Neutron: An Implementation of the Transformer Translation Model and its Variants

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Abstract

The Transformer translation model is easier to parallelize and provides better performance comparing with recurrent seq2seq models, which makes it popular among industry and research community. We implement Neutron in this work, including the Transformer model and several variants from most recent researches. It is easier to modify and provides comparable performance with interesting features while keep readability.

1 Introduction

Vaswani et al. (2017) proposed Transformer architecture which contains only attention mechanism, standard feed-forward neural network with residue connection, dropout, layer normalization and label smoothing loss for its training. Transformer parallelizes better and provides significantly better results comparing with attention enhanced seq2seq models in many cases. It is widely applied in industry and attracts wide attention from researchers, as a result, many enhanced architectures have been proposed for speed or performance.

Most of previous implementations only provide original Transformer, while we also implement some variants of Transformer from recent researches along with the standard implementation of Transformer in Neutron, including Average Attention (to accelerate the decoding of Transformer) proposed by Zhang et al. (2018), Hierarchical Aggregation proposed by Dou et al. (2018), Transparent Attention proposed by Bapna et al. (2018) and Recurrent decoder from Chen et al. (2018) for better machine translation quality. Neutron also supports more efficient training scheduler (dynamic sampling and review mechanism) proposed by Wang et al. (2018).

Our implementation also supports those popular features which are common in most Machine Translation implementations, including beam search, ensemble, length penalty and average of models. Besides, Neutron supports unlimited batch size with limited memory on a single GPU, which is important for the Transformer. Since the learning rate scheduler adopted in the Transformer’s training is different with that of most deep learning experiments, its learning rate increases from a small value for warm-up steps and then decreases until the end of the training. This makes the effect of batch size on performance more significant, because the model will be trained with a very small learning rate for most time with a small batch size, and this can lead to poor local minimum. In addition to support large batch size on a single GPU, Neutron includes almost-from-scratch designed high performance multi-gpu parallelization modules, with experiments can be effectively accelerated with more GPUs.

Its main functions are data processing, training and translating, we will introduce details of these basic functions in the following two sections, followed by sections for design, additional tools, performance, related works and conclusion.

2 Data Processing

This section describes the details for data processing, consists of data cleaning and how plain text are converted and saved into tensors for efficient training.

2.1 Data Cleaning

Normally, parallel corpus for training machine translation system are not collected directly from translators at sentence level. Some of the corpus are crawled from the internet, and automatic sentence alignment tools are applied to extract sentence-level translation pairs. As a result, there

1https://github.com/anoidgit/transformer
might be some wrong translations in the parallel corpus, and we provide some simple tools to clean data sets. Removing those dirty data will reduce the size of data set and vocabulary, and leads to faster training with better quality.

2.1.1 Max Keeper
Parallel corpus are sometimes combination of several corpus, and those corpus may contain some common sentence pairs, which will be redundant after concatenation. In addition to that, alignment tools may wrongly align one sentence of source language into several translations in different context, especially for those short sentences. We provide a tool to filter out noisy data. It will collect all sentences and their translations, and only save those translations with highest frequency. It will also replacing potential repeated blanks or tabular into a single blank during cleaning to normalize the data set.

2.1.2 Cleaning with vocabulary
There are some sentence pairs which are meaningless or even not belonging to language pairs researching on. Vocabulary based cleaning is supported for this case. It first collects the vocabulary and counts frequencies of tokens on training set, and then filter training set with a hyper parameter named vratio, vratio tokens of full vocabulary with least frequencies will be regarded as rare words, and if the percentage of rared tokens in a sentence is higher than $1.0 - vratio$, the sentence is unlikely to be part of the language pair, and will be removed.

2.1.3 Cleaning with length ratios
Length ratio is likely to be applied in MT evaluations, since there are some wrongly aligned sentence pairs in the training data which have abnormally large length ratios. This work provides enhanced supports on top of subword (Sennrich et al., 2015) units, though cleaning on only tokenized text is also supported.

Assume a sentence contains $nsub$ tokens after BPE processing, $nsubadd$ tokens are additionally produced by BPE seperation, $nsep$ tokens of original tokenized sentence which has $ntok$ tokens are segmented by BPE. Following ratios are defined at monolingual level:

\[ cratio = \frac{nsubadd}{nsub} \]  
\[ bratio = \frac{nsub}{ntok} \]  
\[ sratio = \frac{nsep}{ntok} \]

Assume a source sentence contains $nsubsrc$ subword tokens and $nsrc$ tokens before applying BPE, $nsubtgt$ and $ntgt$ correspondingly for its translation, we define two bilingual ratios:

\[ uratio = \frac{\max(nsubsrc, nsubtgt)}{\min(nsubsrc, nsubtgt)} \]  
\[ oratio = \frac{\max(ns, nt)}{\min(ns, nt)} \]

The reason why we cleaning training set with subword units is that those rare words in dirty sentence pairs are likely to be segmented into many subword units, which would significantly increase those subword related ratios if there are many rare words in dirty sentence.

We also provide tools to calculate above ratios with validation set, which are good and safe choices for data cleaning.

2.1.4 Cleaning effects
We clean the training set of WMT 17\(^2\) German to English, Russian to English and Chinese to English news translation task with 0.2 as vratio and the other ratios calculated on development sets, 7.18%, 24.41% and 15.04% of the training set are removed respectively\(^3\). Cleaning is supported but not forced, datasets can be converted to tensors directly as in section 2.2.

2.2 Convert text into tensors
Neural models take tensors as inputs and outputs, rather than text. To prevent converting text into matrix in every epoch, Neutron converted text into tensors before training. Besides, tensors saved in HDF5 format on the disk is much easier and faster to index than text, which enables Neutron to shuffle over the whole dataset, rather than cached adjacent sentence pairs. HDF5 library employs hash and caching mechanism, can load data from disk efficiently. So, Neutron does not need to load whole data sets into memory, which enables it to train on extremely large corpus efficiently with considerably low memory usage.

During conversion, data sets are first sorted, by doing so, sentences with similar length will be collected in a matrix, thus reducing the amount of

\(^{2}\)http://data.statmt.org/wmt17/translation-task/preprocessed/
\(^{3}\)Results depend on and slightly vary with different BPE settings
useless padding. During sorting, sentence pairs which have the same total number of tokens are first saved into a chunk, then the chunk is sorted again according to the number of tokens on the target side, because the cost of matrix multiplication in the classifier is higher than embedding lookup in the encoder, and reduced number of padding tokens on the target side with more padding tokens is more efficient comparing with the contrary.

After sorting, vocabularies are collected on both sides. 4 additional special tokens ("<pad>, <sos>, <eos>, <unk>") which stands for padding token, start of sentence, end of sentence and words out-of-vocabulary correspondingly are included. Neutron supports shared vocabulary for source side and target side, which is important for sharing the embedding matrix between encoder and the decoder, but we observe that there are still some unique tokens which only exist on one side even joint-BPE is applied, using separate vocabulary will reduce vocabulary size and accelerate both training and decoding.

Finally, parallel corpus are made into small batches, mapped with built vocabularies, and saved to disk with HDF5 library. Batch size is the number of tokens in one batch, depends on the memory available on GPU.

During data processing, “dataid” is passed as an argument, and results will be saved under “cache/dataid/”. Note that, the first training epoch will load converted data sequentially, so the training will start with shorter data and move to longer data (Intuitively, learn word translations at first, then phrase translations, finally sentence translations), but after every epoch, the data indexes will be shuffled, following training epochs run on shuffled dataset.

3 Configurations

Neutron does not use arguments for configuration. Instead a file named “conf.py” is provided. Thus users only need to save this file to record settings of experiments.

3.1 Configuration for Model, Loss and Optimizer

“bindDecoderEmb” is used to control weight sharing between the embedding matrix and the weight of the last classifier, by default it is set to True. Another similar argument is “share_emb” which controls the sharing of embedding between encoder and decoder, the only case to turn this on is when a shared vocabulary is applied. According to Chen et al. (2018), outputs of last encoder layer and decoder layer are normalized to prevent potential explosion caused by residue connections, “norm_output” is set to True by default to enable layer normalization to outputs, but for hierarchical variant proposed by Dou et al. (2018) which already employs layer normalization to layers’ outputs in aggregation model, a redundant layer normalization is useless, in which case “norm_output” should be set to False. “src_emb” and “tgt_emb” can be assigned to initialize embedding matrix with pre-trained embedding for encoder and decoder, “freeze_srcemb” and “freeze_tgtemb” switch the updating of pre-trained embedding.

In addition to above variables, “isize”, “nlayer”, “ffhsz”, “drop” are used to configure the dimension of embedding, number of encoder and decoder layers, hidden units and dropout probability in position-wise feed-forward networks. “nhead”, “attn_drop”, “attn_hsize” configure the number of heads, dropout rate and hidden dimension for multi-head attention module. Positional embedding used in Transformer is cached for efficiency, with “cache_len” configuring the maximum number of token embedding cached.

Label smoothing is applied in loss function, configured with “label_smoothing” with 0.1 by default, but there are some classes which will never appear in outputs of classifier, such as “<pad>”, “<sos>”, “<unk>” if subword tokens are used, and there will be more if a shared vocabulary is applied. A variable named “forbidden_indexes” which is a list of indexes which never appear in the target side, and the default value of this variable is [0, 1] for “<pad>” and “<sos>” correspondingly.

There are two additional variables for the configuration of Adam optimizer, with “use_ams” to enable AMSGrad proposed by Reddi et al. (2018), and “weight_decay” to control L2 regularization for small corpus used in Chen et al. (2018). Both variables are disabled by default, as they are not applied in Vaswani et al. (2017).

3.2 Training configuration

“run_id” is an ID for one experiment, and “dataid” is another option to select the data set for experiment. Models, log and state files will be saved in: expm/dataid/run_id/.
With “fine_tune_m”, “train_statesf” and “fine_tune_state”, the training script can load and start with saved model file and corresponding training and optimizer state files. The training state will be saved automatically along with the saving of models, and optimizer states will only be saved when “save_optm_state” is set.

The data set generated as in section 2 are of small batches (we call them batch units) which are able to fit in GPU memory, but larger batch size provides better performance for Transformer. “tokens_optm” is applied to support large batch sizes, the training script will forward and backward many batch units, and update parameters with an optimizer step until it has collected gradient with more than “tokens_optm” number of tokens on the target side.

“save_every”, “num_checkpoint” and “epoch_start_checkpoint_save” configure the saving of checkpoints, mean after how many optimizer steps will one checkpoint be saved, the epoch to start saving checkpoints and number of checkpoints kept on disk respectively. “epoch_save” controls whether to save a model for every epoch regardless whether a lower loss/error rate has been reached. These options might be useful for ensemble or averaging of models.

“maxrun” and “training_steps” configure the maximum number training epochs and number of optimizer steps in training. “earlystop” is the number of continuous epochs to early stop the training according to validation loss and error rate on development set, if there is no smaller validation loss or error rate found in “earlystop” epochs, the training will stop.

“batch_report” controls number of batch units in which reports the averaged training loss, and “report_eva” controls whether to report loss and error rate on evaluation set or not.

Neutron supports multi-GPU training through data parallel, configured by “use_cuda” for using GPU or not and “gpuid” for GPU device(s) to use. The parallel module is designed inside Neutron almost from scratch, it will only collect gradients from GPUs before an optimizer step, replicate parameters and clear previous gradients after an optimizer step, redundant communication between GPUs caused by learning over batch units is avoided.

Batch units level sampling is supported to accelerate training with approaches proposed by Wang et al. (2018), with “dss_ws” and “dss_rm” to set ratios for weighted sampling and review mechanism.

“warm_step” is used to set the number of warm-up steps for the learning rate scheduler. Random seed for the whole training procedure including parameter initialization and shuffle can be controlled with “seed”, which means that users will always get a same result as long as they keep a same random seed, which we think is important for ensuring research outcomes reproducible.

3.3 Translating
Parallel module powered by Neutron also supports multi-gpu decoding, which can be configured with “multi_gpu_decoding”. The last GPU in “gpuid” rather than the first will be the main device which takes more jobs.

Configurations for beam size and length penalty (Wu et al., 2016) is supported for translating with “beam_size” and “length_penalty”, greedy decoding will be used if “beam_size” is set to 1. Ensemble will be activated automatically by assigning more than one model files in test script.

4 Design
In this section, we will introduce the design of Neutron, its components and interfaces provided in core files. Thanks to the powerful pyTorch backend and python, the memory will be cached and managed automatically and efficiently, and we only need to focus on the efficiency of our implementation. All modules implemented meet the standards of pyTorch, which ensures the compatibility of our implementation.

4.1 Basic modules
Most basic modules are implemented in “modules.py”, including “PositionalEmb” class to generate positional embedding of specific length, “PositionwiseFF” class which implements position-wise feed-forward networks with layer normalization, residue connection and dropout inside for efficiency, “AverageAttn” for average attention decoder proposed by Zhang et al. (2018), and “MultiHeadAttn” class to do self attention and cross attention. A “SelfAttn” class which takes same inputs as queries, keys and values for the computation of attention and a “CrossAttn” which takes same inputs for keys and values while different queries are implemented for more efficient
computation of self attention and cross attention. “ResidueCombiner” is implemented to summarise outputs from layers. Dynamic scaled Gaussian noise can be added to tensor with “Noiser” class.

In addition to classes implemented in “modules.py”, “LabelSmoothingLoss” is implemented in “loss.py” to support label smoothing loss function. Learning rate schedule module required according to Vaswani et al. (2017) is implemented in “lrsch.py”.

We implement new parallel modules for more efficient synchronization between GPUs under “parallel/” folder. “parallel.py” contains implementations of “DataParallelModel” class for the parallelization of model and “DataParallelCriterion” class for the parallelization of loss function. “DataParallelModel” class have a “make_replicas” function to replicate model into several GPUs, a “collect_gradients” function to collect gradients from models on GPUs, and a “update_replicas” function to synchronize parameters between GPUs. Besides, “DataParallelMT” class is implemented in “parallelMT.py” which supports calls to “decode” and “train_decode” function based on “DataParallelModel” to enable multi-gpu decoding. These new parallel modules fully comply with PyTorch standard, significantly faster than solution provided by PyTorch, can also be utilized to parallelize the other pytorch models.

Functions for supportive features, for example, freeze / unfreeze parameters of models, padding list of tensors to same size on assigned dimension are implemented in “utils.py”.

4.2 Transformer and its Variants

All Transformer modules are implemented in “Transformer/” folder.

“NMT.py” manages encoder and decoder, “EnsembleNMT.py” encapsulates several NMT models to do ensemble decoding. A “NMT” class is implemented in both file, it has a “forward” function for training, a “decode” function for efficient decoding and a train_decode function to support decoding with decoders’ “forward” function. In PyTorch, a “forward” function is designed for the forward pass of training and evaluation, but the decoding of neural machine translation is different from its training, so normally there is another function implemented for decoding. All decoders implemented in Neutron provide efficient decoding implementations, but Neutron does support decoding with the “forward” function designed for training, the “train_decode” function makes it not essential for prospective researches extended Neutron to implement an efficient decoding function in their decoder, only having a “forward” function implemented for training is enough for translating, and this greatly reduced the difficulty of extending this project. “train_decode” is actually supported by another two functions, “train_greedy_decode” for greedy decoding and “train_beam_decode” for beam decoding. Length penalty is implemented as a part of beam decode function. “Encoder” class and “Decoder” class to construct a NMT model is imported from encoder and decoder implementations.

“Encoder.py”, “TAEncoder.py”, “EnsembleEncoder.py” and “AGG/HierEncoder.py” implement standard Transformer encoder, deeper encoder with transparent attention, ensemble encoder and encoder with hierarchical aggregation proposed by Dou et al. (2018). All files provide an implementation of “Encoder” class which takes index matrix as input and generate corresponding representation. “Encoder.py” also provides a standard encoder layer implementation (class “EncoderLayer”), while class “EncoderLayer” in “AGG/HierEncoder.py” is the implementation of the encoder layer of hierarchical encoder.

“Decoder.py”, “AvgDecoder.py”, “TADecoder.py”, “EnsembleDecoder.py” and “EnsembleAvgDecoder.py” implement the standard Transformer decoder, decoder with average attention as self attention, decoder corresponding to deeper encoder with transparent attention and their ensemble version in class “Decoder”, while “Decoder.py” and “AvgDecoder.py” also contain “DecoderLayer” classes as implementations of a standard decoder layer and a decoder layer with average attention as self attention, decoder corresponding to deeper encoder with transparent attention and their ensemble version in class “DecoderLayer”. “AGG/HierDecoder.py” and “AGG/HierAvgDecoder.py” contain hierarchically aggregated implementation of decoder and average attention decoder with corresponding “Decoder” classes and “DecoderLayer” classes.

“Decoder” class in “RNMTDecoder.py” implements RNMT decoder proposed by Chen et al. (2018), rather than feeding the concatenation of attention embedding and generated representation from last decoder layer directly to classifier, we reduce its dimension by a linear transformation followed by tanh activation function, which allows the matrix sharing between classifier and
decoder embedding. Every "Decoder" class in Neutron implements or inherits a "decode" function supported by a "greedy\_decode" function and a "beam\_decode" function to make efficient decoding, along with a standard "forward" function for training.

5 Additional Tools

Besides fundamental implementations for neural machine translation, there are also several tools for advanced features.

5.1 Averaging models

Many researches do average several checkpoints before evaluating. Neutron supports this function. "tools/average\_model.py" can load parameters of several checkpoints and save averaged parameters to a new model file.

5.2 Ranking

A ranking tool is provided to rank data sets with a pre-trained model, per-token loss will be calculated for efficiency. This tool can be employed for data cleaning or domain adapted data selection.

5.3 Web Server

Neutron provides a simple translation web server with REST API support besides the translating scripts, which we think is helpful for integrating trained models into the other machine translation based applications.

5.4 Conversion to C libraries

Neutron has a converting tool based on Cython\(^4\), it can convert python implementation of core modules and functions into C code and compile these C code into loadable C libraries, which may bring little additional performance and make it easier to put Neutron into practice.

5.5 Forbidden indexes for shared vocabulary

As mentioned in section 3.1, there might be some tokens which only appear in the source side when a shared vocabulary is adopted, and these tokens which will never appear in the target side will still get a small smoothing probability in the loss function. Neutron contains a tool which can collect those indexes and save it into a file which can be loaded into "cnfg.py" and thus preventing encouraging the decoder to generate those tokens which do not belong to that language.

6 Performance

We test our implementation with WMT 17 German to English task. We apply independent BPE (Sennrich et al., 2015) with 32k merge operations and 50 as vocabulary threshold, and the source and target vocabulary size are about 20k and 23k correspondingly. We use all sentence with less than 256 tokens, and a batch size of at least 25,000 target tokens. Warm-up steps is 8,000. The other settings of trained models are the same with Transformer base except embedding of encoder and decoder are not shared.

With a single nVidia TITAN X, Neutron can train about 5800 tokens / s on the target side, and about 10,100 tokens / s with two GPUs. It runs significantly faster with nVidia GTX 1080 Ti, and the speed is competitive according to our experience. Time consumed for training and beam decoding over training set and development set (8,171 sentences) are shown in Table 1.

We test BLEU score with “multi-bleu-detok.perl” on newstest 2017 to evaluate the machine translation quality of trained models. Beam size for decoding is 4 with no length penalty applied. We use the model performs best on the validation set during training saved automatically for every epoch, rather than averaged checkpoints. Results are shown in Table 2.

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\(^4\)https://cython.org/
is hierarchical aggregated architecture proposed by Dou et al. (2018)5. “Case-sens” and “Case-insens” mean case-sensitive and case-insensitive BLEU.

7 Related work
Sutskever et al. (2014); Bahdanau et al. (2014); Luong et al. (2015); Gehring et al. (2017); Vaswani et al. (2017) and many other researchers proposed various kinds of neural machine translation models, corresponding to these work, there are many implementations open sourced by researchers like: Klein et al. (2017); Vaswani et al. (2018); Hieber et al. (2017); Zhang et al. (2017). Those implementations greatly help neural machine translation researches and productive applications. Their works provide valuable experience for us to implement Neutron.

8 Conclusion
We focus on Transformer and its variants for neural machine translation, implement Neutron based on pyTorch which can achieve competitive performance and provides several additional functions for neural machine translation, and introduce it in this paper.

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