End-to-end Training of a Large Vocabulary End-to-end Speech Recognition System

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1 Summary

- Achieves the state of the art speech recognition performance for commercial products using an end-to-end pipeline that performs all of data reading, large scale data augmentation [1], power-mel feature extraction [2], and distributed neural network parameter updates in an on-the-fly way.
- Performs Vocal Tract Length Perturbation and Acoustic Simulation [3] on the CPU queue using example servers.
- Performs Neural Beamforming [4] on the device side for further improvement in far-field noisy environments.
- Performs experiments both using the on-line MoCha [5] and the Bidirectional Full-Attention (BFA) approach.

2 Overall Structure

The overall structure is shown in Fig. 1

- **Data reading**: Using sharded `TFRecords` and `tf.data`.
- **Data augmentation and feature extraction**: VTLP, AS, and power-mel feature extraction are running on the example servers.
- **Connection between the example servers and the GPU servers**: Using `ZeroMQ` for asynchronous message queueing.
- **Distributed neural net training**: Training on the GPU server using `horovod`.

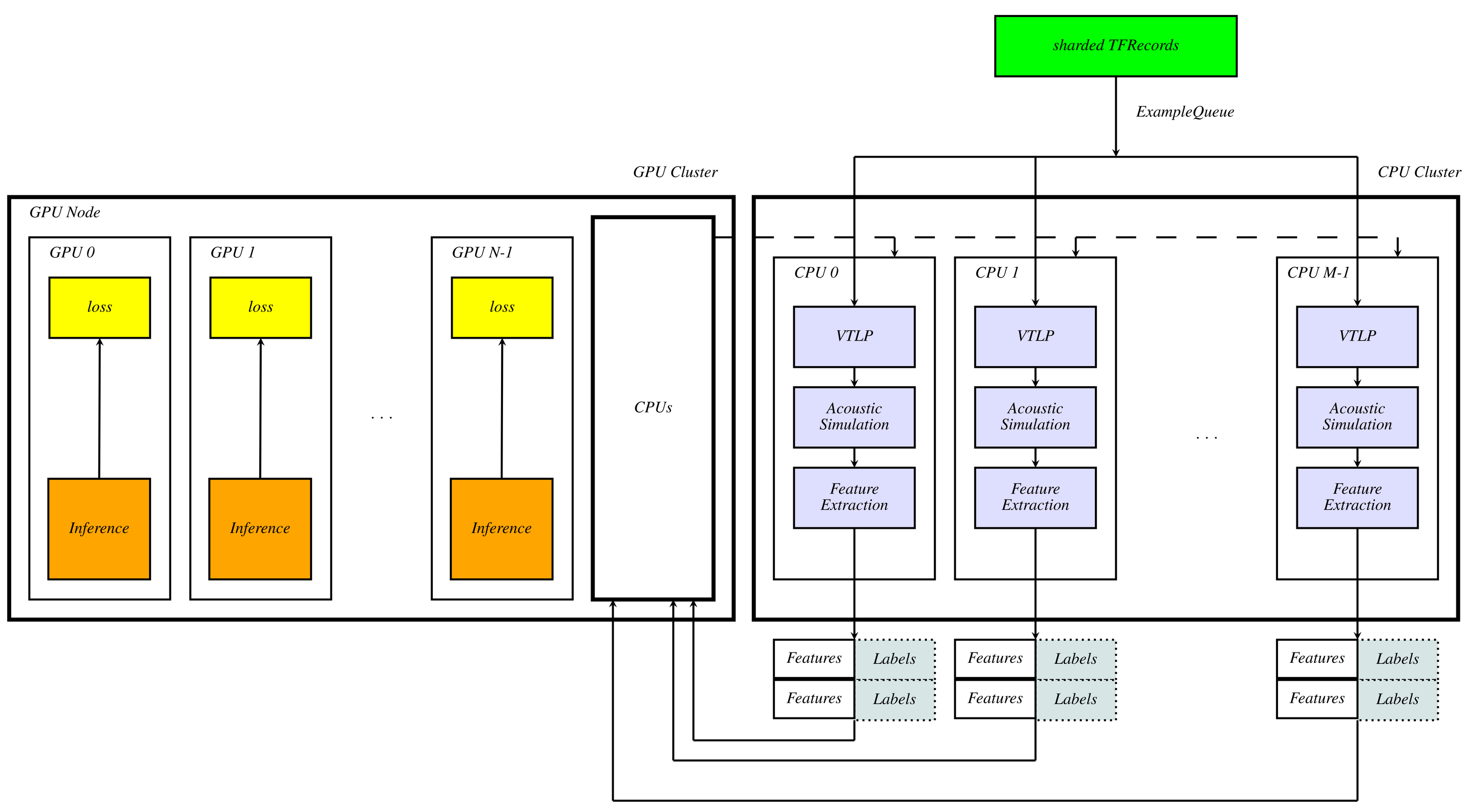


Figure 1: The Samsung Research end-to-end training framework for building an end-to-end speech recognition system with multi CPU-GPU clusters and on-the-fly data processing and augmentation pipeline.

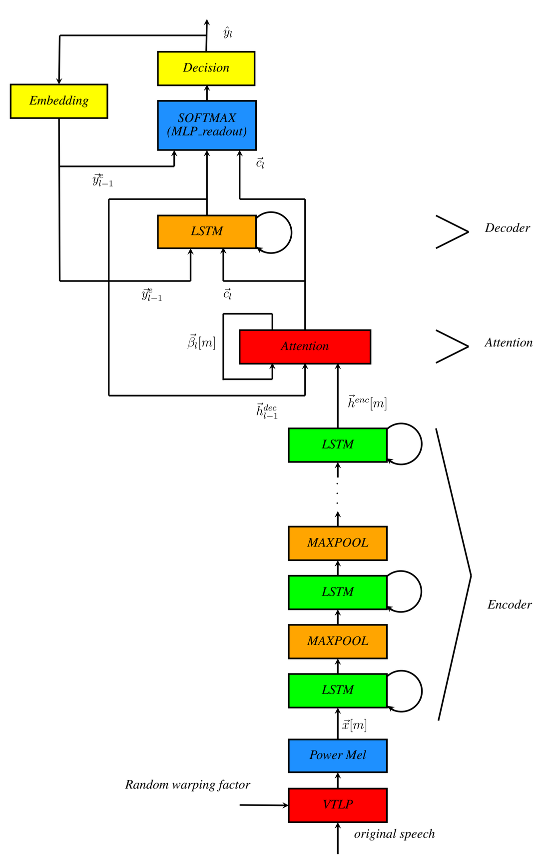


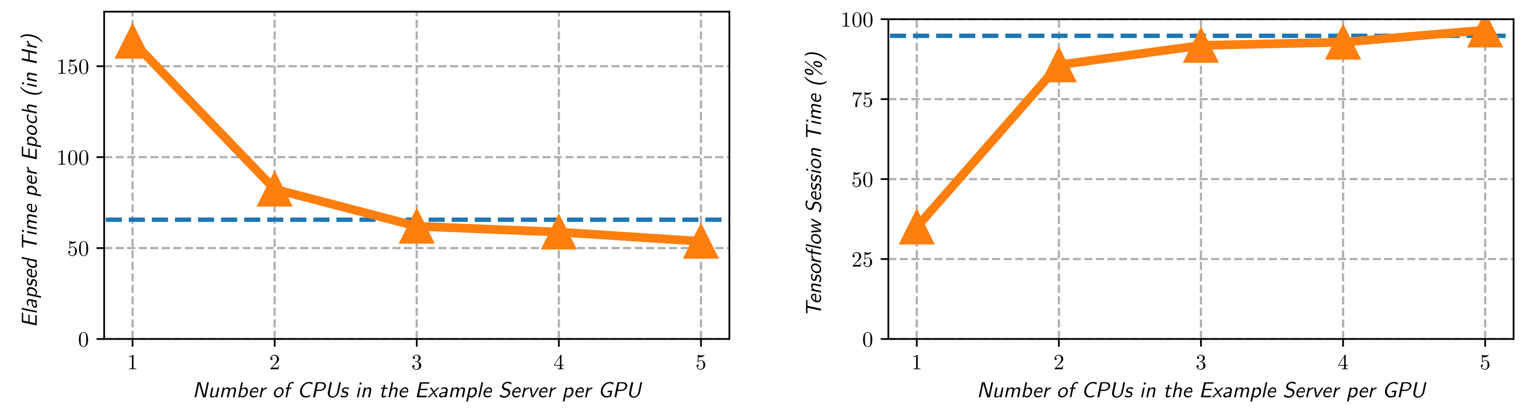
Figure 2: The neural network structure for end-to-end speech recognition.

We used the RETURNN speech recognition system [6] with various modifications:

- MoCha[5] and the modified beam search decoder.
- Gradient clipping, modified learning-late warm-up, and so on.
- Power-mel feature Motivated by the power-law nonlinearity of $((\cdot)^{\frac{1}{15}})$.
- Modified shallow fusion with a Transformer LM [1]

$$y^{*}_{0:L} = \arg\max_{y_{0:L}} \sum_{l=0}^{L-1} \Big[\log P\left(y_l | \vec{x}[0:M], y_{0:l}\right) - \lambda_p \log P(y_l) + \lambda_{\text{lm}} \log P\left(y_l | y_{0:l}\right) \Big], \quad (1)$$

- Example queues for efficient data augmentation



(a) (b)

Figure 3: The efficiency of the *example server* with respect to the number of CPUs per GPU: (a) The required time to process a single epoch during the training phase and (b) the percentage of `Tensorflow` computation time defined by $t_{\text{session}} = \frac{\text{Time Spent in Tensorflow Session}}{\text{Elapsed Time}}$. The blue horizontal dotted lines in each figure represent the case when data augmentation with example servers is not employed.

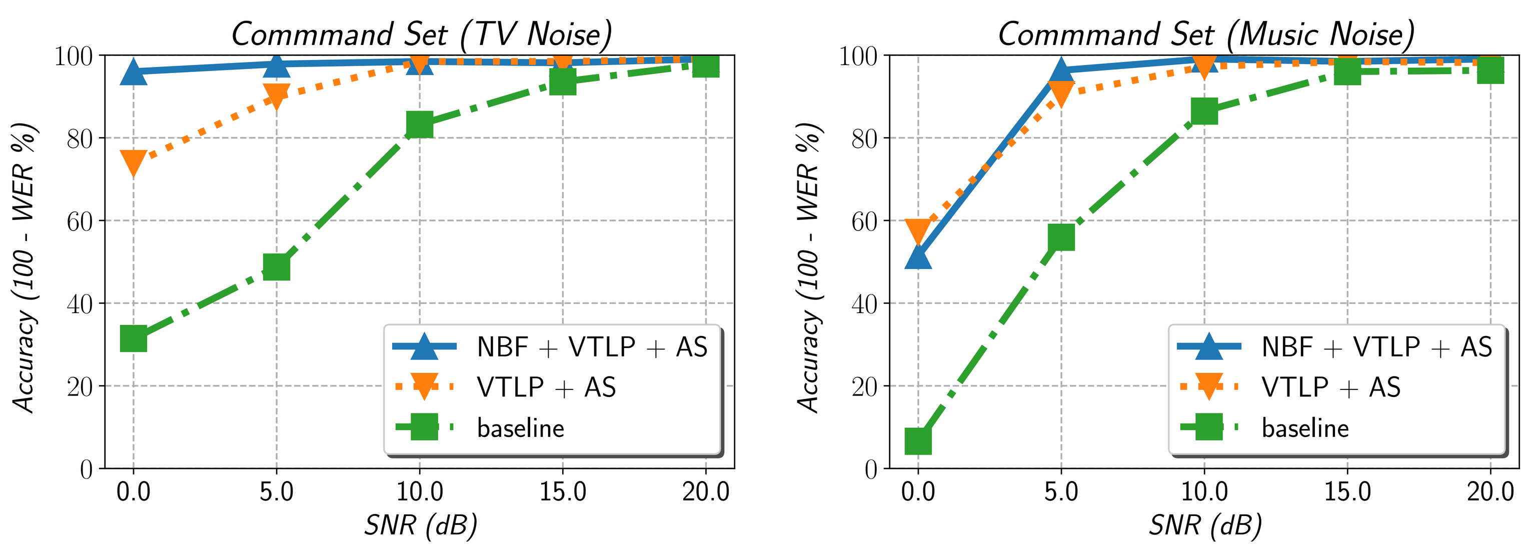
3 Experimental Results

- **LibriSpeech experiments** (960-hr training and evaluation on 5.4-hr LibriSpeech `test-clean`)

Table 1: Summary of Word Error Rates (WERs) obtained for different LibriSpeech and `Bixby` near-field end-to-end ASR models with and without an RNN LM.

Models		BFA	MoChA
LibriSpeech	w/o LM	3.66 %	6.78 %
(1536-cell)	RNN-LM	2.85 %	5.54 %
test-clean	Transformer LM	2.44 %	-
Bixby	w/o LM	8.25 %	10.77 %
(1024-cell)	RNN-LM	7.92 %	9.95 %

- **Bixby English command-set experiments** (10,000-hr `Bixby` training set and `Bixby` command test sets)
- Note that the MoCha version of the system trained using `Bixby` training set was commercialized for on-device dictation for high-end Samsung mobile phones.



(a) (b)

Figure 4: Speech recognition accuracy at different Signal-to-Noise Ratios (SNRs) under three different noisy conditions: direct TV noise (a) , music noise (b), and babble noise (c). NBF, VTLP, and AS stand for Neural Beam Former (NBF) [4], Vocal Tract Length Perturbation (VTLP) [1] , and Acoustics Simulator (AS) [7], respectively.

References

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