OPTIMIZING SPEECH RECOGNITION FOR THE EDGE

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ABSTRACT
While most deployed speech recognition systems today still run on servers, we are in the midst of a transition towards deployments on edge devices. This leap to the edge is powered by the progression from traditional speech recognition pipelines to end-to-end (E2E) neural architectures, and the parallel development of more efficient neural network topologies and optimization techniques. Thus, we are now able to create highly accurate speech recognizers that are both small and fast enough to execute on typical mobile devices. In this paper, we begin with a baseline RNN-Transducer architecture comprised of Long Short-Term Memory (LSTM) layers. We then experiment with a variety of more computationally efficient layer types, as well as apply optimization techniques like neural connection pruning and parameter quantization to construct a small, high quality, on-device speech recognizer that is an order of magnitude smaller than the baseline system without any optimizations.

1 INTRODUCTION
Whether for image processing (Gokhale et al., 2014) or for speech applications (Chen, 2014), neural networks have been finding their way onto edge devices for the better part of a decade now. It stands to reason then that the search for ways to make these networks smaller and faster has become increasingly urgent. The three predominant ways of doing so are through quantization (Alvarez et al., 2016; Jacob et al., 2017), sparsity (LeCun et al., 1990), and architecture variation (Greff et al., 2016) or some combination thereof (Han et al., 2016). This work explores all three to accomplish the goal of creating an all-neural speech recognizer that runs on-device in real time.

We begin by examining neural network pruning. Early approaches explored gradient-based pruning (LeCun et al., 1990; Hassibi et al., 1994), as well as magnitude-based pruning (Yu et al., 2012; Han et al., 2015; Zhu & Gupta, 2018; Frankle & Carbin, 2019) from a dense network already trained to reasonable accuracy. Others have explicitly explored the possibility of obtaining an optimal pruned network without needing to pre-train a dense network (Frankle & Carbin, 2019; Frankle et al., 2019; Liu et al., 2019; Lee et al., 2019).

In this paper, we develop an automated gradual pruning algorithm to obtain pruned speech recognition models with fewer parameters and minimal accuracy loss based on work by (Zhu & Gupta, 2018).

After pruning, we examine alternative recurrent neural network (RNN) layer architectures. The baseline is a fairly standard long short-term memory (LSTM) architecture first proposed by Hochreiter and Schmidhuber (Hochreiter & Schmidhuber, 1997), further enhanced by a forget gate (Gers et al., 2000). The two primary alternatives we explore in this work are the Simple Recurrent Unit (SRU) (Lei et al., 2018) and the Coupled Input-Forget Gate (CIFG) (Greff et al., 2016). Both are less complex conceptually and computationally than the LSTM.

Finally we look at quantization. Numerous methodologies have been developed to convert floating point weights into low-bit representations (Mellempudi et al., 2017; Zhou et al., 2017; Courbariaux et al., 2016). In this paper, we explore low-bit computations either with an efficient mix of 8 and 16-bit integer, or a mix of 8-bit integer and 32 bit float precision (a.k.a. the hybrid approach).

Prior works existed in exploring each of these subtopics, but few have studied the optimal combination of these techniques to run production End-to-End speech recognition systems on edge devices. We explain our techniques in sections 2, 3, and 4. Section 5 delves into experiments on a state-of-the-art end-to-end Recurrent Neural Network Transducer (RNN-T) speech recognizer. Section 6 wraps up with interpretations we derived from our results.

2 PRUNING
Neural networks are often over-parameterized; they occupy expensive computational resources and create unnecessarily large memory footprints. This motivates network pruning (LeCun et al., 1990; Han et al., 2015), through which
sparsity is introduced to reduce model size while maintaining the quality of the original model.

In this work, we adopt the pruning method proposed by Zhu & Gupta. We increase the sparsity of weight matrices from an initial value to a final value in a polynomial fashion (Zhu & Gupta, 2018).

Unlike most iterative pruning methods in the literature that zero out the weight matrices incrementally, our pruned weight elements can be recovered at a later training stage (Zhu & Gupta, 2018). It is achieved by keeping the values of pruned weights instead of setting them to zero even though they do not contribute to forward propagation and are not back propagated. When the mask is updated later, a pruned weight can be recovered if its retained value is bigger than some un-pruned weights. In our experiments, we continue to update the mask even after sparsity reaches the target value so that weights pruned early due to bad initialization can be recovered.

To reduce memory usage and compute more efficiently. We develop a variation of the Block Compressed Sparse Row (BCSR) (Saad, 2003) structure to store models. A stored model contains an array with non-zero blocks in row-major order and a ledger array which contains the number of non-zero blocks of each block row followed by block column indices of non-zero blocks.

3 Efficient RNN Variants

The long short-term memory (LSTM) cell topology has made its way into many speech applications: acoustic models (Sak et al., 2014; McGraw et al., 2016), language models (Jozefowicz et al., 2016), and end-to-end models (Chan et al., 2016; Jaitly et al., 2016; Chiu et al., 2018; He et al., 2019). Our baseline LSTM cell is built from the original topology by Hochreiter and Schmidhuber (Hochreiter & Schmidhuber, 1997), further enhanced with a forget gate (Gers et al., 2000).

In our LSTM cell implementation (equations 1 to 7), $x^t$ is the input at time $t$, $W$ and $R$ the input and recurrent weight matrices respectively, $b$ the bias vectors, $\sigma$ the sigmoid function, $z$, $i$, $f$, $o$ and $c$ the LSTM-block input, input gate, forget gate, output gate and cell activation vectors, $h$ the cell output, $\circ$ the element-wise product of the vectors, and $g$ the activation function, generally tanh. We also adopt the output projection $W_{proj}$ proposed by (Sak et al., 2014) to reduce the cell size.

Layer normalization is added to the input block $z^t$ and gates ($i^t$, $f^t$, and $o^t$). Layer normalization helps to stabilize the hidden layer dynamics and speeds up model convergence (Ba et al., 2016).

$$i^t = \sigma(W_i x^t + R_i h^{t-1} + b_i) \quad (1)$$
$$f^t = \sigma(W_f x^t + R_f h^{t-1} + b_f) \quad (2)$$
$$z^t = g(W_z x^t + R_z h^{t-1} + b_z) \quad (3)$$
$$c^t = i^t \circ z^t + f^t \circ c^{t-1} \quad (4)$$
$$o^t = \sigma(W_o x^t + R_o h^{t-1} + b_o) \quad (5)$$
$$m^t = o^t \circ g(c^t) \quad (6)$$
$$h^t = W_{proj} m^t \quad (7)$$

3.1 CIFG-LSTM

The CIFG-LSTM variant is an LSTM modification (Greff et al., 2016). It is similar to that proposed in the gated recurrent unit (GRU) (Cho et al., 2014). CIFG simplifies the LSTM cell topology by having a single set of weights (i.e. a single gate) controlling both the amount of information and are not back propagated. When the mask is updated even though they do not contribute to forward propagation and are not back propagated. When the mask is updated even though they do not contribute to forward propagation and are not back propagated.

In CIFG, equation 1 is replaced with equation 8. As a result of this coupling, CIFG has 25% fewer parameters compared to the baseline LSTM topology.

$$i^t = 1 - f^t \quad (8)$$

3.2 Simple Recurrent Unit (SRU)

The SRU cell topology emerges in recent works as an alternative tool for speech and language processing tasks. Lei et al. show that SRU cells are not only highly parallelizable in model inferencing but also adequately expressive in capturing the recurrent statistical patterns in the input text-based data (Lei et al., 2018). Park et al. successfully built an on-device acoustic model by combining one layer of SRU cells with one layer of depth-wise 1D Convolutional Neural Network (Park et al., 2018).

We implemented a version of SRU in equations 9 to 13. Output projection (equation 13) in the SRU topology reduces the output dimension of cells. Each layer of SRU also contains layer normalization on the forget gate $f^t$, reset gate $r^t$, and the cell value $c^t$.

$$f^t = \sigma(W_f x^t + b_f) \quad (9)$$
$$r^t = \sigma(W_r x^t + b_r) \quad (10)$$
$$c^t = f^t \circ c^{t-1} + (1 - f^t) \circ (W_z x^t + b_z) \quad (11)$$
$$m^t = r^t \circ g(c^t) + (1 - r^t) \circ (W_o x^t + b_o) \quad (12)$$
$$h^t = W_{proj} m^t \quad (13)$$

SRU and CIFG topologies have not yet been explored in the
4 QUANTIZATION

Quantization reduces the model’s memory consumption (on disk and on RAM), and speeds up the models execution to meet the on-device real-time requirements. It transforms the model’s computation graph such that it can be (entirely or partially) represented and executed in a lower precision. In this work, quantization refers to the affine transformation that linearly maps one or more dimensions of a tensor from a higher to a lower bit representation.

We explored two quantization schemes: Hybrid quantization and Integer quantization. Both schemes have TensorFlow tooling and execution support (TensorFlow model optimization; TensorFlow Lite), and both schemes are in the form of post-training quantization.

4.1 Hybrid Quantization

In the hybrid approach, we operate matrix multiplications in 8-bit integers precision while representing the matrix multiplication products in floating point precision for the activation functions (McGraw et al., 2016; Alvarez et al., 2016; He et al., 2019). It performs on-the-fly quantization of dynamic values (e.g. activations). One of the advantages of hybrid quantization is that it can be performed entirely as a single pass transformation over the graph: no pre-computation is needed.

4.2 Integer Quantization

Integer quantization restricts the computational graph to operate with integer precision. It requires that the dynamic tensors be quantized with a scale pre-computed from dev data statistics. The statistics for all dynamic tensors are collected during inference, the layer normalization applied to a vector $x_i$ results in a vector $x_i$ with zero mean and standard deviation of 1 (equation 14 and 15). Assuming a normal distribution, 99.7% of values in $x_i$ is confined between $[-3.0, 3.0]$. This means that the integer representation of $x_i$ is also limited, $q_i' \in [-3.0, 3.0]$, which is only 7 values or 2.8 bit. This limit causes possible accuracy degradation in the model.

We resolved the restriction by adding a scaling factor for $q_i'$ in the computational graph. With $x_i = q_i' s$, $q_i$ can now be expressed as $q_i = \frac{x_i}{s} = \frac{(q_i - \bar{q})}{\sqrt{\sum_{n=1}^{n} (q_i' - \bar{q})^2} / n} \times \frac{1}{s}$. We choose to use $2^{-10}$ as $s'$, which is the smallest power-of-two number that won’t cause overflows in $q_i$. Substituting $s = 2^{-10}$, the integer inference becomes:

$$q_i = \text{round}(\frac{\sum_{n=1}^{n} (2^{10} q_i')}{n})$$

$$\sigma = \sqrt{\sum_{n=1}^{n} (2^{50} q_i'^2 - \bar{q}^2)}$$

$$q_i' = \text{round}(\frac{2^{10} q_i - \bar{q}}{\sigma})$$

$$q_i'' = \text{round}(\frac{q_i' W_i + q_{bi}}{2^{10}})$$

where $q_{W_i}$ is the quantized value of weight and $q_{bi}$ is quantized value of bias. Weights are quantized with scale $s_W = \frac{\text{range}}{127}$ and the scale of bias $s_b$ is the product between $2^{-10}$ and $s_W$.

5 EXPERIMENTS

5.1 Model Architecture Details: RNN-Transducer

The speech recognition architecture at the core of our experiments is the RNN Transducer (RNN-T) (Graves, 2012; Graves et al., 2013), depicted in Figure 1.

Our base model is an RNN-T with a target word-piece output size of 4096, similar to the model proposed by He et al. (He et al., 2019). The encoder network consists of 8 LSTM layers and the prediction network 2 layers. Each
Figure 1. A schematic representation of CTC and RNNT, from (Narayanan et al., 2019). The encoder takes input acoustic frames and plays the analogous role of a traditional acoustic model. The prediction network (a.k.a. decoder) functions as a kind of language model. The joint network combines the outputs of the previous two parts and leads finally to the softmax output.

layer consists of 2048 hidden units followed by a projection size of 640 units. The joint network has 640 hidden units and a softmax layer with 4096 units. Our baseline LSTM RNN-T model has 122M parameters in total.

In training, the learning rate ramps up to 1e-3 linearly in the first 32k steps and decays to 1e-5 exponentially from 100k to 200k steps. We evaluate all models on 3 test datasets with utterances from same domain as used in training: the VoiceSearch, the YouTube and the Telephony dataset. VoiceSearch and Telephony have average utterance length of 4.7s. YouTube contains longer utterances, averaging 16.5 min per utterance.

5.2 Pruning

We first pre-train a base model as described in Section 5.1. Then we apply the pruning algorithm mentioned in Section 2 to the weight matrices in each LSTM layer of the RNNT model. The sparsity increases polynomially from 0 to target sparsity within the first 100k. In order to speed up inference on modern CPUs, a 16 × 1 block sparse structure is enforced on cell. Table 1 shows the Word Error Rates (WER) and number of params of base model and pruned models at different sparsity levels.

5.3 Comparing RNN Topologies

From our experiments, we learnt that that CIFG based RNN-T models are comparable to LSTM-based RNN-T models in its performance. We experimented with using SRU in the encoder and decoder layers and learnt that SRU layers could effectively substitute LSTM layers in the decoder, but did not perform comparable to LSTM layers in the encoders.

Table 2 shows our finalized RNN-T model with sparse CIFG (50% weight sparsity) layers in the encoders, and sparse SRU (30% weight sparsity) layers in the decoder. This model has 59% fewer parameters than the baseline LSTM-based model, but only degraded by 7.5% and 1.2% of WER on VoiceSearch and Telephony test sets. Its WER on YouTube has improved by 3.1%. We show the results of a dense LSTM model (labeled “Small”) with the number of hidden layer cells and projection layer cells at 0.7 × the those of the baseline model. This smaller model is 45% smaller than the original model but suffers a WER degradation of 18.2% on VoiceSearch - much worse than the sparse models.

To summarize, although SRU layers are less expressive to model long-term dependencies between the RNN-T encoders cells, they were smaller and effective substitutes of LSTM layers in the RNN-T encoder. A combination of 50% sparse CIFG (encoder layers) and 30% sparse SRU (decoder layers) eliminated 59% of the parameters with respect to the baseline RNN-T model with a small loss of WER.

5.4 Quantized LSTM

The accuracy and CPU performance comparison between float, hybrid and fully quantized models is listed in Table 3. The results show that our proposed integer quantization has negligible accuracy loss on Voice Search. Longer utterances (in YouTube), which are typically more challenging for sparse models, still see comparable results from sparse models as from float models.

We use Real Time (‘RT’) factor, which is the ratio between the wall time needed for completing the speech recognition and the length of the audio, to measure the end-to-end performance. We denote RT(0.9) as the RT factor at 90 percentile. Using the (TensorFlow Lite) runtime in a typical mobile CPU (Pixel 3 small cores), we compare the RT(0.9) between the float, hybrid and integer models, and see the integer model achieve an RT factor that is around 30% with respect to the float model.

6 CONCLUSION

In this work we present a comprehensive set of optimizations spanning from more efficient neural network building blocks to the elimination, and reduction in precision, of neural network parameters and computations. Altogether they result in a high quality speech recognition system “Sparse CIFG, Sparse SRU” that is 8.5x smaller in size (466MB to 55MB), and 4.6x faster in RT factor (3.223 to 0.704) when comparing to our full precision “LSTM Baseline”. We validate that neural connection pruning is a useful tool to shrink neural network at the cost of a relatively small accuracy loss. Moreover, the use of a particular “block sparsity” configuration enables execution speedups in CPUs widely used in mobile, desktop and server devices, without requiring specialized hardware support. We also demonstrate
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| Sparsity | #Params (millions) | WER | VoiceSearch | YouTube | Telephony |
|----------|-------------------|-----|-------------|---------|-----------|
|          | % of baseline     |     |             |         |           |
| 0%       | 122.1 (100%)      | 6.6 | 19.5        | 8.1     |           |
| 50%      | 69.7 (57%)        | 6.7 | 20.3        | 8.2     |           |
| 70%      | 48.7 (39.9%)      | 7.1 | 20.6        | 8.5     |           |
| 80%      | 38.2 (31.3%)      | 7.4 | 21.2        | 8.9     |           |

Table 1: Comparison of pruned models with different sparsities

| Enc & Dec Cell  | Sparsity | #ParamsM | Size | WER | RT(0.9) |
|-----------------|----------|----------|------|-----|---------|
| LSTM 0.7 x | cell | LSTMx8 | - | 67.7 (55.4%) | 65 | 7.8 | 20.3 | 8.6 | 0.681 |
| Small | LSTMx2 | - | - | | | | | | |
| CIFG-SRU | CIFG-LSTMx8 | - | 89.6 (73%) | 86 | 6.9 | 19.1 | 7.8 | 0.806 |
| SRUx2 | | - | | | | | | | |
| sparse-CIFG | CIFG-LSTMx8 | 50% | 50.6 (41%) | 55 | 7.1 | 18.9 | 8.2 | 0.704 |
| SRUx2 | | 30% | | | | | | | |

Table 2: Comparing smaller dense LSTM model with models trained with sparse CIFG-LSTM and SRU cells. RT factor is calculated using hybrid quantization on Pixel3 small cores. Models are quantized using hybrid quantization.

| Enc&Dec | Sparsity | #Params(M) | Quantization | Size(MB) | VoiceSearch | YouTube | Telephony | RT(0.9) |
|---------|----------|------------|--------------|----------|-------------|---------|-----------|---------|
| LSTM (baseline) | | | | | | | | |
| LSTMx8 | 0% | 122.1 | Float,466MB | 6.6 | 19.5 | 8.1 | 3.223 |
| LSTMx2 | 0% | 100% | Hybrid,117MB | 6.7 | 19.8 | 8.2 | 1.024 |
| | | | Integer,117MB | 6.7 | 19.8 | 8.2 | 1.013 |
| Sparse LSTM | | | | | | | | |
| LSTMx8 | 50% | 69.7 | Float,270MB | 6.7 | 20.2 | 8.2 | 1.771 |
| LSTMx2 | 50% | 57% | Hybrid,71MB | 6.8 | 20.4 | 8.4 | 0.888 |
| | | | Integer, 71MB | 6.9 | 22.9 | 8.7 | 0.869 |
| Sparse CIFG | | | | | | | | |
| CIFGx8 | 50% | 56.3 | Float,219MB | 7.1 | 21.7 | 8.3 | 1.503 |
| CIFGx2 | 50% | 46% | Hybrid,57MB | 7.2 | 21.4 | 8.5 | 0.743 |
| | | | Integer,57MB | 7.2 | 20.6 | 8.7 | 0.709 |

Table 3: Comparison of float, hybrid and fully quantized models. RT factor is calculated on Pixel3 small cores.

that RNN variants result in competitive qualitative performance with respect to the widely accepted and used LSTM topology, while also reducing the number of parameters and potentially enabling other optimizations. CIFG-LSTM, in particular, is an underused simple optimization to take advantage of. We show that quantization is an effective technique that makes neural network models smaller and faster when inferencing in CPUs. Integer quantization opens the door towards using more specialized neural network acceleration chips such as Tensor Processing Units. Finally, we verify that all these techniques are complimentary to each other. Although the accuracy losses of each technique do compound, they do not do it in a way that multiply each other with catastrophic results. On the contrary, our smallest model "Sparse CIFG" achieves better accuracy, even quantized, than that of a small baseline model “LSTM (Baseline small)” evaluated in full precision.

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