Large Margin Training Improves Language Models For ASR

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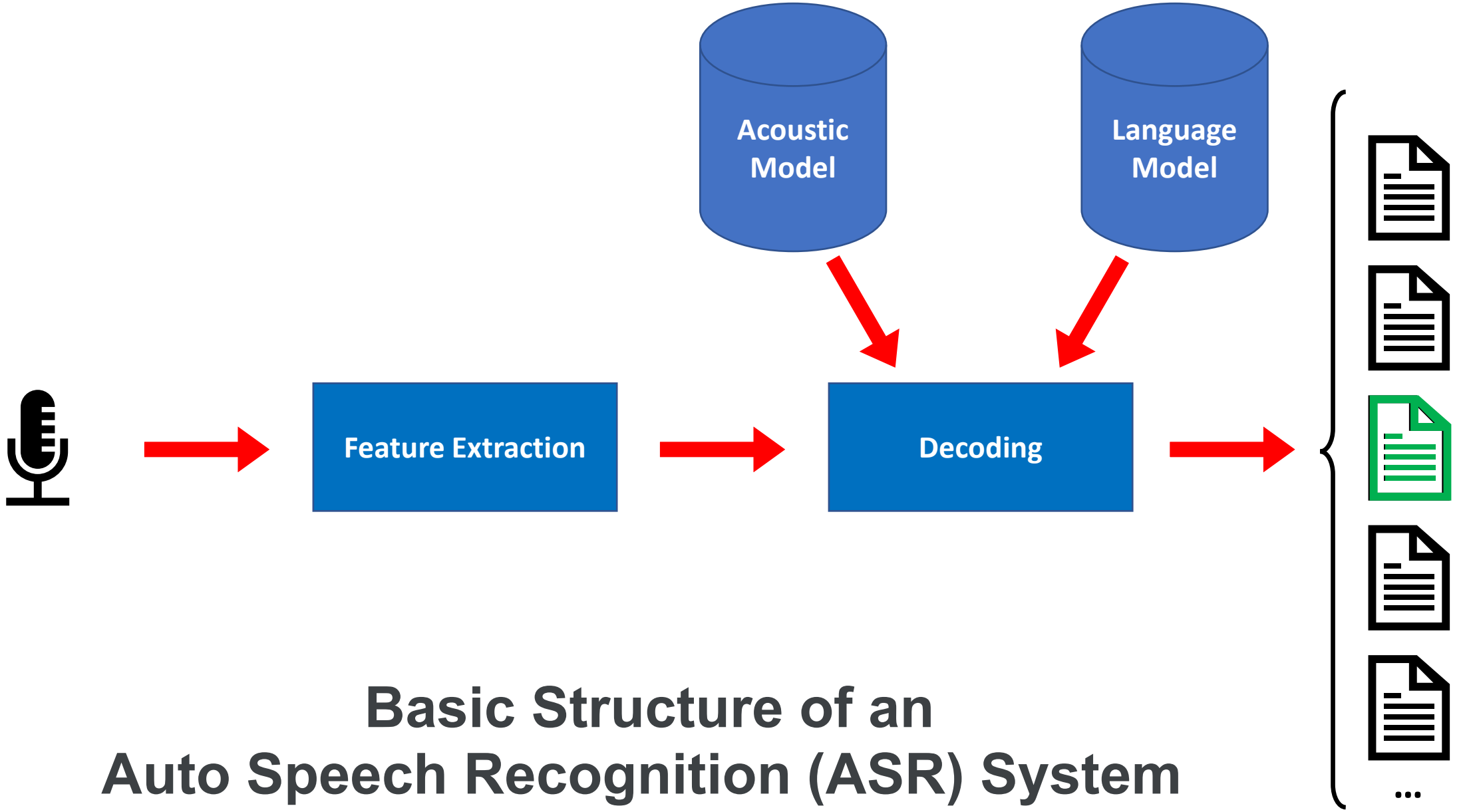
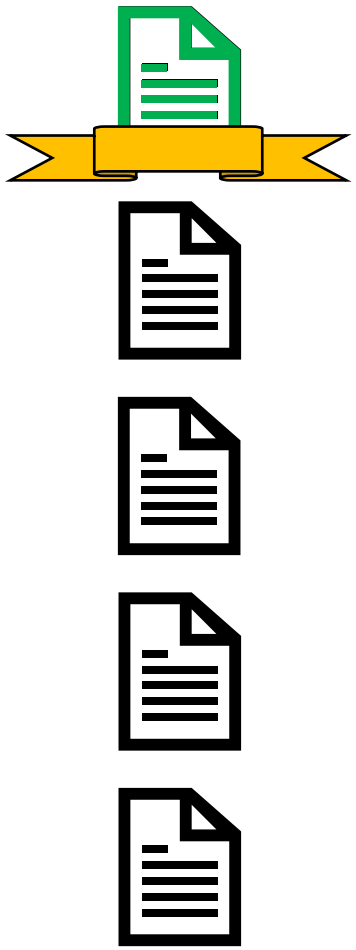


Basic Structure of an Auto Speech Recognition (ASR) System

N-Best Rescoring

Language Model



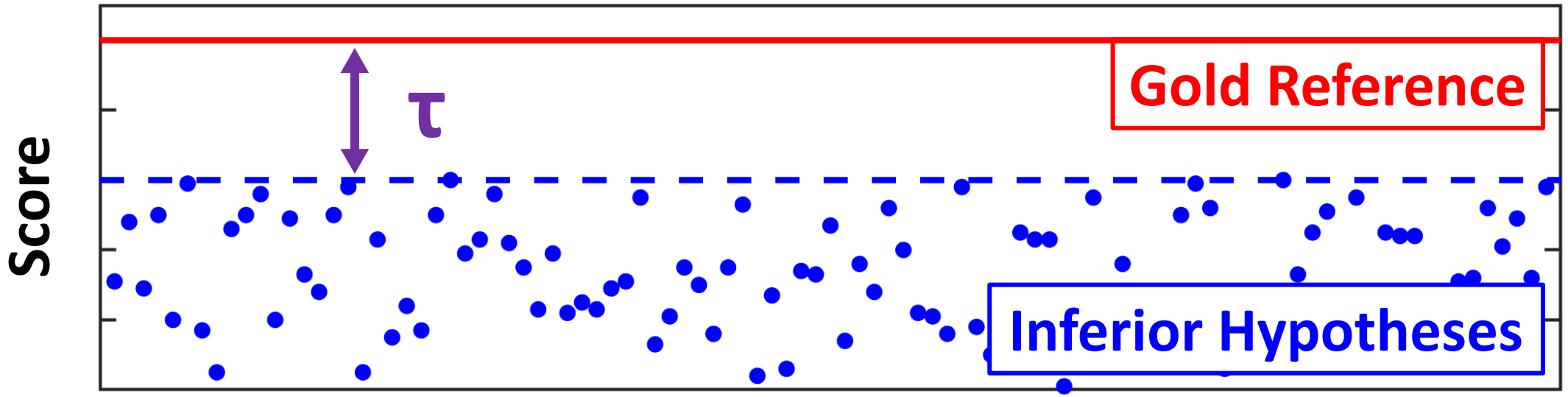
Perplexity

$$PPL = \exp\left\{-\frac{1}{|X|}Score(X)\right\}$$

- Scores of beams candidate from decoder are given by their likelihood
- Fine-tune an LM by minimizing the **Perplexity (PPL)** on the “gold” references could fit it to the ground-truth transcriptions

- **No information from ASR beam candidates utilized**
- **Sometimes propose ``bad'' hypotheses -> give a higher score on inferior hypotheses than the “gold” reference**

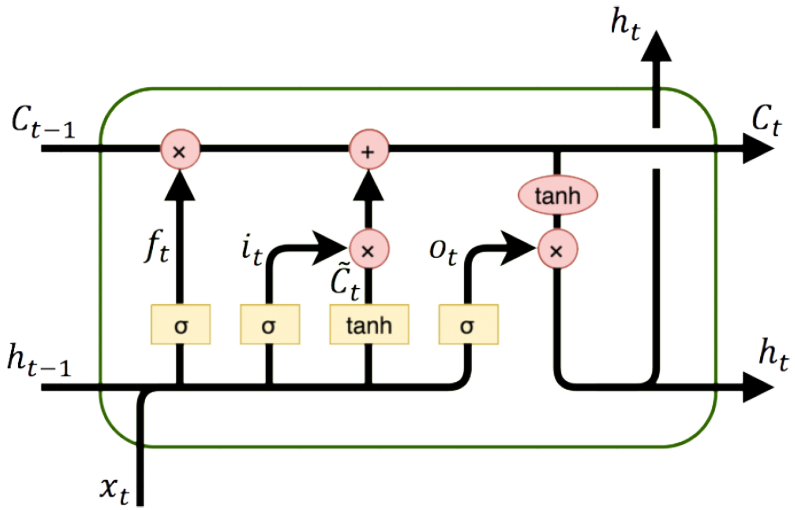
Large Margin Language Model (LMLM)



$$LMLM = \sum_{i=1}^{K} \sum_{j=1}^{N} \max\{0, \tau - (Score(X_i) - Score(X_{i,j})\}$$

Language Model

LSTM



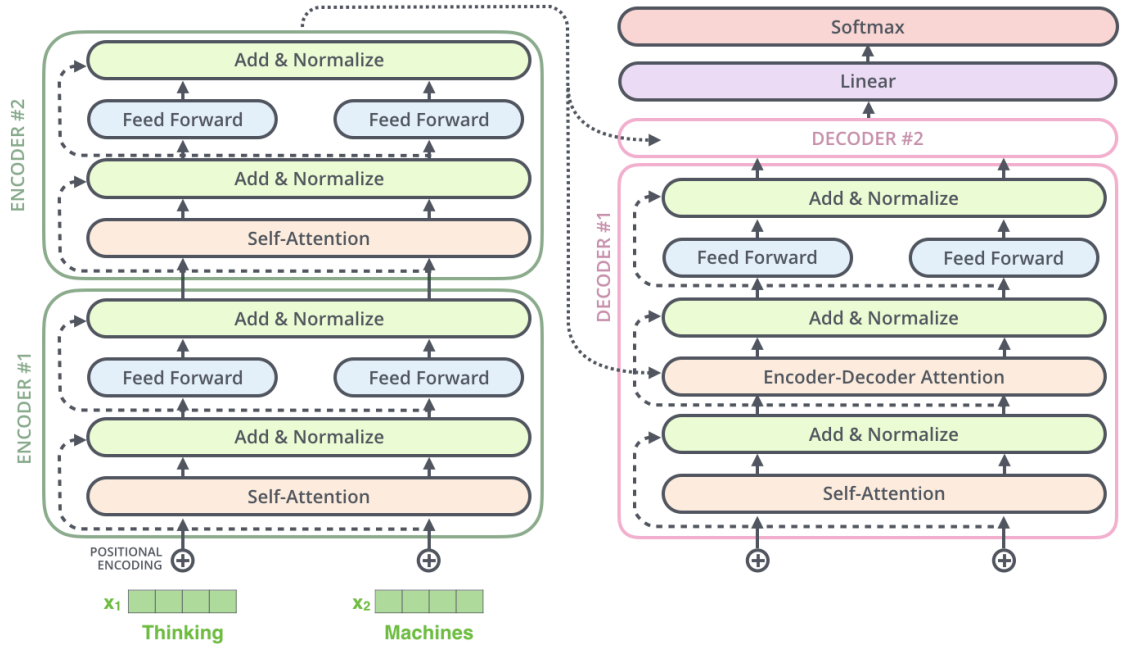
$$h_t = f(h_{t-1}, x_t)$$

Causal

Transformer

Encoder

Decoder



$$h_t = g(x_t, self\ attention(x_t, X_{context}))$$

Non-Causal

Causal

Score (Likelihood) of a Sentence

Causal

$$Score^{c}(X) = \sum_{t=1}^{|X|} \log P(x_t | X_{<t}; \theta)$$

$$X_{<t} = [X_1, \ldots, X_{t-1}]$$

Non-Causal

$$Score^{m}(X) = \sum_{t=1}^{|X|} \log P(x_t | X_{\setminus t}; \theta)$$

$$X_{\setminus t} = [X_1, \ldots, X_{t-1}, X_{t+1}, \ldots, X_{|X|}]$$

Experiment

- Experiment with **LibriSpeech** benchmark.
- Baseline Decoder:

  Acoustic model: chain system based on Factorized Time Delay Neural Network (TDNN-F)

  Language model: Trigram LM
- Language models for rescoring:

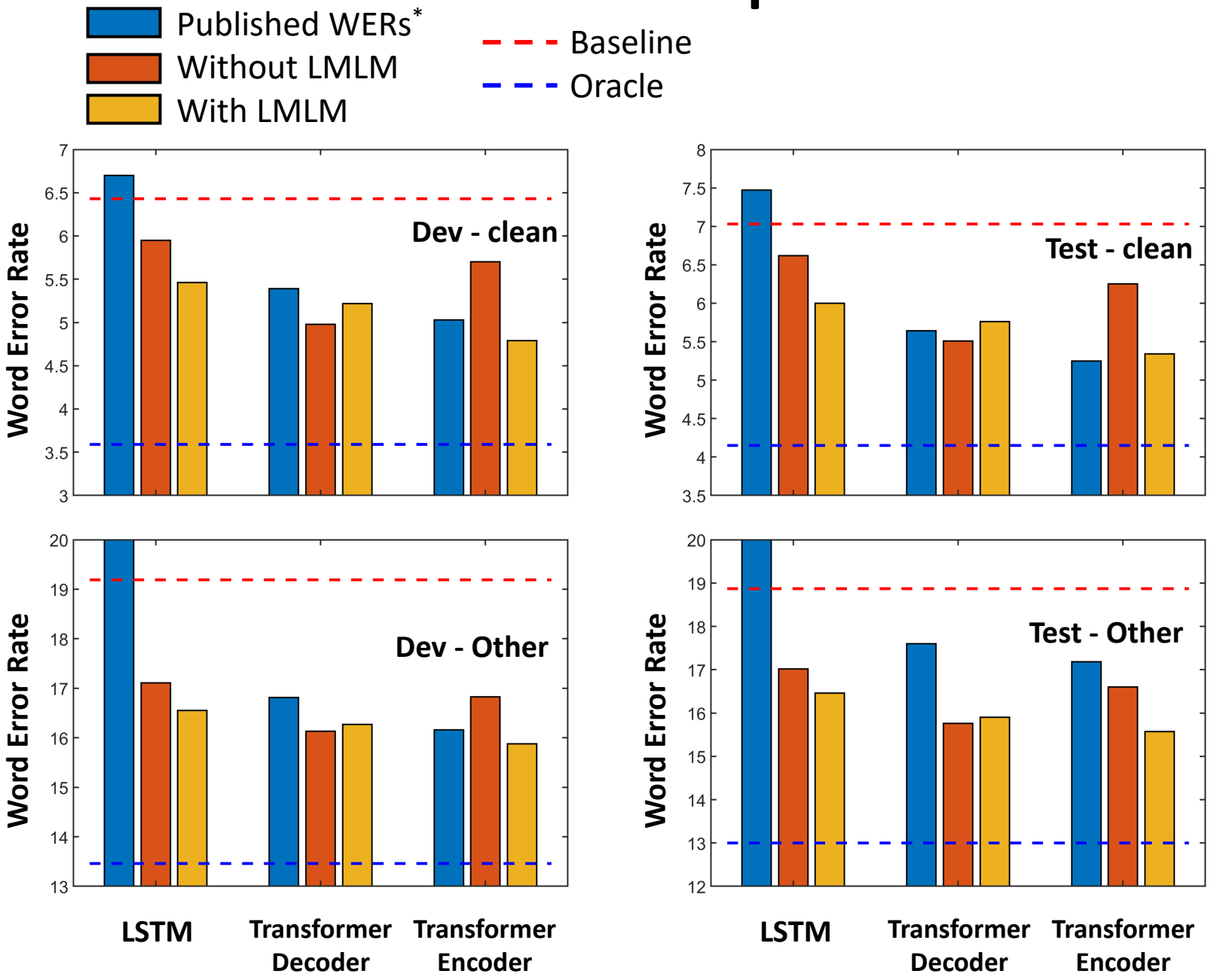
  LSTM: Causal, 4 layers, 512 hidden dimension

  Transformer Decoder: Causal, 12 layers, 768 hidden dimension, 12 self-attention heads

  Transformer Encoder: Non-causal, 12 layers, 768 hidden dimension, 12 self-attention heads

All neural LMs are pretrained on a joint of enWiki and bookCorpus.

Empirical Results



- Lowest WER is achieved with Transformer Encoder+LMLM training
- LMLM training significantly decreases WER for LSTM and Transformer Encoder
- Transformer Decoder without LMLM training is already very competitive.
- May be caused by the fundamental difference between causal LM score and non-causal LM score.

* Julian Salazar, et.al "Masked language model scoring," 58th ACL, 2019, pp. 2699–2712.
* Joonbo Shin, et.al "Effective sentence scoring method using bert for speech recognition," ACML, 2019, pp. 1081–1093
* Lu Huang, et.al. "An improved residual lstm architecture for acoustic modeling," 2nd ICCCS. IEEE, 2017, pp. 101–105.

Thank you!