UNSUPERVISED SPEAKER ADAPTATION USING ATTENTION-BASED SPEAKER MEMORY FOR END-TO-END ASR

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ICASSP 2020

May 2020

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* Currently at UIUC. This work was done during an internship at MERL.

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Introduction

- Mismatch in speaker characteristics reduces ASR accuracy
- At test time, we often encounter unseen speakers
- Speaker adaptation: adjusting an ASR model to make it more robust to speaker variation
- Our goals:
  - An adaptation method for end-to-end (E2E) ASR
  - Applicable in unsupervised settings
  - Providing fast adaptation
  - Useful for streaming applications
  - Robust to internal speaker changes

Previous Work on Speaker Adaptation for E2E ASR

- Strong recent interest in E2E ASR but not many adaptation techniques
  - Append i-vectors [Audhkhasi+ 2017]
  - Use transformed features [Chorowski+ 2014]
  - Speaker adversarial training [Meng+ 2019]
- Utterance-level approaches → cannot handle internal speaker changes
- Some of them are applied only to the input layer
- Some of them require speaker label → supervised

Proposed Method

- Build memory consisting of a set of speaker embeddings (e.g., i-vectors) from training data
- Use this memory to extract an embedding (M-vector) for unseen speakers at each frame
- Append the M-vector to the neural net activations

- Inspired by the neural Turing machine (NTM) [Graves+ 2014]
  – Use memory reading operation to determine instantaneous speaker embeddings

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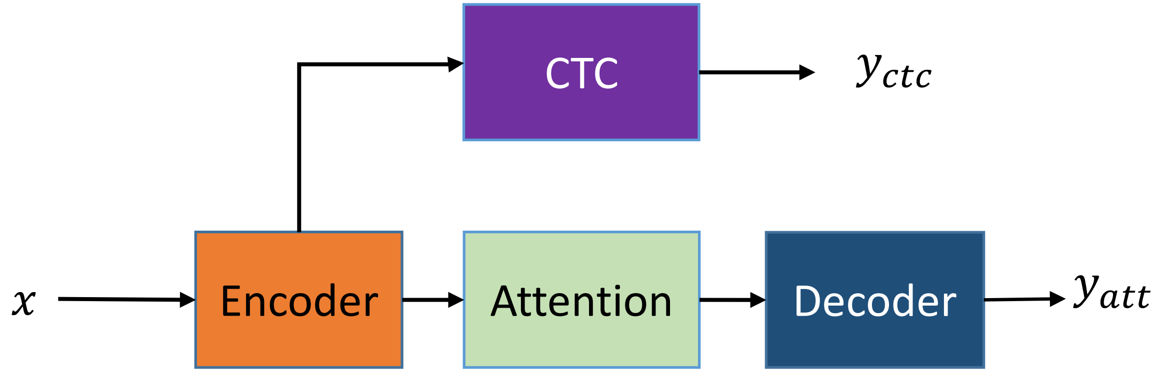
Advantages of the Proposed Method

- Unsupervised during test time
- Frame-level approach
  - Faster adaptation
  - Useful for streaming applications
  - Robust to internal speaker changes
- NTM interpretation allows a direction for writing mechanism (future research)
- Flexible
  - Different embeddings can be used in the memory (i-vectors, x-vectors, etc.)
  - Can be used in different architectures, here joint CTC and attention model

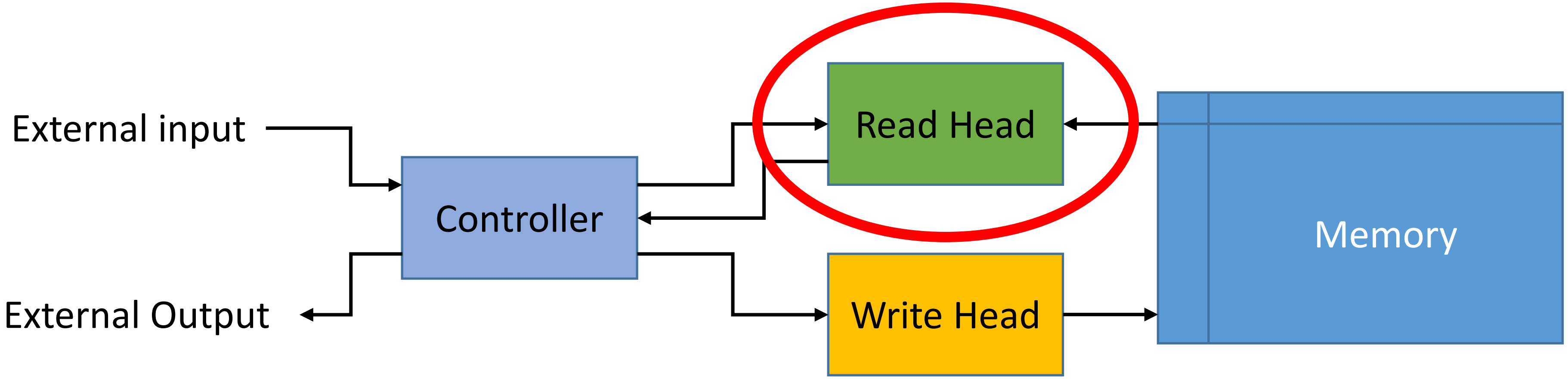
Joint CTC and Attention E2E ASR [Watanabe+ 2017]



- Combination of sequence-to-sequence models to mitigate their individual disadvantages
- Maximize the log-likelihood of the labels given the input features
- Multitask objective

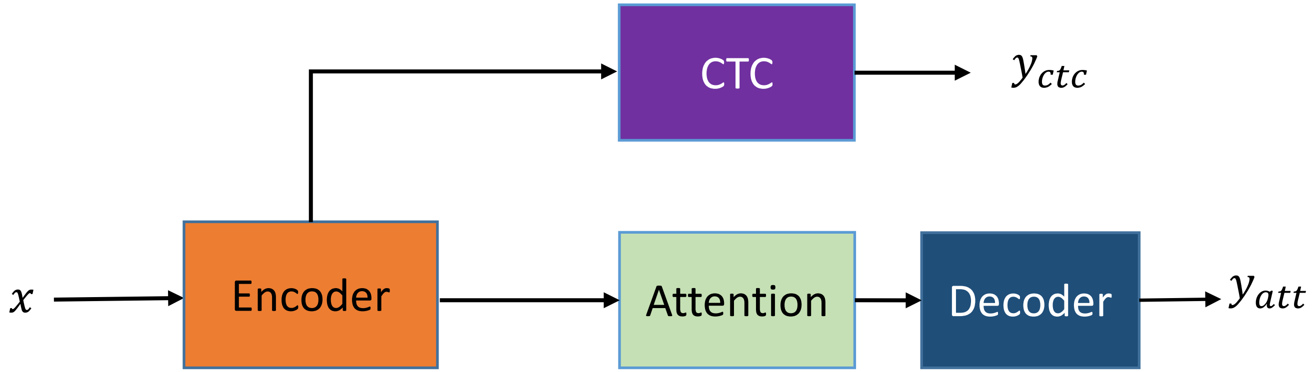
$$L_{joint} = \lambda L_{ctc} + (1 - \lambda) L_{att}$$

Neural Turing Machine [Graves+ 2014]

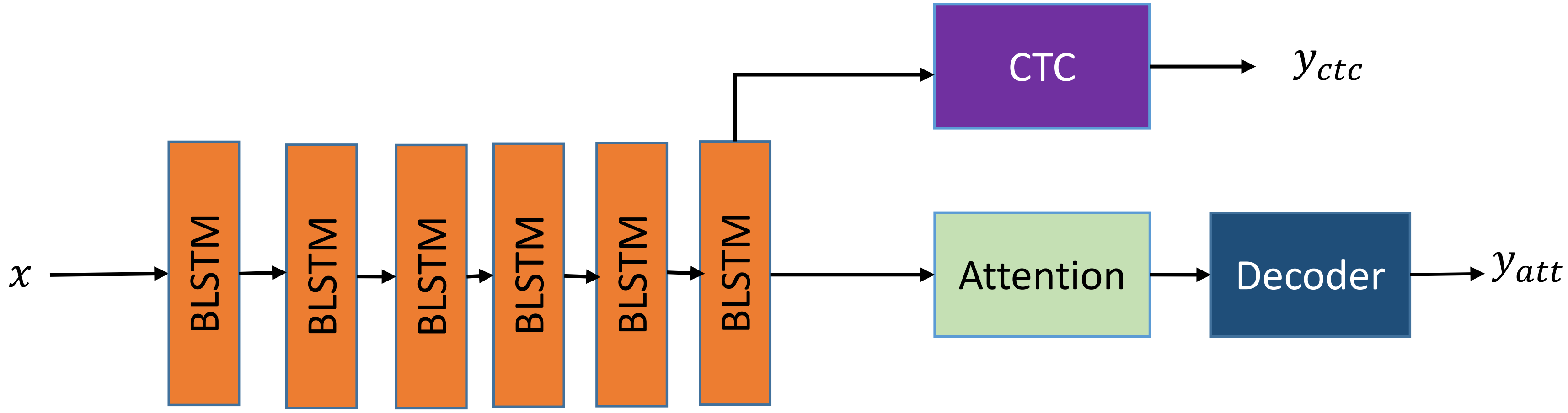


- Dot product: $K(q_t, M_n) = \frac{q_t^T M_n}{||q_t|| \cdot || M_n||}$
- Attention weights : $w_t(n) = \frac{e^{\gamma_t K(q_t, M_n)}}{\sum_l e^{\gamma_t K(q_t, M_l)}}$
- Read vector : $r_t = \sum_{n=1}^{N} w_t(n) M_n$

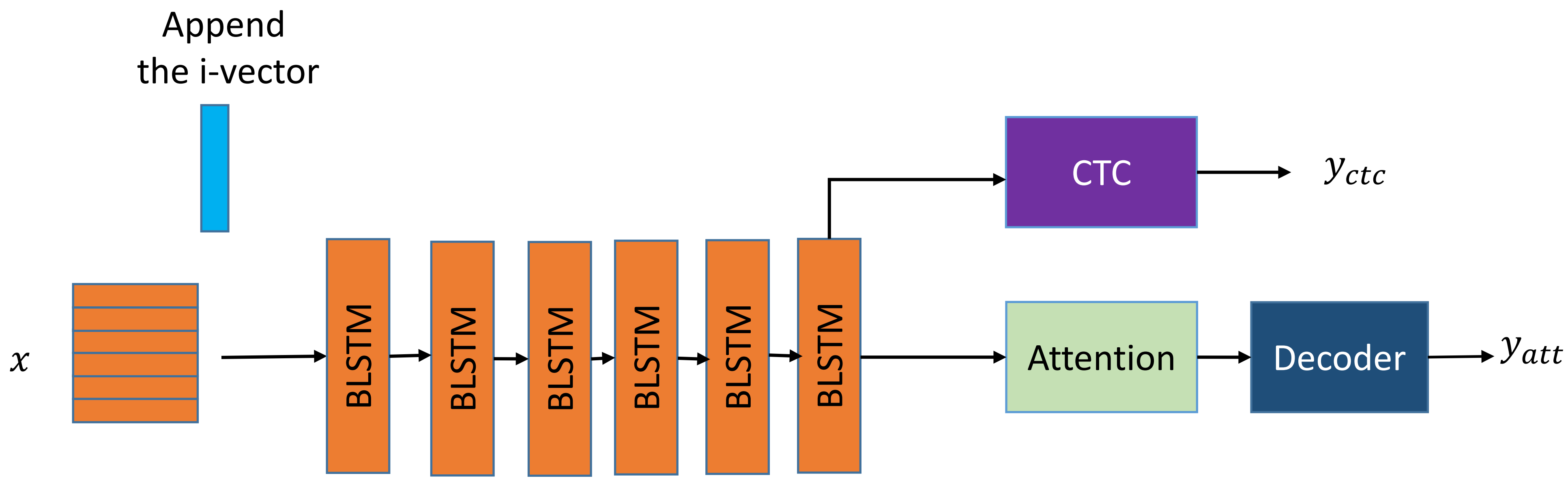
Adaptation with i-vectors



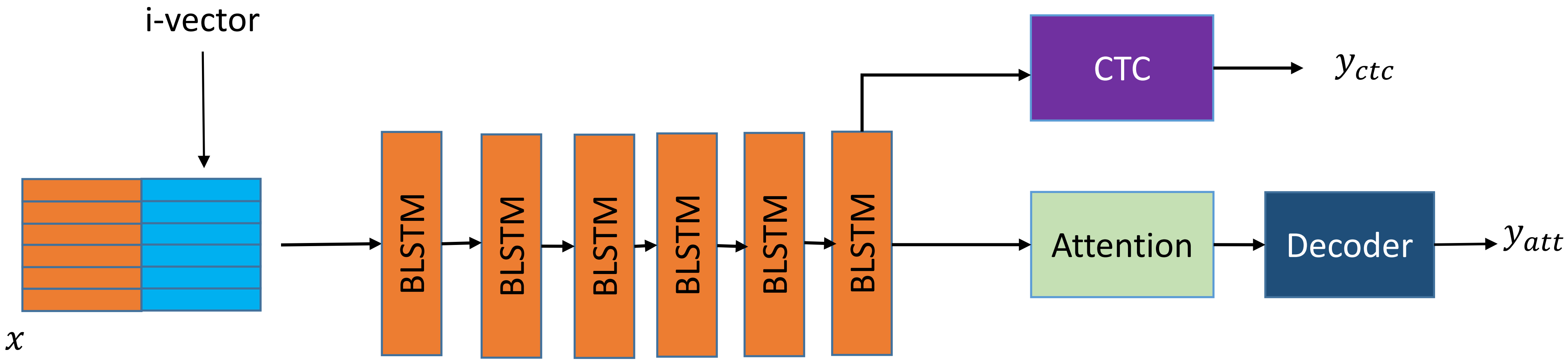
Adaptation with i-vectors



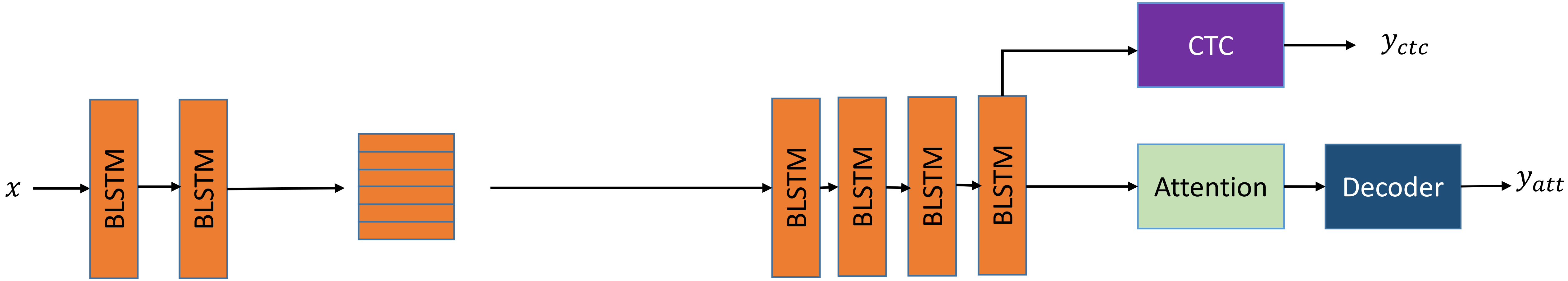
Adaptation with i-vectors



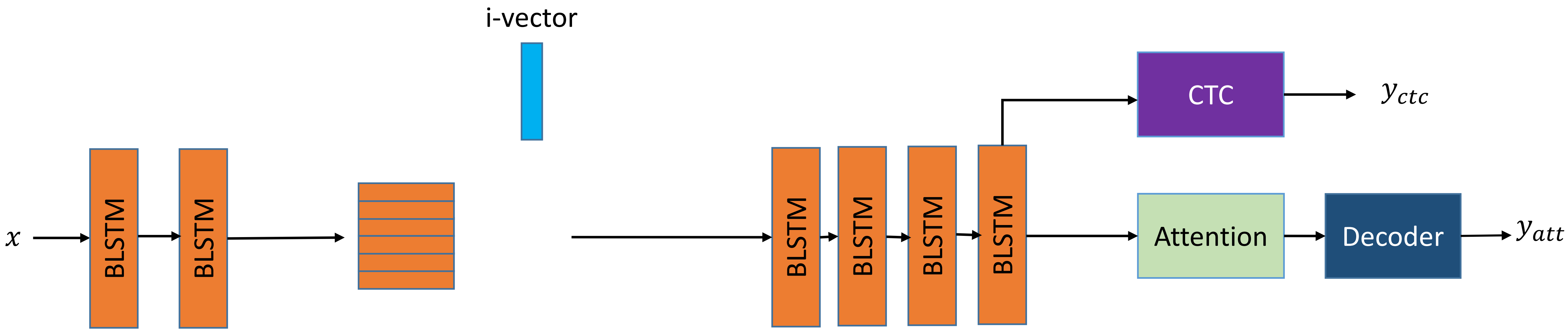
Adaptation with i-vectors



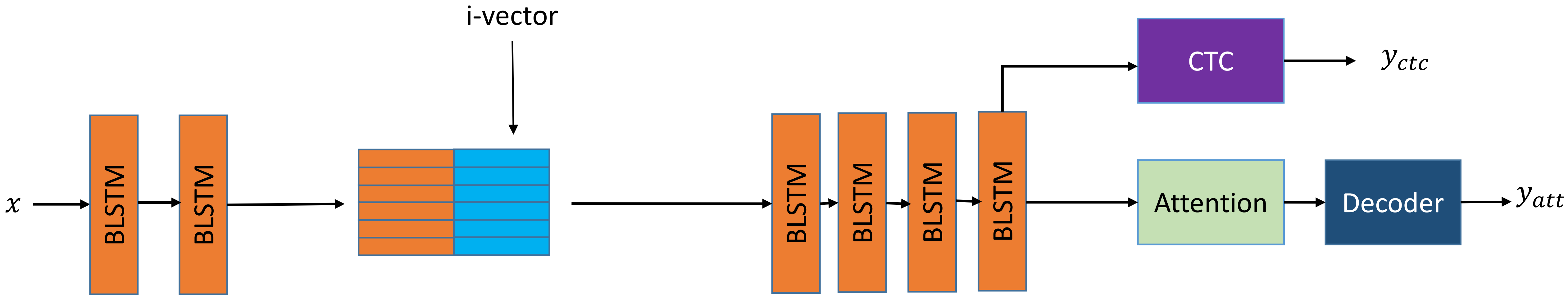
Adaptation with i-vectors



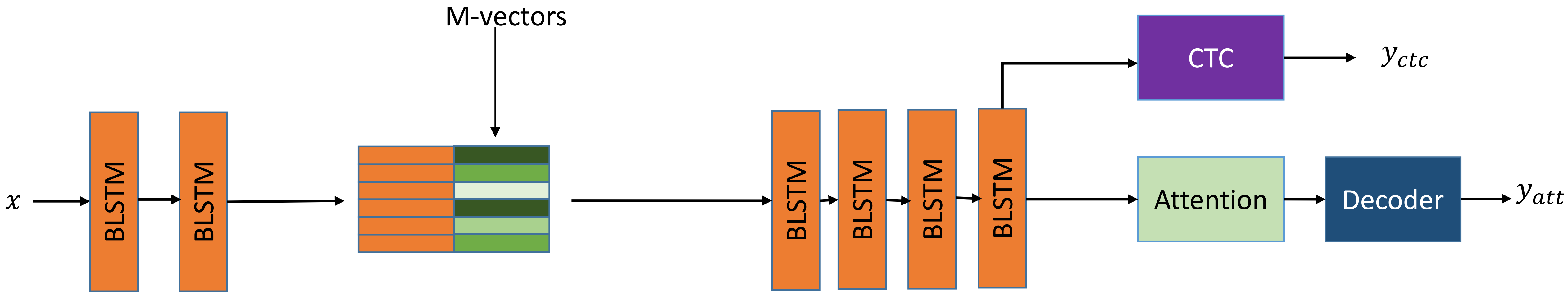
Adaptation with i-vectors



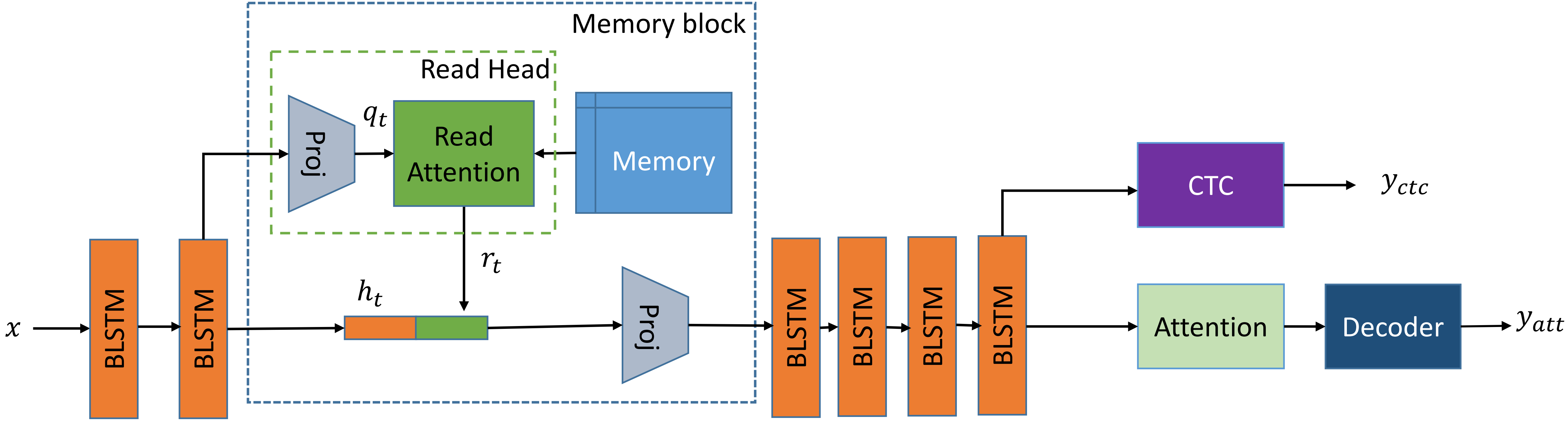
Adaptation with i-vectors



Adaptation with M-vectors



Memory-based Adaptation for E2E ASR



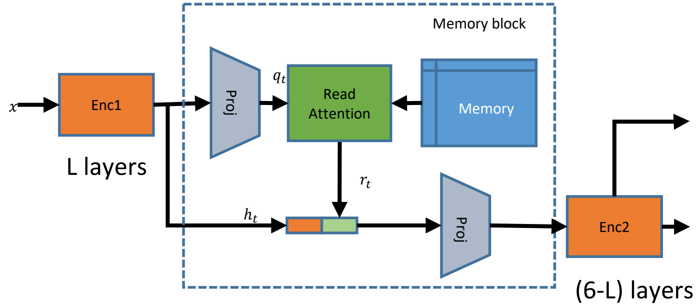
- Scaled dot product: $K(q_t, M_n) = \frac{q_t^T M_n}{\sqrt{d}}$
- Attention weights : $w_t(n) = \frac{e^{\gamma_t K(q_t, M_n)}}{\sum_l e^{\gamma_t K(q_t, M_l)}}, \gamma_t = 1$
- Read vector (M-vector) : $r_t = \sum_{n=1}^{N} w_t(n) M_n$

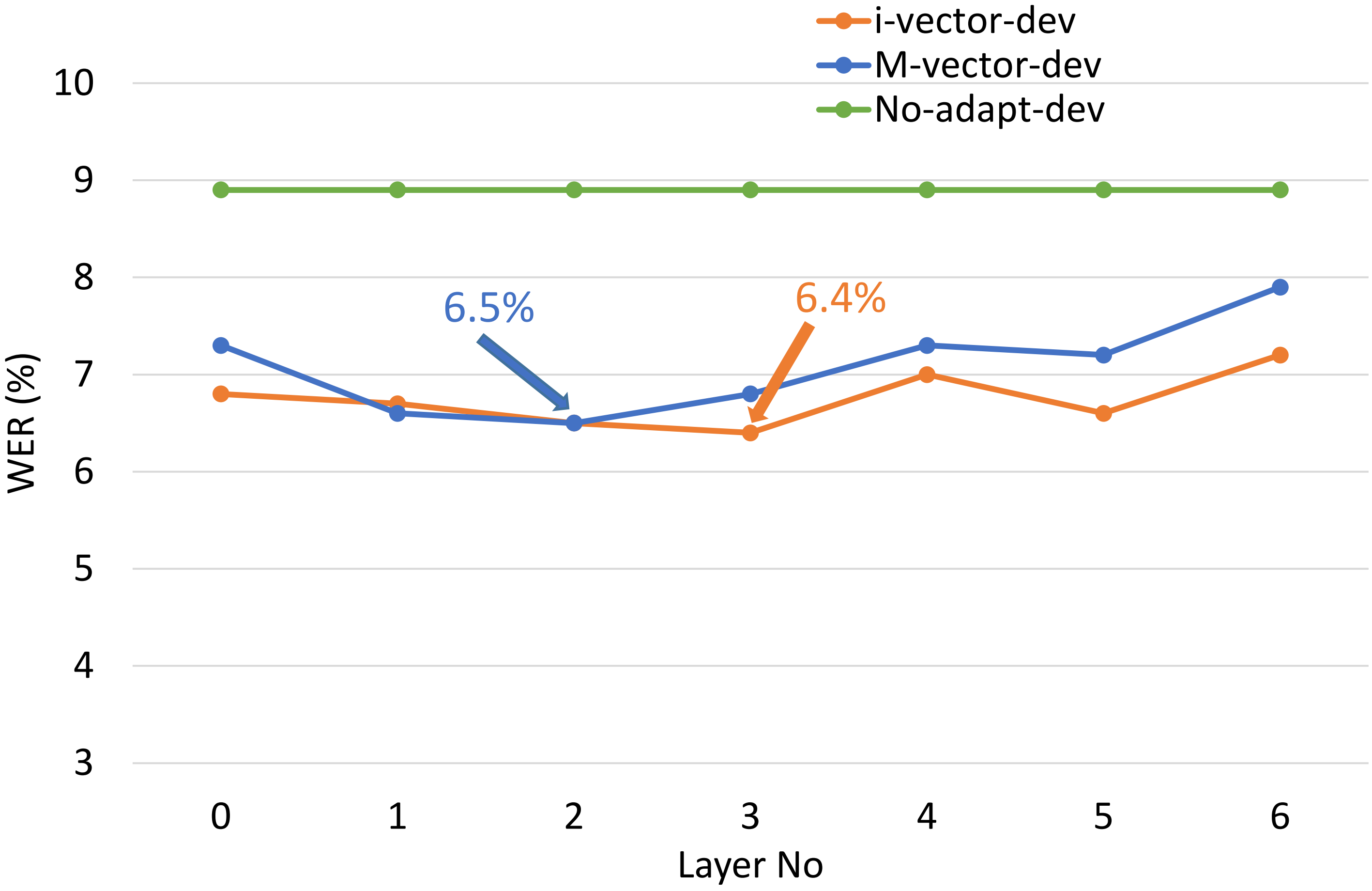
Experimental Setup

- ESPnet [Watanabe+ 2018] joint CTC and attention framework
- Experiments on two datasets
  - WSJ (81.3/1.1/0.7hr, 283 train speakers)
  - TED-LIUM2 (211.1/1.6/2.6hr, 1267 train speakers)
- BLSTM based encoder, LSTM based decoder, location-based attention in between
- Unadapted baseline: ESPnet default recipes
- Speaker adapted baseline: appending i-vectors to hidden layers
- Experiments on the location of the memory block
- Experiments on utterances with speaker change point
- Run for four times with different seeds and report the best results (based on dev set)

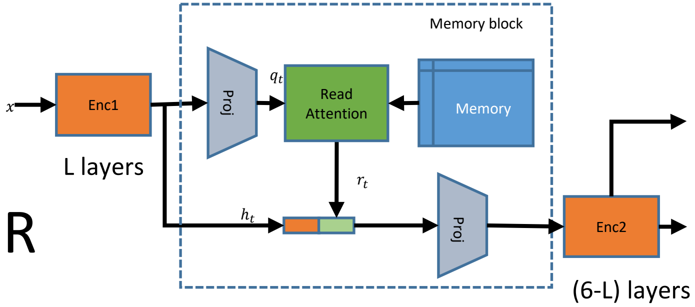
WER as a function of the adaptation layer: WSJ

- Layer=0 denotes input features
- M-vector: similar on dev set WER

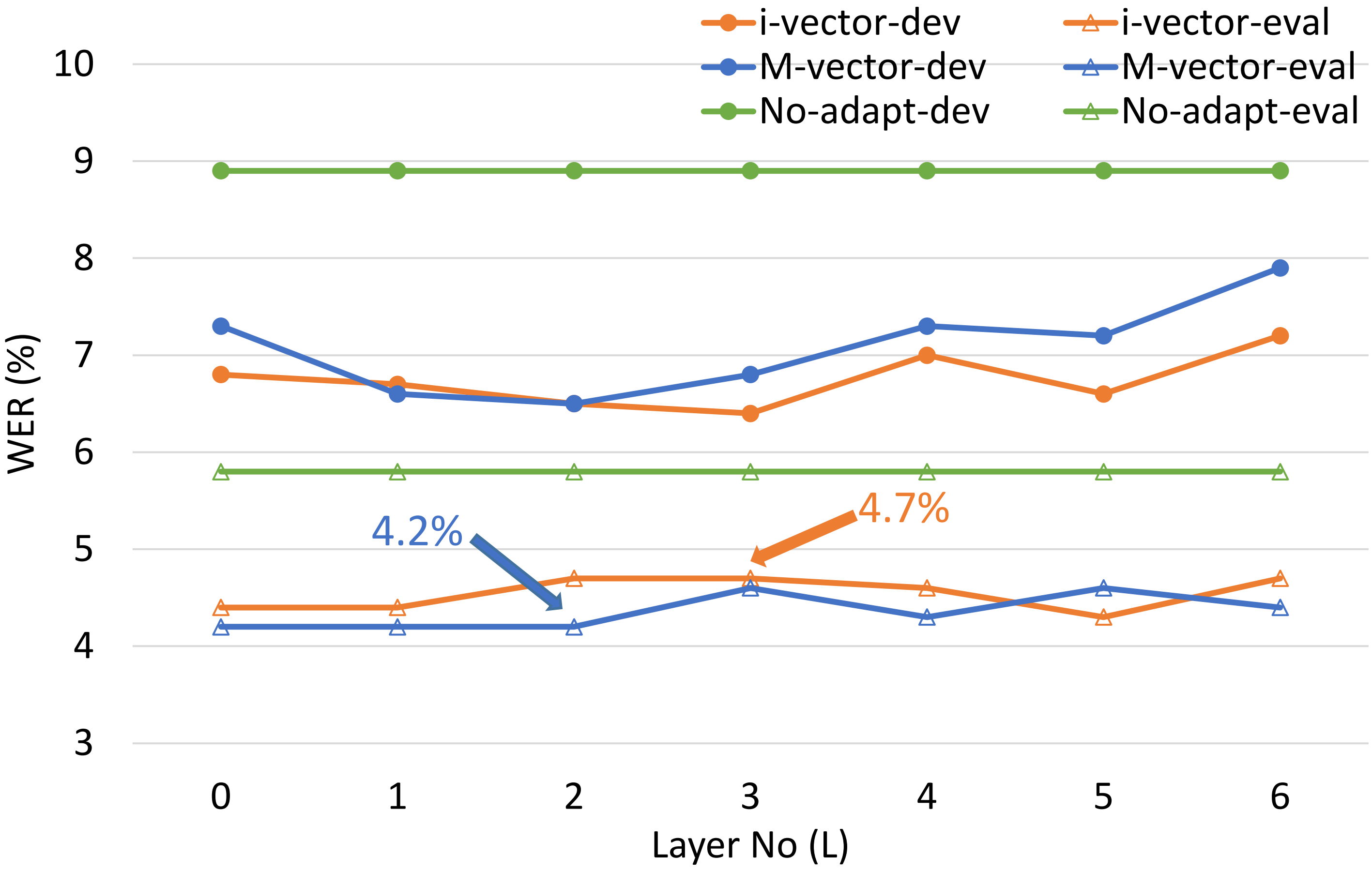




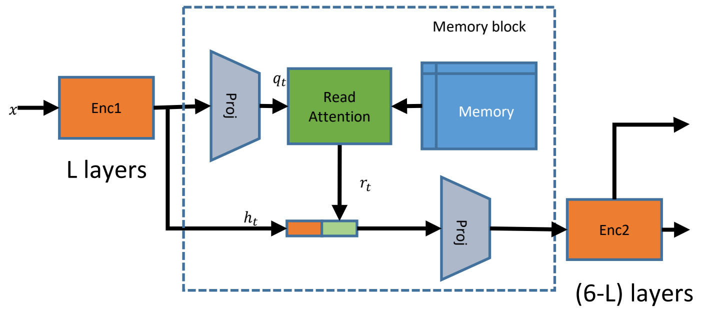
WER as a function of the adaptation layer: WSJ



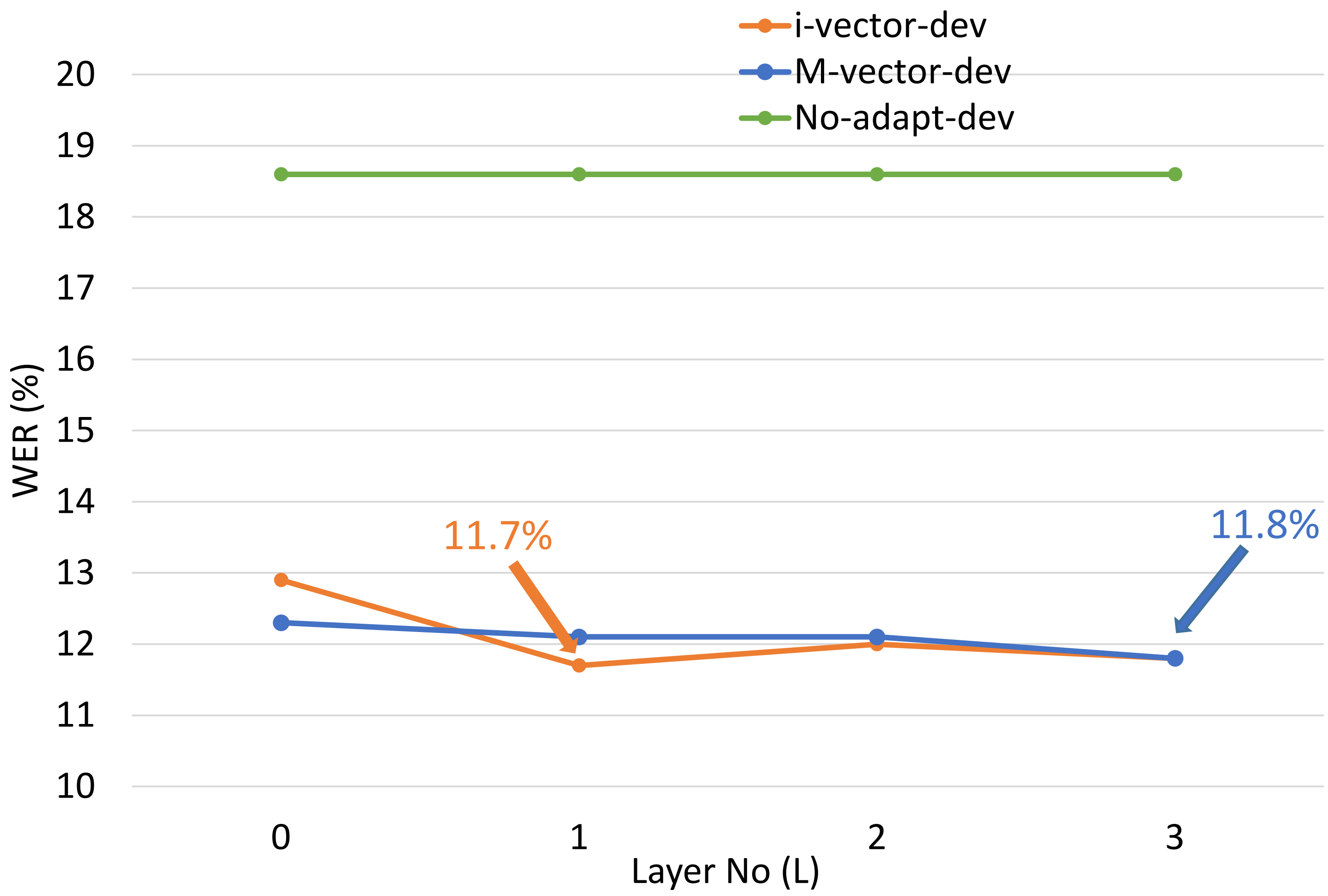
- Layer=0 denotes input features
- M-vector: similar on dev set WER, 10.6% better on eval set WER



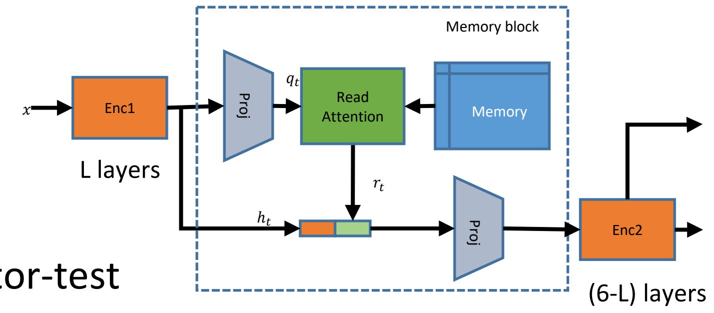
WER as a function of the adaptation layer: TED-LIUM2



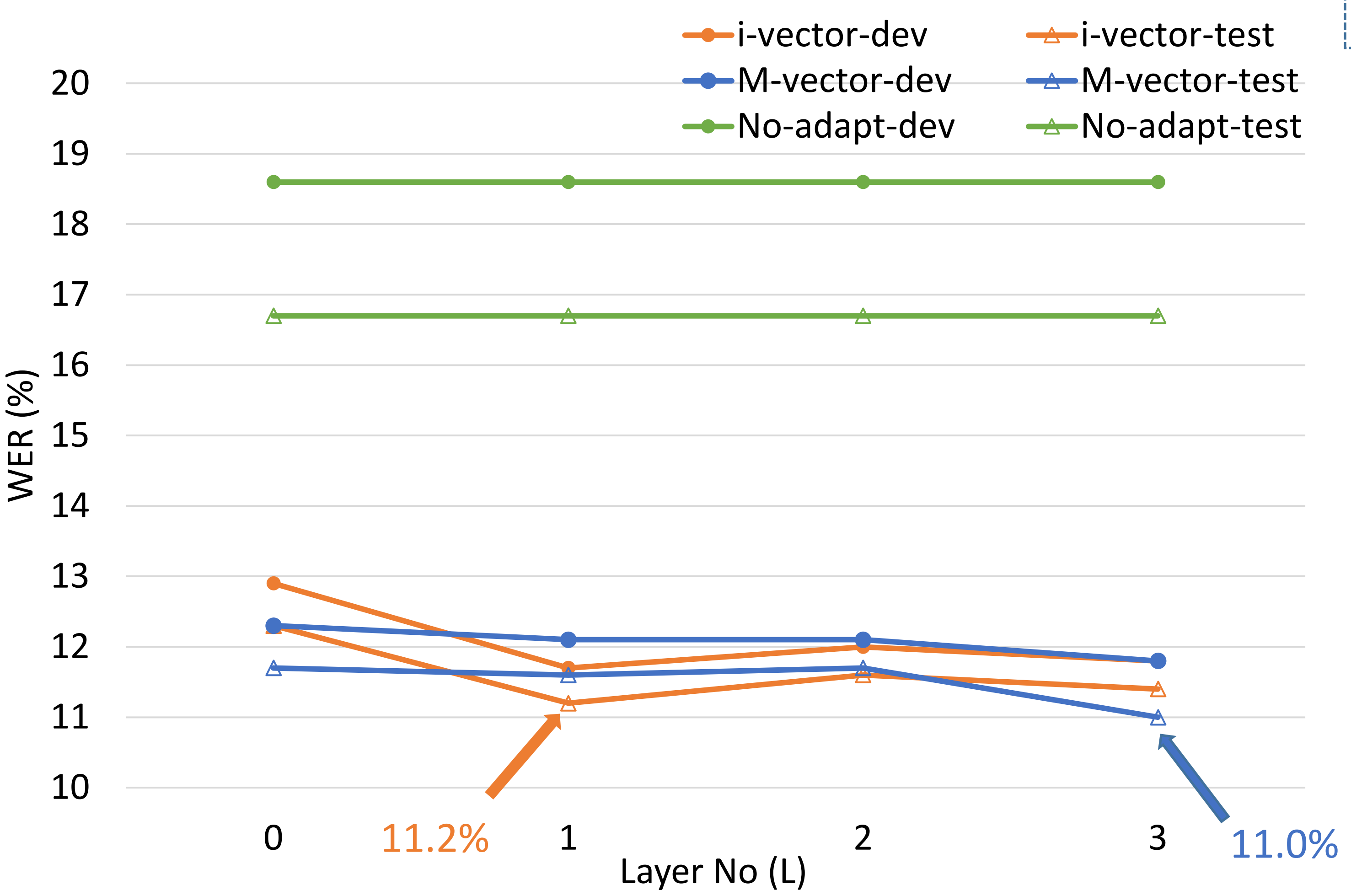
- Similar performance with i-vectors and M-vectors



WER as a function of the adaptation layer: TED-LIUM2



- Similar performance with i-vectors and M-vectors



Speaker level vs Utterance level i-vectors

- i-vector system uses speaker i-vectors, hence requires speaker knowledge during test time
- Remove the advantage by using utterance level i-vectors
- M-vectors perform better than speaker or utterance i-vectors on the test data

	Speaker i-vector		Utterance i-vector		M-vector	
Dataset	dev	test	dev	test	dev	test
WSJ	6.4	4.7	6.4	4.7	6.5	**4.2**
TED-LIUM2	11.7	11.2	11.7	11.8	11.8	**11.0**

Utterances with Speaker Change

- Utterance i-vectors are repeated for all frames in an utterance
- M-vectors are computed at frame-level
- Compare the speaker change performance
- Simulate the condition by removing silences at the boundary and concatenating audio
- Denote the new test sets with *, e.g. dev93*, eval92*

Utterances with Speaker Change: Results

- M-vectors are more robust to speaker change

	single speaker		**speaker change**	
WSJ	dev93	eval92	dev93*	eval92*
i-vector	6.4	4.7	10.4	7.8
M-vector	6.5	4.2	**7.6**	**4.9**

	single speaker		**speaker change**	
TED-LIUM2	dev	test	dev*	test*
i-vector	11.7	11.2	16.1	15.9
M-vector	11.8	11.0	**14.1**	**11.9**

Summary

- An NTM-inspired unsupervised speaker adaptation method for E2E ASR
  - Frame-level approach
  - Online adaptation
  - The M-vector at each frame is a weighted combination of the memory vectors
  - Weights are determined by the attention-based read mechanism
- M-vectors
  - Perform similarly or slightly better than using the oracle i-vectors
  - More robust to speaker changes within utterances than the i-vectors

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