This work concentrates on reducing the RTF and word error rate of a hybrid HMM-DNN. Our baseline system uses an architecture with TDNN and LSTM layers. We find this architecture particularly useful for lightly reverberated environments. However, these models tend to demand more computation than is desirable. In this work, we explore alternate architectures employing singular value decomposition (SVD) is applied to the TDNN layers to reduce the RTF, as well as to the affine transforms of every LSTM cell. We compare this approach with specifying bottleneck layers similar to those introduced by SVD before training. Additionally, we reduced the search space of the decoding graph to make it a better fit to operate in real-time applications. We report -61.57% relative reduction in RTF and almost 1% relative decrease in WER for our architecture trained on Fisher data along with reverberated versions of this dataset in order to match one of our target test distributions.

Index Terms— WER, realtime, TDNN, factorized, LSTM

1. INTRODUCTION

Sequence discriminative models such as those trained with the lattice free–maximum mutual information (LF-MMI) criterion are continuously improving with better deep learning strategies and more data from different distributions either by pooling strategies [1] or fine tuning [2]. The state-of-the-art hybrid architecture comprises bi-directional long short term Memory (BLSTM) neural networks used together with time-delay neural networks (TDNNs) stacked one over the other. This hybrid ASR setup still requires complementary help from Hidden Markov Models (HMMs), which are responsible for aligning the sequence triphones with the variable length audio data. However, these models are difficult to use in a real-time setting due to the very large number of parameters involved in LSTMs. To overcome this barrier to using an LSTM-TDNN architecture in real-time, we compare and contrast parameter reduction approaches such as SVD and its comparably equivalent bottleneck architectures.

2. BACKGROUND AND RELATED WORK

Recent acoustic models have been trained using sequence discriminative cost functions without cross-entropy pre-training [3]. Different types of sequence-discriminative cost functions are MMI (Maximum Mutual Information), bMMI (boosted-MMI), MPE (Minumum Phone Error), MBR (Minimum Bayes Rate) and sMBR (state-level MBR) [4]. In our work, we use MMI as the cost function for all of the architectures, though cross entropy is used for regularization.

Though the main focus of our work is latency reduction, one could consider it similar to other model compression techniques proposed in [5] and [6]. [5] and [6] use low-rank factorization for bottlenecking but this technique differs from our work in the way bottlenecking is applied. Also, techniques in [5] are effective only when bottlenecks are deployed in the input and output layers. And authors in [6] apply model compression techniques to a Keyword Search (KWS) task whereas in our work we concentrate on ASR.

2.1. TDNN and its factorized variant

TDNN architecture progressively captures more temporal context as the layers get deeper. The temporal modelling at every layer is controlled by two factors: subsampling and splicing [7]. In the TDNN-F (factorized) variant [8], the layers are modified in two ways. In addition to factorization, highway layers are introduced, which connect non-adjacent layers. This contrasts with [6], where layers are only factorized. Layer factorization is done using SVD. Factorization bottlenecks the affine transformation matrix (weight matrix). This reduced weight matrix has lower dimensionality. There are two side effects of factorization: while there is an improvement in computational efficiency, as the dimensionality is reduced, there is also a reduction in representational expressiveness. Unfortunately, instability is introduced by pruning away dimensions at every layer and by randomly initializing the weight matrices.

To stabilize training, the highway layers from [9] are used. Highway layers are not standalone layers, but when applied to an existing layer, they forward the output dimensions to a deeper layer by skipping one or more immediately following layers. These layers are used in scenarios where information loss occurs at deeper layers. By skipping one or more lay-
ers, unimpeded information flows across several deeper layers. This also helps avoid vanishing gradients in backpropagation through very deep layers. Authors from [8] claim that the TDNN-F models perform about as well as LSTM-TDNN hybrids. However, from our experiments in Table 3.2, the claim did not hold; hence, we continued to explore other possibilities.

2.2. Frame splicing

TDNN, as discussed in section 2.1, captures narrow windows at the initial layers and complete input at the deeper layers. From [10], we derive two architectures by tweaking the frames that are spliced at different layers which are described in table 2.1. For our first architecture (LSTM-TDNN-I), we changed the frame splicing from \{-2,-1,0,+1,+2\} to \{-1,0,1\}. Our second choice (LSTM-TDNN-II) was to architect a model with a lower splice window (\{-3, 0, +3\} to \{0\}) at the deeper layers. Since traditionally we do not splice frames to the LSTM layers, we deployed different splices only before the TDNN layers. Our first architecture (LSTM-TDNN-I) reduced the number of parameters from 49,945,168 to 49,904,288 (reduction of 40,880 parameters). The second choice resulted in 46,840,480 parameters, from 49,945,168 (reduction of 3,104,688).

3. ARCHITECTURE: LSTM-TDNN-SVD

3.1. LSTM-TDNN-SVD

Training an LSTM-TDNN-SVD network is a two-part process. The standard LSTM-TDNN architecture is first trained from the work\(^1\) until its convergence. Then the model is compressed by applying SVD [11] to all of the affine transformations in the layers, a process that is controlled by two parameters. To decompose a matrix, the weight matrix of the affine layer (before applying ReLU non-linearity) is forced to be an identity matrix when multiplied with its transpose. The singular values and two Eigen matrices are produced as the result:

\[
SVD : Wx = \omega \epsilon \upsilon
\]

where \(\omega, \upsilon\) are Eigen matrices, and \(\epsilon\) is the singularity matrix.

For matrix \(E\), only the singular values which contribute to energy threshold times the total energy of the singularity parameters are retained. These singularity parameters are sorted in descending order, and lower values are pruned out until the total energy (sum of squares) of the pruned set of parameters is just above (threshold * total energy). The values which are pruned away are replaced with 0 in the singularity matrix (\(E\)), and the weights matrix after SVD is derived with shrunken dimensions. Also, if the shrinkage ratio of the SVD refactored weights matrix is higher than the shrinkage threshold for any of the TDNN layers, the SVD process is omitted for that particular affine weights layer. This omission of SVD did not happen at any of the layers in our architecture. The architecture of stacked TDNN and LSTM layers, which we call “LSTM-TDNN-SVD”, can be found in Figure 3.2. The \(\hat{\cdot}\) in the figure represent the application of SVD at respective layers.

3.2. Stabilized bottlenecked-LSTM-TDNN

Instead of adopting the approach of [8] to achieve stability in training, we achieve convergence in training by interleaving LSTM layers in the bottlenecked architecture. In our approach, we start the training from scratch by randomly initializing the weight matrices. The configuration of this architecture along with the number of output dimensions are the same as those from the “LSTM-TDNN-SVD” architecture. We would like to emphasize the fact that no SVD is happening in this approach; only SVD dimensions are being copied. LSTM layers stabilize the training because the LSTM cells retain the important dimensions that carry valid temporal information before feeding their matrices to the next bottlenecking TDNN layer.

![Fig. 1. Figure. LSTM-TDNN-SVD architecture](image)

4. EXPERIMENTAL SETUP

Experiments were conducted using the Kaldi toolkit [13]. We report a set of results for various models trained on the Fisher data set [14] along with its reverberated versions.

4.1. Data

Fisher [14] and its reverberated versions were used for training. The audio data were reverberated as one of our target test distributions typically occur in reverberated ambience. The
development set and test set were curated by collecting audio data of in-domain conversational telephone speech (CTS). The work was concentrated towards using this system for this domain, hence the choice of novel test and development sets.

### 4.2. Experiment details

This work focused on obtaining the best WER possible while at the same time maintaining the real-time constraints of our system in production. Thus, the LSTM-TDNN architecture with the highest RTF was considered as the baseline. ’LSTM+TDNN-I’ from Table 3.2 was architected by modelling a narrower window at the initial layers and maintaining the frame rate at the deeper layers. The other model had a single frame input at the deeper layers by having a wider context window at the initial layers. Though these architectures were chosen primarily to reduce the real-time factor, previous work [10] has shown that the low-frame-rate architectures outperformed the considered baseline models in both RTF and WER. However, the reduced RTF was still not ideal for our real-time environment. The proposed architecture (LSTM-TDNN-SVD) was also evaluated by training on the same data, and we report our observations in Table 3.2. The architecture reduced the real-time factor by 40.99% relative to the baseline model. We performed more decoder parameter tuning to further reduce the RTF to 61.57% relative as reported in Table 3.2.

### 4.3. Observation and Results

In this section we share our intuition about the observations seen in various experiments performed by us.

In Table 2 for the LSTM-TDNN-SVD models, reducing the active states from 5000 to 500 gives a reasonable reduction in RTF with a tolerable increase in WER. ‘LSTM-TDNN-SVD+random init’ yields optimum WER and RTF. We also found one other interesting observation. Though SVD is used here to reduce the latency of the larger model, SVD implicitly retains the important dimensions, and we prune out the dimensions of lesser temporal information. In Table 3.2, for the layers TD2, TD3, TD5, TD7, TD9 which have the same input dimension ‘3072’, the reduced SVD dimensions generally increased: 319 → 317 → 372 → 385 → 433. This trend confirms that the instability in a purely factorized but non-highway TDNN layer training is likely stabilized by the LSTM layers, as the increase in important

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2 RTF = (total time taken by the system) / (total duration of the audio)
features take place only after the interleaving LSTM layers and not between two LSTM layers.

5. CONCLUSION

In conclusion, SVD during training gives us the optimum number of output dimensions, although that does not necessarily mean that WER will be optimal. However, the SVD-obtained output dimensions can further be explored in future experiments. For example, we could round them to nearest multiple of eight or four and train the models from scratch. This technique is not only expected to reduce training time but based on our current results and observations it would also likely improve WER. Now that we know that SVD-inspired linear bottleneck layers can train from scratch, we have started multiple training experiments for different variants of output dimensions. We will include additional results after this paper’s acceptance and submit as the final paper.

6. ACKNOWLEDGEMENT

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