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

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Interspeech 2021, Brno

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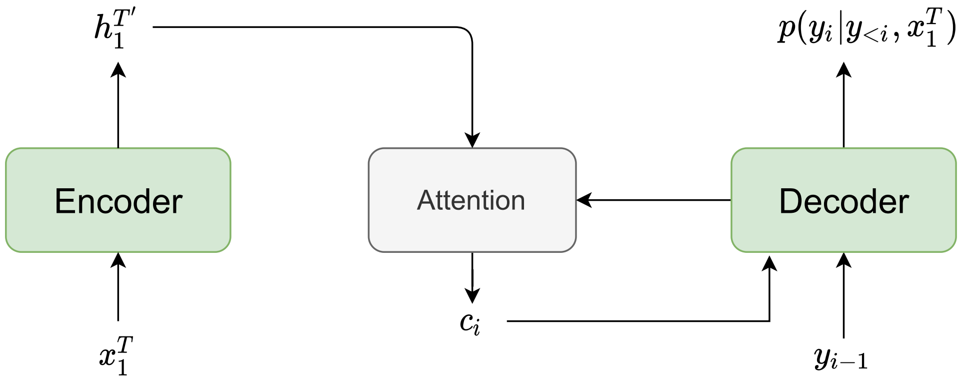
- **Problem**: AED models learn an implicit **internal language model** (ILM) from the training data



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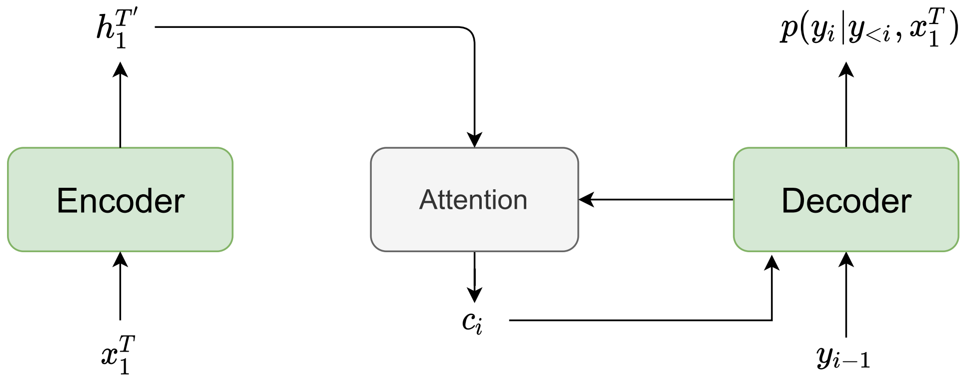

- How to compute the ILM probability for prior correction during recognition for better performance?

Internal Language Model Estimation

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

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$\rightarrow$ We propose different novel methods to estimate the ILM for AED models

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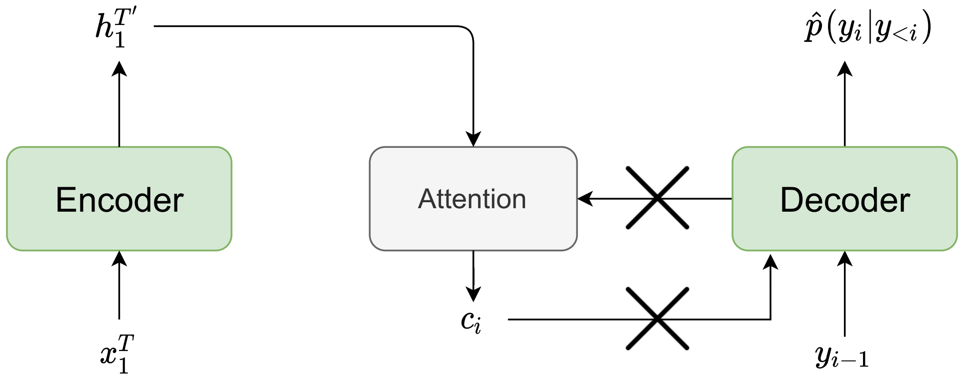

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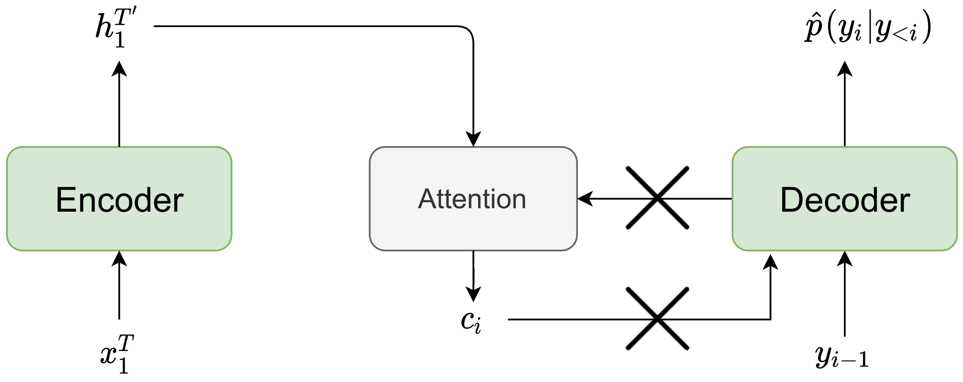

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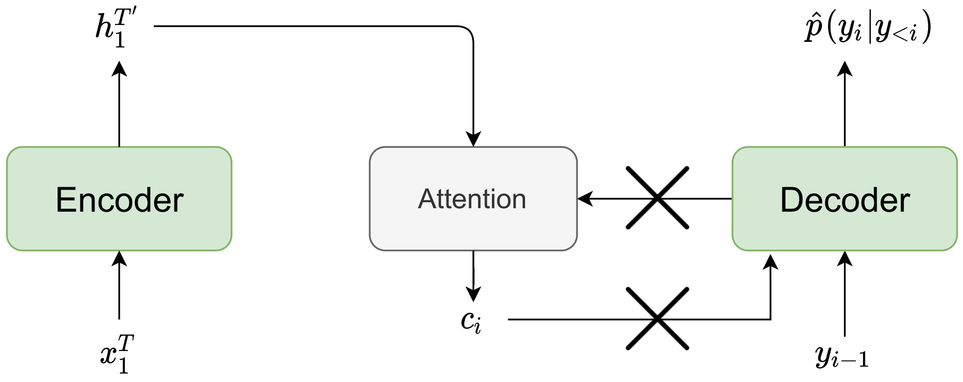
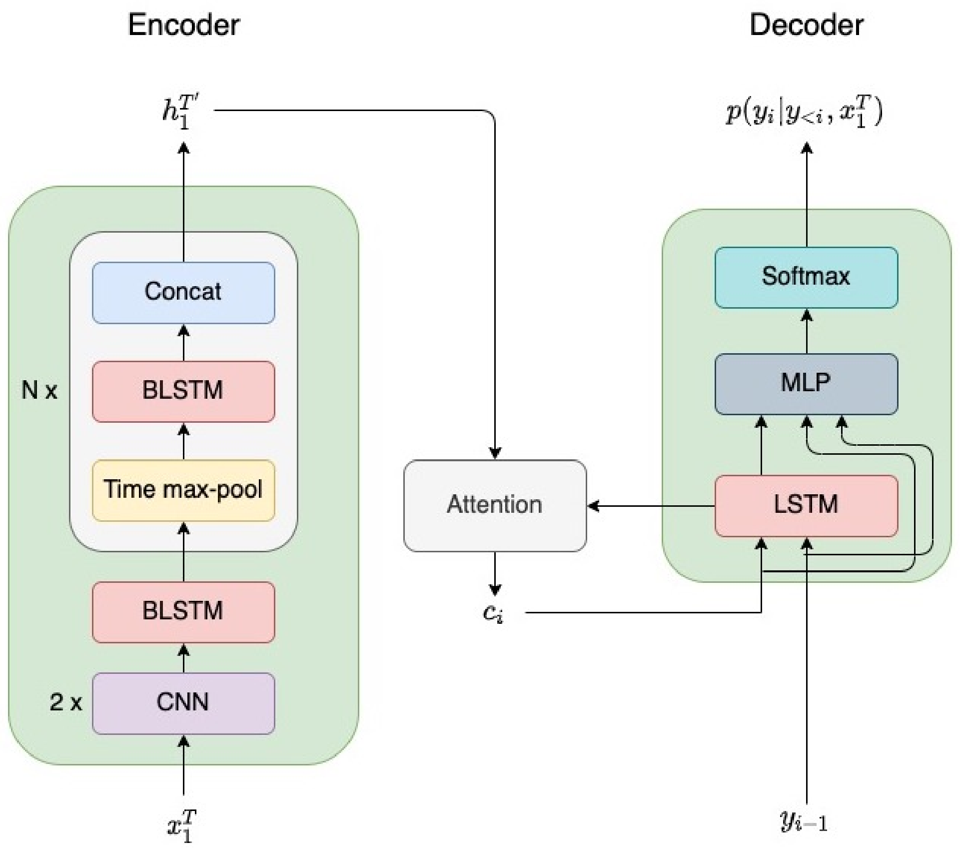
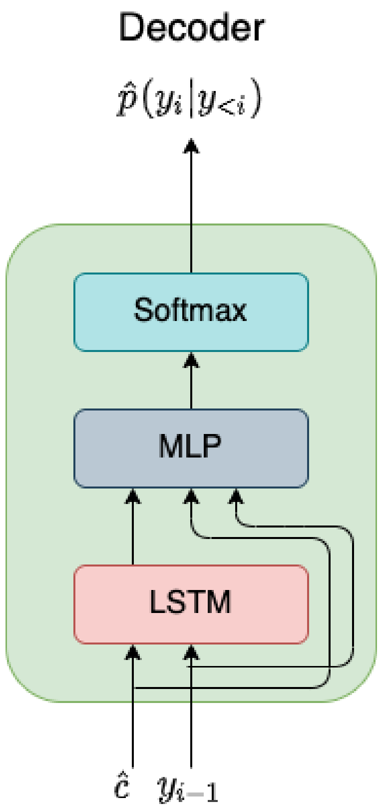


- We argue that using **encoder bias** can be helpful and this is more consistent with training
- This work focuses on **model-specific** estimation methods by replacing attention context vector with either static or trained context vectors

Attention Encoder-Decoder Model



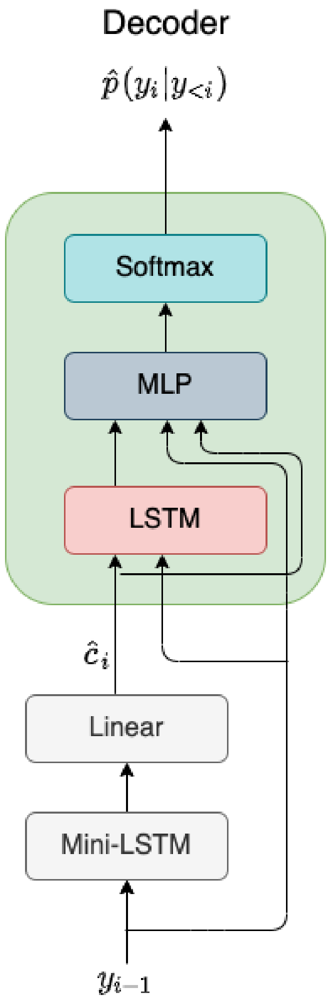
Static Context Vector Estimation



- Static vector $\rightarrow$ position independent
- Replace original context vector c_i by $\hat{c}$:
  - Zero vector (all elements are zero)
  - **Average** of all encoder states over train data
  - **Average** of all context vectors over train data

Trained Context Vector Estimation

- Training Steps
  1. **Freeze** all the parameters of AED model
  2. Add Linear and Mini-LSTM **trainable** layers
  3. Retrain the AED model for few epochs
- **Minimizes** directly the **perplexity**
- Trained only on transcription



ILM Suppression

- Limited Context Decoder
  - Replace the LSTM in the decoder with feed-forward layers
  - Less effective ILM
- Train AED together with LM via sequence training or local log-linear combination [Michel & Schlüter^{+} 20]
  - ASR model relies on the LM for language modeling and focuses on acoustic modeling

Results on Switchboard 300h

Method	WER [%]	
	Hub5'01	RT03
None	13.4	16.3
Shallow Fusion	13.0	15.7
Density Ratio	12.7	15.3
zero	12.9	15.6
$\mathbb{E}_{\mathcal{D}}[h]$	12.3	15.0
$\mathbb{E}_{\mathcal{D}}[c]$	12.4	14.9
$\mathbb{E}_{x}[h]$	12.6	15.2
Mini-LSTM	**12.2**	**14.8**

- ILM estimation by replacing attention context vector by:
  - zero: zero vector
  - $\mathbb{E}_{\mathcal{D}}[h]$: average of encoder states over train data
  - $\mathbb{E}_{\mathcal{D}}[c]$: average of context vectors over train data
  - $\mathbb{E}_{x}[h]$: average encoder states during recognition
  - Mini-LSTM: trained context vector
- Achieved **6% relative improvement** in terms of WER compared to Shallow Fusion

Results on LibriSpeech 960h

Method	WER [%]	
	dev-other	test-other
None	10.37	10.88
Shallow Fusion	6.80	7.59
Density Ratio	6.68	7.22
train w. LM	6.19	6.81
zero	6.43	6.96
$\mathbb{E}_{\mathcal{D}}[h]$	6.19	6.76
$\mathbb{E}_{\mathcal{D}}[c]$	6.19	6.74
$\mathbb{E}_{x}[h]$	6.34	7.01
Mini-LSTM	**5.76**	**6.53**

- train w. LM: train AED model with LM to suppress ILM
- ILM estimation by replacing attention context vector by:
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  - $\mathbb{E}_{\mathcal{D}}[h]$: average of encoder states over train data
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  - Mini-LSTM: trained context vector
- Achieved **15% and 16% relative improvement** in terms of WER compared to Shallow Fusion

Cross-domain Evaluation

- ASR model trained on LibriSpeech 960h dataset
- Evaluated on TED-LIUM-V2 [Rousseau & Deléglise+ 14] dev and test datastes

Method	WER [%]	
	TLv2-dev	TLv2-test
None	22.0	22.9
Shallow Fusion	18.5	19.3
Density Ratio	16.6	17.8
zero	17.3	18.3
$\mathbb{E}_{\mathcal{D}}[h]$	16.7	17.5
$\mathbb{E}_{\mathcal{D}}[c]$	16.8	18.0
$\mathbb{E}_{x}[h]$	16.7	18.0
Mini-LSTM	**16.1**	**16.9**

- ILM estimation by replacing attention context vector by:
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Limited Context Decoder - Switchboard 300h

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  - Mini-LSTM: trained context vector
- 1-layer FF decoder with context size 3
- **Average-based static** estimation methods perform better

Conclusions

- Subtracting the internal language model (ILM) during recognition gives significant improvements in terms of WER
- We proposed a novel method to train the attention context vector for ILM estimation which outperforms other methods
- We achieved 6% relative improvement in terms of WER on Switchboard 300h test sets as well as 15%-16% on LibriSpeech test sets
- Feed-forward or limited context decoder AED model can achieve comparable results to a recurrent decoder on Switchboard 300h task with ILM subtraction
- This work shows the importance of considering ILM subtraction in order to acheive better results

Thank you for your attention

Any questions?

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