Mixed-Precision Training for NLP and Speech Recognition with OpenSeq2Seq

Oleksii Kuchaiev, Boris Ginsburg, Igor Gitman, Vitaly Lavrukhin, Jason Li, Huyen Nguyen, Carl Case, Paulius Micikevicius
NVIDIA
Santa Clara, CA 95051
{okuchaiev,bginsburg,igitman, vlavrukhin,jasoli,chipn,carlc,pauliusm}@nvidia.com

Abstract

We present OpenSeq2Seq – a TensorFlow-based toolkit for training sequence-to-sequence models that features distributed and mixed-precision training. Benchmarks on machine translation and speech recognition tasks show that models built using OpenSeq2Seq give state-of-the-art performance at 1.5-3x less training time. OpenSeq2Seq currently provides building blocks for models that solve a wide range of tasks including neural machine translation, automatic speech recognition, and speech synthesis.

1 Introduction

The sequence-to-sequence (seq2seq) paradigm (Cho et al., 2014) has been successfully used for tasks that traditionally require a sequential encoder and a sequential decoder such as machine translation (Wu et al., 2016), abstractive summarization (Rush et al., 2015), and automatic speech recognition (ASR) (Chan et al., 2015; Battenberg et al., 2017). However, seq2seq models can be used for other tasks as well. For example, a neural network to solve a sentiment analysis task might consist of an RNN encoder and a softmax linear decoder. An image classification task might need an convolutional encoder and a softmax linear decoder. A model that translates from English to multiple languages might have one encoder with multiple decoders.

There have been a number of toolkits that use the seq2seq paradigm to construct and train models to solve various tasks. Some of the most popular include Tensor2Tensor (Vaswani et al., 2018), seq2seq (Britz et al., 2017), OpenNMT (Klein et al., 2017), and fairseq (Gehring et al., 2017a). The first two are based on TensorFlow (Abadi et al., 2016) while the last two are based on PyTorch (Paszke et al., 2017). These frameworks feature a modular design with many off-the-shelf modules that can be assembled into desirable models, lower the entrance barrier for people who want to use seq2seq models to solve their problems, and have helped push progress in both AI research and production.

OpenSeq2Seq builds upon the strengths of these existing frameworks with additional features to reduce the training time and make the API even easier to use. We chose to work with TensorFlow. We created OpenSeq2Seq with the following goals in mind:

- Modular architecture to allow easy assembling of new models from available components.
- Support for mixed-precision training (Micikevicius et al., 2017), that utilizes Tensor Cores introduced in NVIDIA Volta GPUs.
- Fast, simple-to-use, Horovod-based distributed training via data parallelism, supporting both multi-GPU and multi-node.

*work done while the author was an intern at NVIDIA

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Modular architecture

OpenSeq2Seq was designed for extensibility and modularity. It provides core abstract classes from which users can inherit their own modules: DataLayer, Model, Encoder, Decoder and Loss.

At a high level, the Encoder consumes data processed by DataLayer and produces a representation; while the Decoder consumes that representation and produces data and/or output. We assume that any encoder can be combined with any decoder, thus improving flexibility and simplicity of experimentation. It is possible to have a model consisting of only an encoder, or having more than one encoder and/or decoder.

An OpenSeq2Seq model is described by a Python configuration file that specifies parts of the model (i.e. data layer, encoder, decoder, and loss function) and their configuration hyperparameters (i.e. regularization, learning rate, dropout). A configuration file to create a GNMT (Wu et al., 2016) model for machine translation might look like this:

```python
base_params = {
    "batch_size_per_gpu": 32,
    "optimizer": "Adam",
    "lr_policy": exp_decay,
    "lr_policy_params": {
        "learning_rate": 0.0008,
    },
},
"encoder": GNMTLikeEncoderWithEmbedding,
    "encoder_params": {
        "core_cell": tf.nn.rnn_cell.LSTMCell,
        "encoder_layers": 7,
        "src_emb_size": 1024,
    },
"decoder": RNNDecoderWithAttention,
    "decoder_params": {
        "core_cell": tf.nn.rnn_cell.LSTMCell,
    },
"loss": BasicSequenceLoss,
}
```

To create a model, OpenSeq2Seq provides `run.py` script which takes as arguments the model’s configuration file and the execution mode (`train`, `eval`, `train_eval` or `infer`).

Currently, OpenSeq2Seq provides configuration files to create models for machine translation (GNMT, ConvS2S, Transformer), speech recognition (Deep Speech 2, Wave2Letter), speech synthesis (Tacotron 2), image classification (ResNets, AlexNet), language modeling (LSTM-based), and transfer learning for sentiment analysis. These are stored in the folder `example_configs`. You can create a new model configuration using the modules available in the toolkit with basic knowledge in TensorFlow. It’s also straightforward to write a new module or to modify an existing module.

OpenSeq2Seq provides a variety of data layers that can process popular datasets, including WMT for machine translation, WikiText-103 (Merity et al., 2016) for language modeling, LibriSpeech (Panayotov et al., 2015) for speech recognition, Stanford Sentiment Treebank (Socher et al., 2013) and IMDB (Maas et al., 2011) for sentiment analysis, LJ Speech dataset (Ito et al., 2017) for speech synthesis, and more.

Mixed-precision training

Mixed-precision algorithm

Tensor Cores, available on Volta and Turing GPUs, allow matrix-matrix multiplication, the operations at the core of neural network training and inferencing, to be done in both single-precision floating
point (FP32) and half-precision floating point (FP16). For training, Tensor Cores provide up to 12x higher peak TFLOPS compared to standard FP32 operations on P100. For inference, that number is 6x [NVIDIA (2017)].

Taking advantage of Tensor Cores’ computational power requires models to be trained using FP16 arithmetic. OpenSeq2Seq provides a simple interface to do so via mixed-precision training. When mixed-precision training is enabled, the math is done in FP16, but the results are accumulated and stored in FP32. In current generation GPUs, reduced precision math increases the computational throughput. Mixed-precision also reduces the amount of memory required, allowing users to increase the size of batches or models, which, in turn, increases the learning capacity of the model and reduces the training time.

To prevent accuracy loss due to the reduced precision, we use two techniques suggested by Micikevičius et al. (2017):

1. Automatically scale loss to prevent gradients from underflow and overflow during backpropagation. The optimizer inspects gradients at each iteration and scales the loss for the next iteration to ensure that the values stay within the FP16 range.
2. Maintain a FP32 copy of weights to accumulate the gradients after each optimizer step.

While having two copies of weights increases the memory consumption, the total memory requirement is often decreased because activations, activation gradients, and other intermediate tensors are kept in FP16. This is especially beneficial for models with a high degree of parameter sharing, such as recurrent neural networks.

To enable mixed-precision training in OpenSeq2Seq, simply change dtype parameter of model_params to "mixed" in your configuration file. You can enable loss scaling either statically by setting loss_scale parameter to the desired number, or dynamically by setting loss_scaling parameter to "Backoff" or "LogMax". You may need to pay attention to the types of the inputs and outputs to avoid mismatched types for certain types of computations. There’s no need to modify the architecture or hyperparameters.

```python
base_params = {
    ...,
    "dtype": "mixed",
    # "loss_scale": 10.0, # static loss scaling
    # "loss_scaling": "Backoff", # dynamic loss scaling
}
```

### 3.2 Mixed-precision optimizer

Our implementation is different from the approach explained in [NVIDIA (2018)]: instead of using a custom variable getter, we introduce a wrapper around the standard TensorFlow optimizers. The model is created with FP16 – all variables and gradients are in FP16 by default, except for the layers which are explicitly redefined as FP32 such as data layers or operations on CPU. The wrapper then automatically converts FP16 gradients to FP32 and submits them to TensorFlow optimizer, which updates the master copy of weights in FP32. Updated FP32 weights are converted back to FP16, which are then used by the model in the next forward-backward iteration. Figure 1 illustrates the MixedPrecisionOptimizerWrapper architecture.

### 3.3 Mixed-precision regularization

Mixed-precision training may require special care for regularization. Consider, for example, weight decay regularization. Given that the weights are commonly initialized with small values, multiplying them with weight decay coefficient - which is usually on the order of $[10^{-5}, 10^{-3}]$ – can result in numerical underflow.

To overcome this problem, the regularizer function is wrapped with mp_regularizer_wrapper function that disables the underlying regularization function for FP16 copy and adds the regularized variables to a TensorFlow collection. This collection will later be retrieved by MixedPrecisionOptimizerWrapper. The corresponding regularizer functions will be applied to the FP32 copy of the weights to ensure that their gradients always stay in full precision. Since this
regularization is not in the loss computation graph, we explicitly call `tf.gradients` and add the result to the gradients passed in the `compute_gradients` in the optimizer.

4 Distributed training with Horovod

OpenSeq2Seq takes advantage of the two main approaches for distributed training:

- Parameter server-based approach (used in native TensorFlow towers)
  - Builds a separate graph for each GPU
  - Sometimes faster for 2 to 4 GPUs
- MPI-based approach (used in Uber’s Horovod \cite{Sergeev2018})
  - Uses MPI and NVIDIA’s NCCL library to utilize NVLink between GPUs
  - Significantly faster for 8 to 16 GPUs
  - Fast multi-node training

To use the first approach, you just need to update the configuration parameter `num_gpus` to the number of GPUs you want to use.

To use Horovod, you need to install Horovod for GPU, MPI and NCCL\footnote{Detailed instructions can be found on Horovod official website at \url{https://github.com/uber/horovod/blob/master/docs/gpus.md}}. After that, all you need to do is set the parameter `use_horovod` to True in the configuration file and execute `run.py` script using `mpirun` or `mpiexec`. For example:

```
mpirun --allow-run-as-root -np <num_gpus> python run.py
--config_file=... --mode=train_eval --use_horovod=True --enable_logs
```

Horovod also allows you to enable multi-node execution. The only thing required from users is to define data “split” solely for evaluation and inference. Otherwise, users write exactly the same code for multi/single GPU or Horovod/Tower cases. Horovod gives significantly better scaling for multi-GPU training comparing to TensorFlow native tower-based approach. The specific scaling depends on many factors such as data type, model size, compute amount. For example, the scaling factor for Transformer model is 0.7, while that number for ConvS2S is close to 0.875, as you can see in Figure\[^2\].

5 Models

OpenSeq2Seq currently offers full implementation of models for the tasks of Neural Machine Translation, Automatic Speech Recognition, Speech Synthesis. On these tasks, mixed-precision training, using the same architecture and hyperparameters as FP32, can speed up training time 1.5-3x without losing model accuracy. Performance boosts vary depending on the batch size. The general

\[^2\]Detailed instructions can be found on Horovod official website at \url{https://github.com/uber/horovod/blob/master/docs/gpus.md}
Figure 2: Multi-GPU speed-up for ConvS2S

| Model         | sacreBLEU |
|---------------|-----------|
| GNMT          | 23        |
| ConvS2S       | 25.0      |
| Transformer base | 26.6   |
| Transformer big  | 27.5    |

Table 1: BLEU scores for different NMT models using mixed-precision training.

A rule of thumb is that bigger batch size yields better performance. All configuration files are available on GitHub. Figure 3 demonstrates that mixed precision has no effect on convergence.

Figure 3: Training loss curves for: (A) GNMT-like model, and (B) Deep-Speech-2-like model using FP32 and mixed-precision. For both models, mixed-precision training matches FP32 closely.

5.1 Neural Machine Translation

Currently OpenSeq2Seq has all the necessary blocks for three models for Neural Machine Translation: (1) Google NMT (Wu et al., 2016) (2) Facebook ConvS2S (Gehring et al., 2017b) (3) Google Transformer (Vaswani et al., 2017). These blocks can be mixed and matched to create new models.

In our experiments, we used WMT 2016 English→German dataset obtained by combining the Europarlv7, News Commentary v10, and Common Crawl corpora, resulting in roughly 4.5 million sentence pairs. The scores for these models can be found in Table 2. These scores are computed using sacreBLEU (Post, 2018) against newstest2014.tok.de file.

In our experiments, total GPU memory consumption with mixed-precision is reduced to about 55%, making the training 1.5-2.7x faster comparing to using only FP32.

https://github.com/NVIDIA/OpenSeq2Seq
| Model          | Greedy WER (%) |
|---------------|--------------|
| Wave2Letter+  | 5.4          |
| DeepSpeech2   | 6.71         |

Table 2: WERs for ASR models using mixed-precision training.

5.2 Automatic Speech Recognition

OpenSeq2Seq currently has two models for the Automated Speech Recognition task:

- Wave2Letter+: fully convolutional model based on Wav2Letter [Collobert et al., 2016]
- Deep Speech 2: recurrent model [Amodei et al., 2016]

These models were trained on LibriSpeech dataset [Panayotov et al., 2015] that contains approximately 1000 hours of audio. WERs (word error rates) were measured on dev-clean part of the dataset using a greedy decoder - taking at each time step the most probable character without any additional language model re-scoring. During training in mixed-precision, we observed a total memory reduction to around 57%, making it 3.6x faster than training using only FP32.

5.3 Speech Synthesis

OpenSeq2Seq supports Tacotron 2 [Shen et al., 2018] with Griffin-Lim [Griffin and Lim, 1984] for speech synthesis. The model currently uses only the LJ Speech dataset [Ito et al., 2017]. We plan on additionally supporting the M-AILABS dataset [M-AILABS, 2018]. Sample audio on both datasets can be found on our documentation website[^4]. Tacotron 2 can be trained 1.6x faster in mixed-precision compared to FP32.

6 Conclusion and future plans

OpenSeq2Seq is a TensorFlow-based toolkit that builds upon the strengths of the currently available seq2seq toolkits with additional features that speed up the training of large neural networks up to 3x. It lets users switch to mixed-precision training that takes advantage of the computational power of Tensor Cores available in Volta-based [NVIDIA, 2017] and Turing-based [NVIDIA, 2018] GPUs with one single tag. It incorporates Horovod library to reduce training time for multi-GPU and multi-node systems.

OpenSeq2Seq aims to offer a rich library of commonly used encoders and decoders. It currently features a large set of state-of-the art models for speech recognition, machine translation, speech synthesis, language modeling, sentiment analysis, and more to come in the near future as our team is working hard to improve it. Its modular architecture allows quick development of new models out of existing blocks. We plan to extend it with other modules such as text classifications and image-to-text. The entire code base is open-source.

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