PARAGen: A Parallel Generation Toolkit

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Abstract

PARAGen is a PyTorch-based NLP toolkit for further development on parallel generation. PARAGen provides thirteen types of customizable plugins, helping users to experiment quickly with novel ideas across model architectures, optimization, and learning strategies. We implement various features, such as unlimited data loading and automatic model selection, to enhance its industrial usage. ParaGen is now deployed to support various research and industry applications at ByteDance. PARAGen is available at https://github.com/bytedance/ParaGen.

1 Introduction

Recently, neural sequence generation model achieve great success (Vaswani et al., 2017; Lewis et al., 2020; Liu et al., 2020). Among a surge of sequence generation algorithms, parallel generation or non-autoregressive generation methods gain increasing attention on various tasks for high inference speed (Gu et al., 2018; Saharia et al., 2020; Qian et al., 2021a; Gu and Kong, 2021; Huang et al., 2022) and competitive performance against auto-regressive transformer (Gu et al., 2019; Chan et al., 2020; Qian et al., 2021b). Apart from natural language processing, parallel generation also demonstrates its superiority and scalability on text-to-speech synthesis (Ren et al., 2021) and high-resolution image synthesis (Chang et al., 2022).

Several toolkits on sequence generation has been presented for developing sequence generation algorithms, such as FairSeq (Ott et al., 2019), Tensor2Tensor (Vaswani et al., 2018), Transformers (Wolf et al., 2020) and OpenNMT (Klein et al., 2017). These toolkits are mostly born with autoregressive transformers with maximum likelihood estimation training and are used for research purposes.

* Work was done at ByteDance.

In this paper, we present PARAGen, an extensible toolkit for parallel generation, which is first developed with Glancing Transformer on WMT-21 Competition (Qian et al., 2021b). We redesign the code architecture for easy modification on training and decoding methods, such as glancing training (Qian et al., 2021a), imitation learning (Wei et al., 2019), inference algorithms (noisy parallel decoding) (Gu et al., 2018), and mask-predict decoding (Ghazvininejad et al., 2019), which are critical to enhancing parallel generation algorithm developments. Besides, PARAGen also suits industrial usage with robust implementations and attractive features, such as unlimited data loading, asynchronized input/output, plug-in Huggingface tokenizers/models (Wolf et al., 2020) and fast training/inference with LightSeq (Wang et al., 2021, 2022). Apart from parallel generation, PARAGen also reproduces typical tasks.
with step-by-step scripts, such as autoregressive translation (Vaswani et al., 2017), text summarization (Lewis et al., 2020), text classification (Wang et al., 2018), and extractive question answering (Rajpurkar et al., 2016). As for large-scale pretraining, PARAGEN supports BERT pretraining (Devlin et al., 2019), and multilingual translation with mBART pretraining (Liu et al., 2020). PARAGEN is now deployed to support various research and industrial applications at ByteDance.

2 Architecture Design

The overall architecture of PARAGEN is shown as Figure 1. PARAGEN consists of four main functional blocks: data, model, trainer, and evaluator. The data block focuses on data input, processing, sampling, and loading; the model block consists of neural models in training and inference; the trainer is implemented for scheduling the training process; the evaluator defines the evaluation metrics. Compared with the previous frameworks, we offer 13 types of plug-ins across the three blocks, which makes PARAGEN more extensible for experimenting with new ideas.

2.1 Data

We design the data organization block on four base concepts, including reading, preprocessing, sampling strategy and loading, deriving four customizable class or functions respectively, i.e. Dataset, Data Processing, Sampler and DataLoader. We address PARAGEN ’s data processing paradigm along with two key topics: online-offline data processing and unlimited data loading challenge.

Dataset The Dataset instances read data and organize it to a dict-format object, despite their storage format on disks. Users are allowed to develop their own Dataset class for customization usage by implementing load and callback functions. Currently, PARAGEN supports data stored in various formats, including raw texts, parallel texts, and JSON files. The Datasets as well as other classes in PARAGEN co-work with an underlying io module to suit different file systems, reading and writing data on a local disk or a Hadoop file system. It is worth noting that the io module is also modularized and extensible to suit data input/output under more scenarios. Besides, we also develop StreamingDataset, reading data in a streaming way. The StreamingDataset can read extremely large-scale data with constant memory consumption, making it extensible to industrial usage.

Data Processing Data preprocessing, such Byte-Pair Encoding (Sennrich et al., 2016), is critical to sequence generation and varies from task to task. To enhance task-specific data preprocessing, PARAGEN provides interfaces within Task class to allow customization. The data processing is roughly divided into two categories, offline data processing as data_collate_fn and online data processing collate_fn. The data_collate_fn refers to offline data processing and proceeds before the training/inference stage start with input from Dataset. Thus data processed by data_collate_fn remains unchanged during the training/inference process, which speeds up training and inference by eliminating repeated data processing. The collate_fn is designed as online processing to enhance flexibility and to allow users to adjust data processing strategies, such as batching, during training and inference. We believe the combination of offline and online data processing would make data processing more flexible and extensible.

Sampler The sampling strategy is a non-negligible algorithm in the online data processing. Although PyTorch provides a base class of sampling strategy, it is still often ignored by existing generation frameworks. PARAGEN allows users to develop their sampling strategies by implementing a Sampler instance to decide how data are organized into batches. A technical challenge of incorporating customizable sampling strategies is their compatibility with the feature of unlimited data loading. We solve this problem in the DataLoader with a cache mechanism.

DataLoader DataLoader is the final stage of data processing and the beginning of neural model processing, acting as a bridge to connect data and neural models. It can also be viewed as a coordinator of data processing. It first fetches a batch of samples, according to the sampling strategy determined by Sampler, from data memory with offline processed data. Then it sends the data batches to online data processing, which becomes a private object of DataLoader instance at initialization, and gets a batch to feed the neural network. However, in the original PyTorch, DataLoader is incompatible with streaming data.
loading. We extend the dataloader and implement a StreamingDataLoader to read data streamingly, further featuring unlimited data loading.

2.2 Module
A key principle of designing PARAGEN’s model block is based on the concept separation of training and inference. Unlike classification models, sequence generation ones become different when they are applied in training and inference. For example, a sequence generation model is trained in a teacher-forcing way whilst it generates sequences with the help of the beam search algorithm. Thus we defines four sub-modules for PARAGEN model block: Model, Generator, Criterion and Search. Model and Criterion are often used in training process whereas Generator and Search are in inference. We argue that the training-inference separation of neural models would benefit the downstream neural model optimization (Wang et al., 2021) in industrial usage without harming flexibility in developing new models.

Model We implement the architecture of neural models with learnable parameters by inheriting PARAGEN’s Model class. Similar to the models in the existing, it consumes a batch of samples and produces logits over the predicted target. We provide several popular implementations, including parallel generation, autoregressive sequence generation, extraction model, and sequence classification/regression. Besides, Huggingface models at present are widely-used for their large-scale pre-training models, and we implemented a Huggingface model wrapper to make it compatible in PARAGEN.

Generator In PARAGEN, we advocate Generator, instead of the original Model, to apply to the inference stage. Generator is designed as a wrapper to Model with extra decoding algorithms, such as beam search and greedy search in autoregressive sequence generation (Vaswani et al., 2017), noisy padding mask in parallel generation (Gu et al., 2018), and even extraction algorithms in extractive tasks. Although the extra decoding algorithms could also be implemented as post-processing, they would benefit from tensor computation on GPUs, which further speeds up the computations. It is also recommended in PARAGEN to have decoding algorithms on GPUs and post-processing on CPUs work with each other to achieve the tradeoff between flexibility and speedup. We here argue that it is essential for industrial usage to separate Generator from Model, because Generator, which is gradient-free, requires more elaborated and extreme optimization to enhance efficiency. Previous study (Wang et al., 2021) shows that joint optimization on neural models and decoding algorithms achieves significant speedup and reduces GPU memory consumption. Nevertheless, such joint optimization does not suit Model in training. In PARAGEN, we implement Generators for sequence extraction, auto regressive sequence generation and parallel sequence generation.

Criterion Like previous frameworks, we define Criterion class as the objective functions across various tasks. It measures the divergence between predicted logits and golden reference. From the Criterion, we compute the gradients of all the learnable parameters for optimization. We also allow neural models, such as Huggingface models, to compute loss by themselves. Due to the modularization in PARAGEN, Criterion classes can be combined to enhance multi-task learning.

Search Search or decoding algorithms, such as beam search and noise padding mask, are critical to sequence generation. We modularize Search to support users in developing their awesome sequence search algorithms, for both autoregressive or parallel generation, more than existing ones. The Search algorithms act as a part of Generator, co-working with Model to produce final sequences.

2.3 Trainer
One big difference between PARAGEN and existing learning framework is customizing the training process. Recent research shows that a neural model with the same architecture trained with a well-designed training strategy performs significantly better. Customizing a Trainer helps the users to experiment with training strategies conveniently. The Trainer formulate the whole training process and includes several types of customization: loss computation, optimizer, and rate scheduler.

Loss computation Trainer leaves an interface forward_loss for implementation of loss computation. Elaboration on loss computation is critical to deep learning algorithms to enhance mod-
els’ performance. For examples, a) GLAT (Qian et al., 2021a) can be used for computing a three-stage objective, glancing at the target, modifying neural network inputs/targets, and learning; b) FreeLB (Zhu et al., 2020) adopts an adversarial gradient to inject to neural model to learn it robustly; c) CoNT (An et al., 2022) leverage a generation process to adopt contrastive learning to enhance sequence generation. Thus we believe that customization on loss computation frees developers from the stereotyped training process and encourage new experimental training algorithms.

Optimizer PARAGEN provides Optimizer customization following the original PyTorch. All the optimizers implemented in PyTorch and Huggingface can be used directly, and experimental optimizers are also encouraged. The coordination of Optimizer to advanced optimization algorithms, such as mix-precision training, apex support, and distributed training, is automatic.

Rate Scheduler We implement a functional tool called Rate Scheduler to define how a rate typed as an integer or float is scheduled. The rate in PARAGEN could be any hyper-parameter beyond the learning rate, allowing users to schedule their training process more flexibly. In design, the original PyTorch treats the optimizer as an attribute to the learning rate scheduler, but PARAGEN does this differently by setting the scheduled learning rate as a part of the optimizer. The learning rate is actively scheduled through the interaction between Optimizer and Trainer.

2.4 Evaluator

Evaluator formulates the overall evaluation process in PARAGEN, supporting customization on two aspects, including data sets and metrics. In evaluations, we compute the Cartesian product of data sets and metrics to obtain several performance scores. The scores are averaged to obtain an overall judgment on the current neural model. These scores will further return to Trainer for model selection.

Metric We provide Metric for independent evaluation of the divergence between predicted hypotheses and ground-truth references. Metric in PARAGEN can be designed as lexical metrics (BLEU (Papineni et al., 2002a) and Rouge (Lin, 2004)), numeric metrics (Accuracy and F1-score), and model-based metrics (BERT-score (Zhang et al., 2019))

2.5 Difference to FairSeq

A close sequence generation toolkit to PARAGEN is FairSeq (Ott et al., 2019). PARAGEN differs from FairSeq in four aspects: a) FairSeq is for general purpose sequence generation, while PARAGEN is carefully designed for parallel generation; b) Fairseq’s standard pipeline requires binarizing the data first, which is extremely fast and efficient for training. Such a way may make on-the-fly data manipulation a bit difficult. PARAGEN allows reading the raw data and modifying it dynamically in the training loop, without sacrificing the speed. c) FairSeq supports 5 types of customizable modules whereas PARAGEN offers 13 classes. Fairseq provides a unified training loop, PARAGEN disentangles the training and inference process into independent modules (Trainer, Evaluator), so that the customization for each task is more user-friendly. d) PARAGEN implements more features specially designed for industrial usage.

3 Implementation & Features

PARAGEN implements fundamental functions, such as distributed training on multiple machines and GPUs (with Horovod (Sergeev and Balso, 2018)), mix-precision training (with apex\(^1\)), incremental decoding for the autoregressive models, breakpoint resuming, out-of-memory recovery, early stopping, and accumulated gradients. Moreover, we also implement advanced functions, including unlimited data loading, automatic model selection, multi-task training, and fast training/inference with LightSeq. In this section, we focus on these advanced features.

Unlimited Data Loading Pretrained models have shown its strong capability in generalizing to new tasks (Devlin et al., 2019; Liu et al., 2019; Radford et al., 2019; Lewis et al., 2020; Raffel et al., 2020; Floridi and Chiriatti, 2020). However, such pretrained models usually demand billions, trillions, and even more of the training data. Moreover, for industrial usage, the large amount of internal data is a challenge for data loading. In PARAGEN, we implement a StreamingDataLoader that reads data from disk in a streaming way with the file input stream. It also features data distribution with multi-

\(^1\)https://github.com/NVIDIA/apex
GPU training and local shuffling for data batching. With the help of StreamingDataLoader, PARA GEN can read unlimited data with limited memory usage.

**Automatic Model Selection** PARA GEN automatically selects the best models with a customized assessment metric during the training process. By providing the trainer with an assess_by arguments as `{DATA_NAME}.{METRIC_NAME}`, the trainer picks up the checkpoints that performs the best on `{DATA_NAME}` with respect to `{METRIC_NAME}`. Note that once a checkpoint is selected to save, PARA GEN also saves the average of $k$ checkpoints before and marks the averaged checkpoints as `best_avg`.\(^2\)

**Asynchronized Input/Output** PARA GEN uses an asynchronized input/output implementation for reading and writing to maximize the utility of GPU resources. Asynchronized output is important for model selection. Because the computation of `best_avg` checkpoints costs a long time to finish, especially for large models in industrial applications.

**Multi-Task Learning** PARA GEN provides an easy-to-use way for multi-task learning. PARA GEN implements a `MultiTaskCriterion` which automatically combines a list of criteria.

**Plug-in Hugginface Tokenizers and Models** Hugginface (Wolf et al., 2020) is a widely used pre-trained model library and demonstrates its effectiveness among various tasks. In PARA GEN, Hugginface can be directly used in an import-register way. It allows researchers to develop algorithms upon pre-trained models and to use advanced features provided in PARA GEN.

**Fast Training and Inference with LightSeq** In PARA GEN, researchers and developers can use LightSeq easier to speedup their transformer models/modules in training (Wang et al., 2022) and inference (Wang et al., 2021). Without understanding the details of LightSeq, users can speed up their transformer models/modules by simply appending a `LS` prefix to the model/module class name in the configuration.

\(^2\)We find it performs better compared with the average of the last-$k$ checkpoints after the training process ends.

### 4 Reproducibility

PARA GEN can be used for various tasks beyond parallel generation. We provide reproducible results and scripts on six benchmarks on PARA GEN, including: a) glancing transformer on WMT14 En-De; b) transformer on IWSLT14 De-En, WMT14 En-De, and WMT14 En-Fr; b) transformer on Multi-News and XSum; c) mBART on Multilingual Translation; d) plug-in Hugginface on SQuAD 1.1; e) BERT pretraining and fine-tuning on GLUE benchmark. For simplicity, we eliminate the details of reproduction configurations and hyper-parameters. The reproduction results are shown in Appendix A and scripts can be found in our repository.

### 5 Conclusions

We present the ParaGen toolkit for parallel sequence generation. It supports 13 types of modules for customization and advocates a plug-in usage for further development. Its robust implementation and features enhance the research algorithm design and industrial development. In the future, we will create more plugins to extend PARA GEN to more research areas.

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A Reproducible Results

We implement typical models on various tasks: a) glancing transformer on WMT14 En-De; b) transformer on IWSLT14 De-En, WMT14 En-De, and WMT14 En-Fr; c) mBART on Multilingual Translation; d) plug-in Huggingface on SQuAD 1.1; e) BERT pretraining and fine-tuning on GLUE benchmark. These models are implemented with reproducible scripts. The detailed reproducible results are shown in the rest of the section.

A.1 Glancing Transformer on WMT14 En-De

We trained Glancing Transformer on Transformer-AT distilled data. We report sacrebleu (Post, 2018) and tokenized BLEU (Papineni et al., 2002b) for completeness.

| Model         | sacrebleu | tok bleu |
|---------------|-----------|----------|
| GLAT          | 24.40     | 24.98    |
| GLAT + avg-ckpt | 24.58     | 25.29    |

Table 1: BLEUs on distilled WMT14 En-De. GLAT+avg-ckpt is the average checkpoint among the last 10 checkpoints.

A.2 Transformer on Machine Translation

We implement widely-used transformer architecture and provide its results on IWSLT/WMT benchmarks. For IWSLT14 De-En, we use transformer-small architecture; for WMT14 En-De and WMT14 En-Fr, we use transformer-big architecture. Similar to Glancing Transformer, we report its results with sacrebleu and tokenized bleu.

| Task          | Model | sacrebleu | tok bleu |
|---------------|-------|-----------|----------|
| IWSLT14 De-En | small | 33.1      | 34.5     |
| WMT14 En-De   | base  | 26.9      | 27.5     |
| WMT14 En-De   | big   | 27.7      | 28.4     |
| WMT14 En-Fr   | big   | 40.3      | 43.3     |

Table 2: BLEUs on machine translation benchmarks.

A.3 mBART on Multilingual Translation

PARAGEN provides implementation to pre-train mBART from scratch. We finetune the pre-trained mBART on XX-en translation tasks.

Language Pairs | mBART | mBART + avg-ckpt
---------------|-------|------------------|
  de-en        | 41.45 | 41.84            |
  fr-en        | 39.09 | 39.41            |
  ja-en        | 21.68 | 22.84            |
  pl-en        | 32.03 | 32.50            |
  ro-en        | 36.75 | 37.24            |
  nn-en        | 12.75 | 14.14            |
  hi-en        | 26.34 | 27.78            |

Table 3: Results on XX-en translation with mBART pre-trained from scratch.

| Task      | model   | rouge-1 | rouge-2 | rouge-n |
|-----------|---------|---------|---------|---------|
| Multi-News| tr-base | 33.59   | 5.91    | 30.71   |
| XSum      | bart-base | 46.80   | 17.93   | 43.01   |

Table 4: Results on abstractive text summarization.

A.4 Abstractive Text Summarization

A.5 Question Answering

PARAGEN also provides results on extractive question answering with plug-in Huggingface models. We test various pre-trained models in Huggingface on SQuAD 1.1.

| Model         | F1    | Exact Match |
|---------------|-------|-------------|
| BERT-base-uncased | 88.31 | 81.02       |
| BERT-base-cased  | 88.34 | 81.11       |
| BERT-large-cased | 90.73 | 83.87       |
| RoBERTa-base     | 91.88 | 85.34       |
| RoBERTa-large    | 93.44 | 87.26       |
| BART-base        | 91.27 | 84.52       |
| BART-large       | 93.14 | 86.70       |

Table 5: Plug-in Huggingface Pretrained Models on SQuAD 1.1.

A.6 BERT

PARAGEN supports training BERT from scratch with customized data. We train BERT on two data sets, news and wibo, and test it on GLUE benchmarks (Wang et al., 2018). We use standard evaluation metrics for each task.
| Task      | Metric                  | news   | wibo   |
|-----------|-------------------------|--------|--------|
| CoLA      | Matthews’ Corr          | 61.82  | 58.36  |
| SST-2     | Accuracy                | 93.00  | 91.86  |
| STS-B     | Pearson/Spearman Corr   | 86.97/86.88 | 87.95/87.65 |
| MRPC      | F1/Accuracy             | 91.13/87.75 | 91.13/87.50 |
| QQP       | F1/Accuracy             | 87.95/91.05 | 88.05/91.16 |
| MNLI-m/mm | Accuracy                | 83.42/83.28 | 83.24/83.06 |
| QNLI      | Accuracy                | 89.22  | 90.81  |
| RTE       | Accuracy                | 67.15  | 61.37  |

Table 6: Results on GLUE by BERT pre-trained on news and wibo dataset.