evaluations. We also showed that, in general, it is better to use encoder bias information instead of masking out the input representation for the ILM estimation. We showed that it is possible to train a feed-forward or limited context decoder for an AED model achieving comparable results to a recurrent decoder on Switchboard. This can have further applications, for example, for lattice recombination. Moreover, we showed that the capacity of the decoder can be reduced without a huge degradation in word error rate.

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