Sequence to Sequence Training and Evaluation

This directory contains examples for finetuning and evaluating transformers on summarization and translation tasks.

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Supported Architectures

- `BartForConditionalGeneration` (and anything that inherits from it)
- `MarianMTModel`
- `PegasusForConditionalGeneration`
- `MBartForConditionalGeneration`
- `FSMTForConditionalGeneration`
- `T5ForConditionalGeneration`

Note

⚠ This project should be run with pytorch-lightning==1.0.4 which has a potential security vulnerability

Datasets

XSUM

```
cd examples/contrib/pytorch-lightning/seq2seq
wget https://cdn-datasets.huggingface.co/summarization/xsum.tar.gz
tar -xzvf xsum.tar.gz
export XSUM_DIR=${PWD}/xsum
```

this should make a directory called `xsum/` with files like `test.source`. To use your own data, copy that files format. Each article to be summarized is on its own line.

CNN/DailyMail

```
cd examples/contrib/pytorch-lightning/seq2seq
wget https://cdn-datasets.huggingface.co/summarization/cnn_dm_v2.tgz
tar -xzvf cnn_dm_v2.tgz  # empty lines removed
mv cnn_cln cnn_dm
export CNN_DIR=${PWD}/cnn_dm
```

this should make a directory called `cnn_dm/` with 6 files.

WMT16 English-Romanian Translation Data

download with this command:

```
wget https://cdn-datasets.huggingface.co/translation/wmt_en_ro.tar.gz
tar -xzvf wmt_en_ro.tar.gz
export ENRO_DIR=${PWD}/wmt_en_ro
```

this should make a directory called `wmt_en_ro/` with 6 files.

WMT English-German

```
wget https://cdn-datasets.huggingface.co/translation/wmt_en_de.tgz
tar -xzvf wmt_en_de.tgz
export DATA_DIR=${PWD}/wmt_en_de
```

FSMT datasets (wmt)

Refer to the scripts starting with `eval_` under:
https://github.com/huggingface/transformers/tree/main/scripts/fsmt

Pegasus (multiple datasets)

Multiple eval datasets are available for download from:
https://github.com/stas00/porting/tree/master/datasets/pegasus

Your Data

If you are using your own data, it must be formatted as one directory with 6 files:

```
train.source
train.target
val.source
val.target
test.source
test.target
```

The `.source` files are the input, the `.target` files are the desired output.

Potential issues

- native AMP (`--fp16` and no apex) may lead to a huge memory leak and require 10x gpu memory. This has been fixed in pytorch-nightly and the minimal official version to have this fix will be pytorch-1.8. Until then if you have to use mixed precision please use AMP only with pytorch-nightly or NVIDIA's apex. Reference: https://github.com/huggingface/transformers/issues/8403

Tips and Tricks

General Tips:

- since you need to run from this folder, and likely need to modify code, the easiest workflow is fork transformers, clone your fork, and run `pip install -e .` before you get started.
- try `--freeze_encoder` or `--freeze_embeds` for faster training/larger batch size. (3hr per epoch with bs=8, see the "xsum_shared_task" command below)
- `fp16_opt_level=O1` (the default works best).
- In addition to the pytorch-lightning .ckpt checkpoint, a transformers checkpoint will be saved. Load it with `BartForConditionalGeneration.from_pretrained(f'{output_dir}/best_tfmr)` .
- At the moment, `--do_predict` does not work in a multi-gpu setting. You need to use `evaluate_checkpoint` or the `run_eval.py` code.
- This warning can be safely ignored:

  > *"Some weights of BartForConditionalGeneration were not initialized from the model checkpoint at facebook/bart-large-xsum and are newly initialized: ['final_logits_bias']"*

- Both finetuning and eval are 30% faster with `--fp16`. For that you need to install apex.
- Read scripts before you run them!

Summarization Tips:

- (summ) 1 epoch at batch size 1 for bart-large takes 24 hours and requires 13GB GPU RAM with fp16 on an NVIDIA-V100.
- If you want to run experiments on improving the summarization finetuning process, try the XSUM Shared Task (below). It's faster to train than CNNDM because the summaries are shorter.
- For CNN/DailyMail, the default `val_max_target_length` and `test_max_target_length` will truncate the ground truth labels, resulting in slightly higher rouge scores. To get accurate rouge scores, you should rerun calculate_rouge on the `{output_dir}/test_generations.txt` file saved by `trainer.test()`
- `--max_target_length=60 --val_max_target_length=60 --test_max_target_length=100` is a reasonable setting for XSUM.
- `wandb` can be used by specifying `--logger_name wandb`. It is useful for reproducibility. Specify the environment variable `WANDB_PROJECT='hf_xsum'` to do the XSUM shared task.
- If you are finetuning on your own dataset, start from `distilbart-cnn-12-6` if you want long summaries and `distilbart-xsum-12-6` if you want short summaries. (It rarely makes sense to start from `bart-large` unless you are a researching finetuning methods).

Update 2018-07-18 Datasets: `LegacySeq2SeqDataset` will be used for all tokenizers without a `prepare_seq2seq_batch` method. Otherwise, `Seq2SeqDataset` will be used. Future work/help wanted: A new dataset to support multilingual tasks.

Finetuning Scripts

All finetuning bash scripts call finetune.py (or distillation.py) with reasonable command line arguments. They usually require extra command line arguments to work.

To see all the possible command line options, run:

```
./finetune.py --help
```

Finetuning Training Params

To override the pretrained model's training params, you can pass them to `./finetune.sh`:

```
./finetune.sh \
    [...]
    --encoder_layerdrop 0.1 \
    --decoder_layerdrop 0.1 \
    --dropout 0.1 \
    --attention_dropout 0.1 \
```

Summarization Finetuning

Run/modify `finetune.sh`

The following command should work on a 16GB GPU:

```
./finetune.sh \
    --data_dir $XSUM_DIR \
    --train_batch_size=1 \
    --eval_batch_size=1 \
    --output_dir=xsum_results \
    --num_train_epochs 6 \
    --model_name_or_path facebook/bart-large
```

There is a starter finetuning script for pegasus at `finetune_pegasus_xsum.sh`.

Translation Finetuning

First, follow the wmt_en_ro download instructions. Then you can finetune mbart_cc25 on english-romanian with the following command. **Recommendation:** Read and potentially modify the fairly opinionated defaults in `train_mbart_cc25_enro.sh` script before running it.

Best performing command:

```
# optionally
export ENRO_DIR='wmt_en_ro' # Download instructions above
# export WANDB_PROJECT="MT" # optional
export MAX_LEN=128
export BS=4
./train_mbart_cc25_enro.sh --output_dir enro_finetune_baseline --label_smoothing 0.1
--fp16_opt_level=O1 --logger_name wandb --sortish_sampler
```

This should take < 6h/epoch on a 16GB v100 and achieve test BLEU above 26 To get results in line with fairseq, you need to do some postprocessing. (see `romanian_postprocessing.md`)

MultiGPU command (using 8 GPUS as an example)

```
export ENRO_DIR='wmt_en_ro' # Download instructions above
 # export WANDB_PROJECT="MT" # optional
export MAX_LEN=128
export BS=4
./train_mbart_cc25_enro.sh --output_dir enro_finetune_baseline --gpus 8 --
logger_name wandb
```

Finetuning Outputs

As you train, `output_dir` will be filled with files, that look kind of like this (comments are mine). Some of them are metrics, some of them are checkpoints, some of them are metadata. Here is a quick tour:

```
output_dir
├── best_tfmr  # this is a huggingface checkpoint generated by save_pretrained. It
is the same model as the PL .ckpt file below
│   ├── config.json
│   ├── merges.txt
│   ├── pytorch_model.bin
│   ├── special_tokens_map.json
```

```
│   ├── tokenizer_config.json
│   └── vocab.json
├── git_log.json   # repo, branch, and commit hash
├── val_avg_rouge2=0.1984-step_count=11.ckpt  # this is a pytorch lightning checkpoint associated with the best val score. (it will be called BLEU for MT)
├── metrics.json  # new validation metrics will continually be appended to this
├── student  # this is a huggingface checkpoint generated by SummarizationDistiller. It is the student before it gets finetuned.
│   ├── config.json
│   └── pytorch_model.bin
├── test_generations.txt
# ^^ are the summaries or translations produced by your best checkpoint on the test data. Populated when training is done
├── test_results.txt  # a convenience file with the test set metrics. This data is also in metrics.json['test']
├── hparams.pkl  # the command line args passed after some light preprocessing. Should be saved fairly quickly.
```

After training, you can recover the best checkpoint by running

```
from transformers import AutoModelForSeq2SeqLM
model = AutoModelForSeq2SeqLM.from_pretrained(f'{output_dir}/best_tfmr')
```

Converting pytorch-lightning checkpoints

pytorch lightning `-do_predict` often fails, after you are done training, the best way to evaluate your model is to convert it.

This should be done for you, with a file called `{save_dir}/best_tfmr`.

If that file doesn't exist but you have a lightning `.ckpt` file, you can run

```
python convert_pl_checkpoint_to_hf.py PATH_TO_CKPT
randomly_initialized_hf_model_path save_dir/best_tfmr
```

Then either `run_eval` or `run_distributed_eval` with `save_dir/best_tfmr` (see previous sections)

Experimental Features

These features are harder to use and not always useful.

Dynamic Batch Size for MT

`finetune.py` has a command line arg `--max_tokens_per_batch` that allows batches to be dynamically sized. This feature can only be used:

- with fairseq installed
- on 1 GPU
- without sortish sampler
- after calling `./save_len_file.py $tok $data_dir`

For example,

```
./save_len_file.py Helsinki-NLP/opus-mt-en-ro  wmt_en_ro
./dynamic_bs_example.sh --max_tokens_per_batch=2000 --output_dir
benchmark_dynamic_bs
```

splits `wmt_en_ro/train` into 11,197 uneven lengthed batches and can finish 1 epoch in 8 minutes on a v100.

For comparison,

```
./dynamic_bs_example.sh --sortish_sampler --train_batch_size 48
```

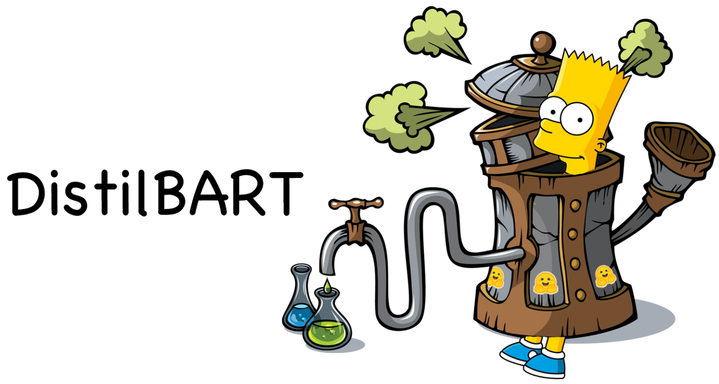
uses 12,723 batches of length 48 and takes slightly more time 9.5 minutes.

The feature is still experimental, because:

- we can make it much more robust if we have memory mapped/preprocessed datasets.
- The speedup over sortish sampler is not that large at the moment.

DistilBART

This section describes all code and artifacts from our Paper



- For the CNN/DailyMail dataset, (relatively longer, more extractive summaries), we found a simple technique that works, which we call "Shrink and Fine-tune", or SFT. you just copy alternating layers from `facebook/bart-large-cnn` and fine-tune more on the cnn/dm data. `sshleifer/distill-pegasus-cnn-16-4` , `sshleifer/distilbart-cnn-12-6` and all other checkpoints under `sshleifer` that start with `distilbart-cnn` were trained this way.
- For the XSUM dataset, training on pseudo-labels worked best for Pegasus (`sshleifer/distill-pegasus-16-4`), while training with KD worked best for `distilbart-xsum-12-6`
- For `sshleifer/dbart-xsum-12-3`
- We ran 100s experiments, and didn't want to document 100s of commands. If you want a command to replicate a figure from the paper that is not documented below, feel free to ask on the forums and tag `@sshleifer` .
- You can see the performance tradeoffs of model sizes here. and more granular timing results here.

Evaluation

use run_distributed_eval, with the following convenient alias

```
deval () {
    proc=$1
    m=$2
    dd=$3
    sd=$4
    shift
    shift
    shift
    shift
    python -m torch.distributed.launch --nproc_per_node=$proc
run_distributed_eval.py \
        --model_name $m  --save_dir $sd --data_dir $dd $@
}
```

On a 1 GPU system, here are four commands (that assume `xsum`, `cnn_dm` are downloaded, cmd-F for those links in this file).

`distilBART`:

```
deval 1 sshleifer/distilbart-xsum-12-3 xsum dbart_12_3_xsum_eval --fp16  # --help
for more choices.
deval 1 sshleifer/distilbart-cnn_dm-12-6 cnn_dm dbart_12_6_cnn_eval --fp16
```

`distill-pegasus`:

```
deval 1 sshleifer/distill-pegasus-cnn-16-4 cnn_dm dpx_cnn_eval
deval 1 sshleifer/distill-pegasus-xsum-16-4 xsum dpx_xsum_eval
```

Distillation

- For all of the following commands, you can get roughly equivalent result and faster run times by passing `--num_beams=4`. That's not what we did for the paper.
- Besides the KD section, you can also run commands with the built-in transformers trainer. See, for example, builtin_trainer/train_distilbart_cnn.sh.
- Large performance deviations (> 5X slower or more than 0.5 Rouge-2 worse), should be reported.
- Multi-gpu (controlled with `--gpus` should work, but might require more epochs).

Recommended Workflow

- Get your dataset in the right format. (see 6 files above).
- Find a teacher model Pegasus (slower, better ROUGE) or `facebook/bart-large-xsum` / `facebook/bart-large-cnn` (faster, slightly lower.). Choose the checkpoint where the corresponding dataset is most similar (or identical to) your dataset.
- Follow the sections in order below. You can stop after SFT if you are satisfied, or move on to pseudo-labeling if you want more performance.
- student size: If you want a close to free 50% speedup, cut the decoder in half. If you want a larger speedup, cut it in 4.

- If your SFT run starts at a validation ROUGE-2 that is more than 10 pts below the teacher's validation ROUGE-2, you have a bug. Switching to a more expensive technique will not help. Try setting a breakpoint and looking at generation and truncation defaults/hyper-parameters, and share your experience on the forums!

Initialization

We use [make_student.py]() to copy alternating layers from the teacher, and save the resulting model to disk

```
python make_student.py facebook/bart-large-xsum --save_path dbart_xsum_12_3  -e 12 -
d 3
```

or for `pegasus-xsum`

```
python make_student.py google/pegasus-xsum --save_path dpx_xsum_16_4  --e 16 --d 4
```

we now have an initialized student saved to `dbart_xsum_12_3`, which we will use for the following commands.

- Extension: To replicate more complicated initialize experiments in section 6.1, or try your own. Use the `create_student_by_copying_alternating_layers` function.

Pegasus

- The following commands are written for BART and will require, at minimum, the following modifications
- reduce batch size, and increase gradient accumulation steps so that the product `gpus * batch size * gradient_accumulation_steps = 256`. We used `--learning-rate` = 1e-4 * gradient accumulation steps.
- don't use fp16
- `--tokenizer_name google/pegasus-large`

SFT (No Teacher Distillation)

You don't need `distillation.py`, you can just run:

```
python finetune.py \
  --data_dir xsum \
  --freeze_encoder --freeze_embeds \
  --learning_rate=3e-4 \
  --do_train \
  --do_predict \
  --fp16 --fp16_opt_level=O1 \
  --val_check_interval 0.1 --n_val 1000 --eval_beams 2 --length_penalty=0.5 \
  --max_target_length=60 --val_max_target_length=60 --test_max_target_length=100 \
  --model_name_or_path dbart_xsum_12_3 \
  --train_batch_size=64 --eval_batch_size=64 \
  --sortish_sampler \
  --num_train_epochs=6 \
  --warmup_steps 500 \
  --output_dir distilbart_xsum_sft_12_3 --gpus 1
```

- Note: The command that produced `sshleifer/distilbart-cnn-12-6` is at [train_distilbart_cnn.sh]()

```
./train_distilbart_cnn.sh
```

- Tip: You can get the same simple distillation logic by using `distillation.py --no_teacher` followed by identical arguments as the ones in `train_distilbart_cnn.sh`. If you are using `wandb` and comparing the two distillation methods, using this entry point will make your logs consistent, because you will have the same hyper-parameters logged in every run.

Pseudo-Labeling

- You don't need `distillation.py`.
- Instructions to generate pseudo-labels and use pre-computed pseudo-labels can be found [here](). Simply run `finetune.py` with one of those pseudo-label datasets as `--data_dir` (`DATA` , below).

```
python finetune.py \
  --teacher facebook/bart-large-xsum --data_dir DATA \
  --freeze_encoder --freeze_embeds \
  --learning_rate=3e-4 \
  --do_train \
  --do_predict \
  --fp16 --fp16_opt_level=O1 \
  --val_check_interval 0.1 --n_val 1000 --eval_beams 2 --length_penalty=0.5 \
  --max_target_length=60 --val_max_target_length=60 --test_max_target_length=100 \
  --model_name_or_path dbart_xsum_12_3 \
  --train_batch_size=32 --eval_batch_size=32 \
  --sortish_sampler \
  --num_train_epochs=5 \
  --warmup_steps 500 \
  --output_dir dbart_xsum_12_3_PL --gpus 1 --logger_name wandb
```

To combine datasets, as in Section 6.2, try something like:

```
curl -S https://cdn-datasets.huggingface.co/pseudo/xsum/bart_xsum_pl.tgz | tar -xvz
-C .
curl -S https://cdn-datasets.huggingface.co/pseudo/xsum/pegasus_xsum.tgz | tar -xvz
-C .
curl -S https://cdn-datasets.huggingface.co/summarization/xsum.tar.gz | tar -xvz -C
.
mkdir all_pl
cat bart_xsum_pl/train.source pegasus_xsum/train.source xsum/train.source >
all_pl/train.source
cat bart_xsum_pl/train.target pegasus_xsum/train.target xsum/train.target >
all_pl/train.target
cp xsum/val* all_pl
cp xsum/test* all_pl
```

then use `all_pl` as DATA in the command above.

Direct Knowledge Distillation (KD)

- In this method, we use try to enforce that the student and teacher produce similar encoder_outputs, logits, and hidden_states using `SummarizationDistiller`.

- This method was used for `sshleifer/distilbart-xsum-12-6`, `6-6`, and `9-6` checkpoints were produced.
- You must use `distillation.py`. Note that this command initializes the student for you.

The command that produced `sshleifer/distilbart-xsum-12-6` is at ./train_distilbart_xsum.sh

```
./train_distilbart_xsum.sh --logger_name wandb --gpus 1
```

- Expected ROUGE-2 between 21.3 and 21.6, run time ~13H.
- direct KD + Pegasus is VERY slow and works best with `--supervise_forward --normalize_hidden`.

Citation

```
@misc{shleifer2020pretrained,
      title={Pre-trained Summarization Distillation},
      author={Sam Shleifer and Alexander M. Rush},
      year={2020},
      eprint={2010.13002},
      archivePrefix={arXiv},
      primaryClass={cs.CL}
}
@article{Wolf2019HuggingFacesTS,
  title={HuggingFace's Transformers: State-of-the-art Natural Language Processing},
  author={Thomas Wolf and Lysandre Debut and Victor Sanh and Julien Chaumond and
Clement Delangue and Anthony Moi and Pierric Cistac and Tim Rault and Rémi Louf and
Morgan Funtowicz and Joe Davison and Sam Shleifer and Patrick von Platen and Clara
Ma and Yacine Jernite and Julien Plu and Canwen Xu and Teven Le Scao and Sylvain
Gugger and Mariama Drame and Quentin Lhoest and Alexander M. Rush},
  journal={ArXiv},
  year={2019},
  volume={abs/1910.03771}
}
```