OpenCLIP

[Paper] [Citations] [Clip Colab] [Coca Colab] pypi v3.1.0

Welcome to an open source implementation of OpenAI's CLIP (Contrastive Language-Image Pre-training).

Using this codebase, we have trained several models on a variety of data sources and compute budgets, ranging from small-scale experiments to larger runs including models trained on datasets such as LAION-400M, LAION-2B and DataComp-1B. Many of our models and their scaling properties are studied in detail in the paper reproducible scaling laws for contrastive language-image learning. Some of the best models we've trained and their zero-shot ImageNet-1k accuracy are shown below, along with the ViT-L model trained by OpenAI and other state-of-the-art open source alternatives (all can be loaded via OpenCLIP). We provide more details about our full collection of pretrained models here, and zero-shot results for 38 datasets here.

Model	Training data	Resolution	# of samples seen	ImageNet zero-shot acc.
ConvNext-Base	LAION-2B	256px	13B	71.5%
ConvNext-Large	LAION-2B	320px	29B	76.9%
ConvNext-XXLarge	LAION-2B	256px	34B	79.5%
ViT-B-32-256	DataComp-1B	256px	34B	72.8%
ViT-B-16	DataComp-1B	224px	13B	73.5%
ViT-L-14	LAION-2B	224px	32B	75.3%
ViT-H-14	LAION-2B	224px	32B	78.0%
ViT-L-14	DataComp-1B	224px	13B	79.2%
ViT-bigG-14	LAION-2B	224px	34B	80.1%
ViT-L-14-quickgelu (Original CLIP)	WIT	224px	13B	75.5%
ViT-SO400M-14-SigLIP (SigLIP)	WebLI	224px	45B	82.0%
ViT-L-14 (DFN)	DFN-2B	224px	39B	82.2%
ViT-L-16-256 (SigLIP2)	WebLI (multi-lang)	256px	40B	82.5%
ViT-SO400M-14-SigLIP-384 (SigLIP)	WebLI	384px	45B	83.1%
ViT-H-14-quickgelu (DFN)	DFN-5B	224px	39B	83.4%
PE-Core-L-14-336 (PE)	MetaCLIP-5.4B	336px	58B	83.5%
ViT-SO400M-16-SigLIP2-384 (SigLIP2)	WebLI (multi-lang)	384px	40B	84.1%
ViT-H-14-378-quickgelu (DFN)	DFN-5B	378px	44B	84.4%
ViT-gopt-16-SigLIP2-384 (SigLIP2)	WebLI (multi-lang)	384px	40B	85.0%

Model	Training data	Resolution	# of samples seen	ImageNet zero-shot acc.
PE-Core-bigG-14-448 (PE)	MetaCLIP-5.4B	448px	86B	85.4%

Model cards with additional model specific details can be found on the Hugging Face Hub under the OpenCLIP library tag: https://huggingface.co/models?library=open_clip.

If you found this repository useful, please consider citing. We welcome anyone to submit an issue or send an email if you have any other requests or suggestions.

Note that portions of `src/open_clip/` modelling and tokenizer code are adaptations of OpenAI's official repository.

Approach

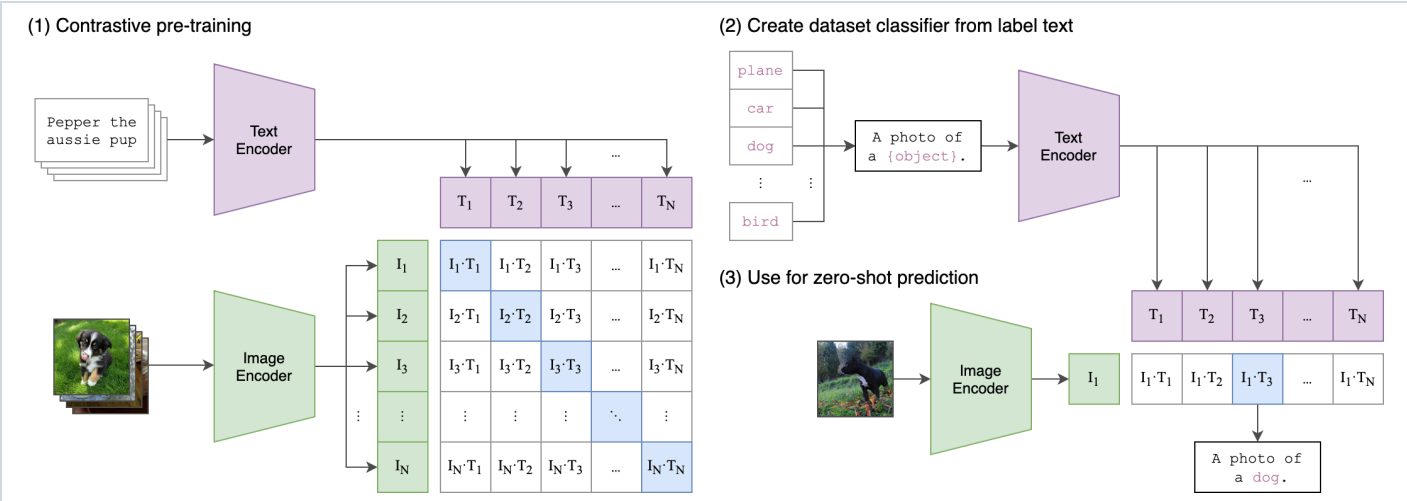


Image Credit: https://github.com/openai/CLIP

Usage

```
pip install open_clip_torch
```

```
import torch
from PIL import Image
import open_clip

model, _, preprocess = open_clip.create_model_and_transforms('ViT-B-32', pretrained='laion2b_s34b
model.eval()  # model in train mode by default, impacts some models with BatchNorm or stochastic
tokenizer = open_clip.get_tokenizer('ViT-B-32')

image = preprocess(Image.open("docs/CLIP.png")).unsqueeze(0)
text = tokenizer(["a diagram", "a dog", "a cat"])

with torch.no_grad(), torch.autocast("cuda"):
    image_features = model.encode_image(image)
    text_features = model.encode_text(text)
    image_features /= image_features.norm(dim=-1, keepdim=True)
    text_features /= text_features.norm(dim=-1, keepdim=True)
```

```
    text_probs = (100.0 * image_features @ text_features.T).softmax(dim=-1)

print("Label probs:", text_probs)  # prints: [[1., 0., 0.]]
```

If model uses `timm` image encoders (convnext, siglip, eva, etc) ensure the latest timm is installed. Upgrade `timm` if you see 'Unknown model' errors for the image encoder.

If model uses transformers tokenizers, ensure `transformers` is installed.

See also this [Clip Colab].

To compute billions of embeddings efficiently, you can use clip-retrieval which has openclip support.

Pretrained models

We offer a simple model interface to instantiate both pre-trained and untrained models. To see which pretrained models are available, use the following code snippet. More details about our pretrained models are available here.

```
>>> import open_clip
>>> open_clip.list_pretrained()
```

You can find more about the models we support (e.g. number of parameters, FLOPs) in this table.

NOTE: Many existing checkpoints use the QuickGELU activation from the original OpenAI models. This activation is actually less efficient than native torch.nn.GELU in recent versions of PyTorch. The model defaults are now nn.GELU, so one should use model definitions with `-quickgelu` postfix for the OpenCLIP pretrained weights. All OpenAI pretrained weights will always default to QuickGELU. One can also use the non `-quickgelu` model definitions with pretrained weights using QuickGELU but there will be an accuracy drop, for fine-tune that will likely vanish for longer runs. Future trained models will use nn.GELU.

Loading models

Models can be loaded with `open_clip.create_model_and_transforms`, as shown in the example below. The model name and corresponding `pretrained` keys are compatible with the outputs of `open_clip.list_pretrained()`.

The `pretrained` argument also accepts local paths, for example `/path/to/my/b32.pt`. You can also load checkpoints from huggingface this way. To do so, download the `open_clip_pytorch_model.bin` file (for example, https://huggingface.co/laion/CLIP-ViT-L-14-DataComp.XL-s13B-b90K/tree/main), and use `pretrained=/path/to/open_clip_pytorch_model.bin`.

```
# pretrained also accepts local paths
model, _, preprocess = open_clip.create_model_and_transforms('ViT-B-32', pretrained='laion2b_s34b
```

Fine-tuning on classification tasks

This repository is focused on training CLIP models. To fine-tune a *trained* zero-shot model on a downstream classification task such as ImageNet, please see our other repository: WiSE-FT. The WiSE-FT repository contains code for our paper on Robust Fine-tuning of Zero-shot Models, in which we introduce a technique for fine-tuning zero-shot models while preserving robustness under distribution shift.

Data

To download datasets as webdataset, we recommend img2dataset.

Conceptual Captions

See cc3m img2dataset example.

YFCC and other datasets

In addition to specifying the training data via CSV files as mentioned above, our codebase also supports webdataset, which is recommended for larger scale datasets. The expected format is a series of `.tar` files. Each of these `.tar` files should contain two files for each training example, one for the image and one for the corresponding text. Both files should have the same name but different extensions. For instance, `shard_001.tar` could contain files such as `abc.jpg` and `abc.txt`. You can learn more about `webdataset` at https://github.com/webdataset/webdataset. We use `.tar` files with 1,000 data points each, which we create using tarp.

You can download the YFCC dataset from Multimedia Commons. Similar to OpenAI, we used a subset of YFCC to reach the aforementioned accuracy numbers. The indices of images in this subset are in OpenAI's CLIP repository.

Training CLIP

Install

We advise you first create a virtual environment with:

```
python3 -m venv .env
source .env/bin/activate
pip install -U pip
```

You can then install openclip for training with `pip install 'open_clip_torch[training]'`.

Development

If you want to make changes to contribute code, you can clone openclip then run `make install` in openclip folder (after creating a virtualenv)

Install pip PyTorch as per https://pytorch.org/get-started/locally/

You may run `make install-training` to install training deps

Testing

Test can be run with `make install-test` then `make test`

`python -m pytest -x -s -v tests -k "training"` to run a specific test

Running regression tests against a specific git revision or tag:

1. Generate testing data

```
python tests/util_test.py --model RN50 RN101 --save_model_list models.txt --git_revision 9d3
```

***WARNING*: This will invoke git and modify your working tree, but will reset it to the current state after data has been generated!**
Don't modify your working tree while test data is being generated this way.

2. Run regression tests

```
OPEN_CLIP_TEST_REG_MODELS=models.txt python -m pytest -x -s -v -m regression_test
```

Sample single-process running code:

```
python -m open_clip_train.main \
    --save-frequency 1 \
    --zeroshot-frequency 1 \
    --report-to tensorboard \
    --train-data="/path/to/train_data.csv"  \
    --val-data="/path/to/validation_data.csv"  \
    --csv-img-key filepath \
    --csv-caption-key title \
    --imagenet-val=/path/to/imagenet/root/val/ \
    --warmup 10000 \
    --batch-size=128 \
    --lr=1e-3 \
    --wd=0.1 \
    --epochs=30 \
    --workers=8 \
    --model RN50
```

Note: `imagenet-val` is the path to the *validation* set of ImageNet for zero-shot evaluation, not the training set! You can remove this argument if you do not want to perform zero-shot evaluation on ImageNet throughout training. Note that the `val` folder should contain subfolders. If it does not, please use this script.

Multi-GPU and Beyond

This code has been battle tested up to 1024 A100s and offers a variety of solutions for distributed training. We include native support for SLURM clusters.

As the number of devices used to train increases, so does the space complexity of the the logit matrix. Using a naïve all-gather scheme, space complexity will be `O(n^2)` . Instead, complexity may become effectively linear if the flags `--gather-with-grad` and `--local-loss` are used. This alteration results in one-to-one numerical results as the naïve method.

Epochs

For larger datasets (eg Laion2B), we recommend setting `--train-num-samples` to a lower value than the full epoch, for example `--train-num-samples 135646078` to 1/16 of an epoch in conjunction with `--dataset-resampled` to do sampling with replacement. This allows having frequent checkpoints to evaluate more often.

Patch Dropout

Recent research has shown that one can dropout half to three-quarters of the visual tokens, leading to up to 2-3x training speeds without loss of accuracy.

You can set this on your visual transformer config with the key `patch_dropout`.

In the paper, they also finetuned without the patch dropout at the end. You can do this with the command-line argument `--force-patch-dropout 0.`

Multiple data sources

OpenCLIP supports using multiple data sources, by separating different data paths with `::`. For instance, to train on CC12M and on LAION, one might use `--train-data "/data/cc12m/cc12m-train-{0000..2175}.tar::/data/LAION-400M/{00000..41455}.tar"`. Using `--dataset-resampled` is recommended for these cases.

By default, on expectation the amount of times the model will see a sample from each source is proportional to the size of the source. For instance, when training on one data source with size 400M and one with size 10M, samples from the first source are 40x more likely to be seen in expectation.

We also support different weighting of the data sources, by using the `--train-data-upsampling-factors` flag. For instance, using `--train-data-upsampling-factors=1::1` in the above scenario is equivalent to not using the flag, and `--train-data-upsampling-factors=1::2` is equivalent to upsampling the second data source twice. If you want to sample from data sources with the same frequency, the upsampling factors should be inversely proportional to the sizes of the data sources. For instance, if dataset `A` has 1000 samples and dataset `B` has 100 samples, you can use `--train-data-upsampling-factors=0.001::0.01` (or analogously, `--train-data-upsampling-factors=1::10`).

Single-Node

We make use of `torchrun` to launch distributed jobs. The following launches a a job on a node of 4 GPUs:

```
cd open_clip/src
torchrun --nproc_per_node 4 -m open_clip_train.main \
    --train-data '/data/cc12m/cc12m-train-{0000..2175}.tar' \
    --train-num-samples 10968539 \
    --dataset-type webdataset \
    --batch-size 320 \
    --precision amp \
    --workers 4 \
    --imagenet-val /data/imagenet/validation/
```

Multi-Node

The same script above works, so long as users include information about the number of nodes and host node.

```
cd open_clip/src
torchrun --nproc_per_node=4 \
    --rdzv_endpoint=$HOSTE_NODE_ADDR \
    -m open_clip_train.main \
    --train-data '/data/cc12m/cc12m-train-{0000..2175}.tar' \
    --train-num-samples 10968539 \
    --dataset-type webdataset \
    --batch-size 320 \
    --precision amp \
```

```
    --workers 4 \
    --imagenet-val /data/imagenet/validation/
```

SLURM

This is likely the easiest solution to utilize. The following script was used to train our largest models:

```
#!/bin/bash -x
#SBATCH --nodes=32
#SBATCH --gres=gpu:4
#SBATCH --ntasks-per-node=4
#SBATCH --cpus-per-task=6
#SBATCH --wait-all-nodes=1
#SBATCH --job-name=open_clip
#SBATCH --account=ACCOUNT_NAME
#SBATCH --partition PARTITION_NAME

eval "$(/path/to/conda/bin/conda shell.bash hook)" # init conda
conda activate open_clip
export CUDA_VISIBLE_DEVICES=0,1,2,3
export MASTER_PORT=12802

master_addr=$(scontrol show hostnames "$SLURM_JOB_NODELIST" | head -n 1)
export MASTER_ADDR=$master_addr

cd /shared/open_clip
export PYTHONPATH="$PYTHONPATH:$PWD/src"
srun --cpu_bind=v --accel-bind=gn python -u src/open_clip_train/main.py \
    --save-frequency 1 \
    --report-to tensorboard \
    --train-data="/data/LAION-400M/{00000..41455}.tar" \
    --warmup 2000 \
    --batch-size=256 \
    --epochs=32 \
    --workers=8 \
    --model ViT-B-32 \
    --name "ViT-B-32-Vanilla" \
    --seed 0 \
    --local-loss \
    --gather-with-grad
```

Resuming from a checkpoint:

```
python -m open_clip_train.main \
    --train-data="/path/to/train_data.csv" \
    --val-data="/path/to/validation_data.csv"  \
    --resume /path/to/checkpoints/epoch_K.pt
```

Training CoCa:

Training CoCa models is enabled through specifying a CoCa config using the `--model` parameter of the training script. Currently available configs are "coca_base", "coca_ViT-B-32", and "coca_roberta-ViT-B-32" (which uses RoBERTa as the text encoder). CoCa configs are different from CLIP configs because they have an additional "multimodal_cfg" component which specifies parameters for the multimodal text decoder. Here's an example from the coca_ViT-B-32 config:

```
"multimodal_cfg": {
    "context_length": 76,
    "vocab_size": 49408,
    "width": 512,
    "heads": 8,
    "layers": 12,
    "latent_dim": 512,
    "attn_pooler_heads": 8
}
```

Credit to lucidrains for initial code, gpucce for adapting the code to open_clip, and iejMac for training the models.

Generating text with CoCa

```
import open_clip
import torch
from PIL import Image

model, _, transform = open_clip.create_model_and_transforms(
  model_name="coca_ViT-L-14",
  pretrained="mscoco_finetuned_laion2B-s13B-b90k"
)

im = Image.open("cat.jpg").convert("RGB")
im = transform(im).unsqueeze(0)

with torch.no_grad(), torch.cuda.amp.autocast():
  generated = model.generate(im)

print(open_clip.decode(generated[0]).split("<end_of_text>")[0].replace("<start_of_text>", ""))
```

See also this [Coca Colab]

Fine Tuning CoCa

To fine-tune coca on mscoco, first create the dataset, one way is using a csvdataset and perhaps the simplest way to do it is using CLIP_benchmark which in turn uses pycocotools (that can be used also by itself).

```
from clip_benchmark.datasets.builder import build_dataset
import pandas as pd
import os

root_path = "path/to/data/dir" # set this to smth meaningful
ds = build_dataset("mscoco_captions", root=root_path, split="train", task="captioning") # this dc
coco = ds.coco
imgs = coco.loadImgs(coco.getImgIds())
future_df = {"filepath":[], "title":[]}
```

```
for img in imgs:
    caps = coco.imgToAnns[img["id"]]
    for cap in caps:
        future_df["filepath"].append(img["file_name"])
        future_df["title"].append(cap["caption"])
pd.DataFrame.from_dict(future_df).to_csv(
  os.path.join(root_path, "train2014.csv"), index=False, sep="\t"
)
```

This should create a csv dataset that one can use to fine-tune coca with open_clip

```
python -m open_clip_train.main \
    --dataset-type "csv" \
    --train-data "path/to/data/dir/train2014.csv" \
    --warmup 1000 \
    --batch-size 128 \
    --lr 1e-5 \
    --wd 0.1 \
    --epochs 1 \
    --workers 3 \
    --model "coca_ViT-L-14" \
    --report-to "wandb" \
    --coca-contrastive-loss-weight 0 \
    --coca-caption-loss-weight 1 \
    --log-every-n-steps 100
```

This is a general setting, open_clip has very parameters that can be set, `python -m open_clip_train.main --help` should show them. The only relevant change compared to pre-training are the two arguments

```
--coca-contrastive-loss-weight 0
--coca-caption-loss-weight 1
```

which make the model only train the generative side.

Training with pre-trained language models as text encoder:

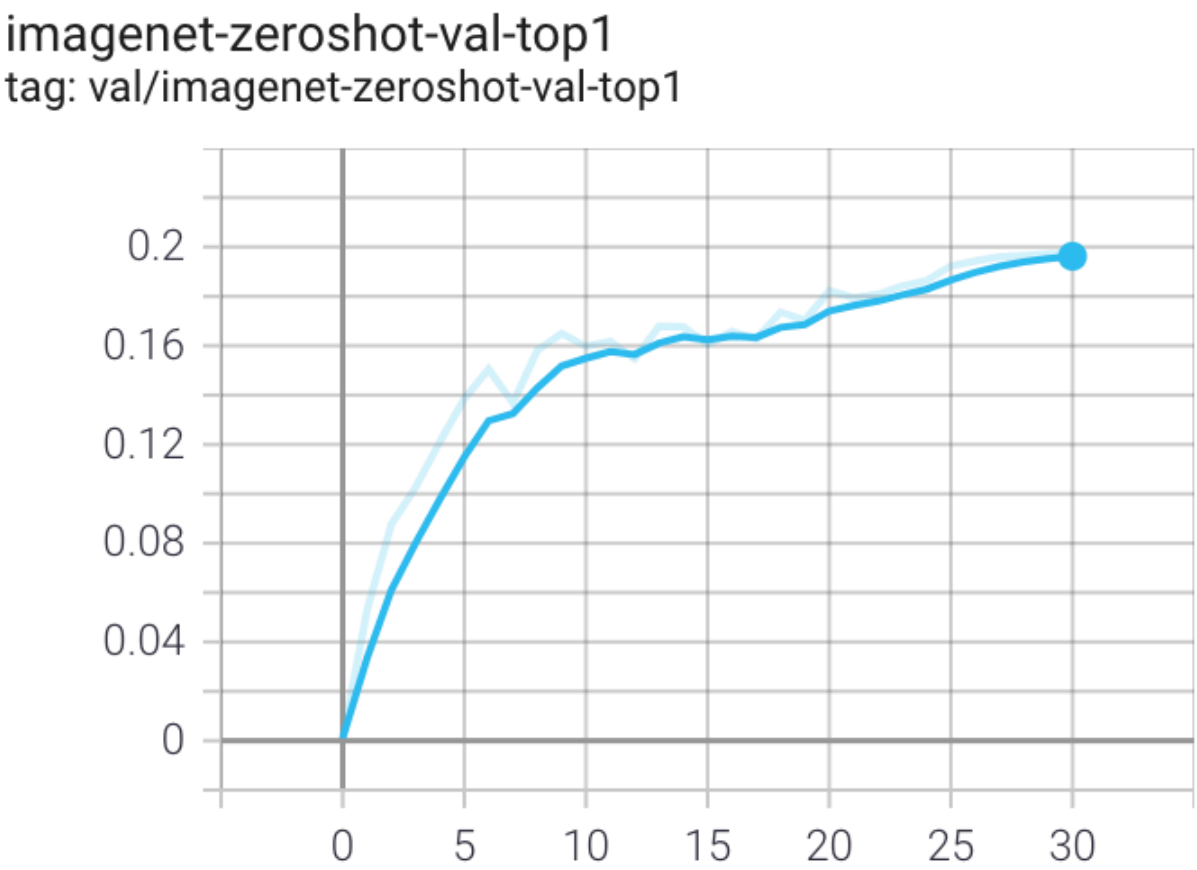
If you wish to use different language models as the text encoder for CLIP you can do so by using one of the Hugging Face model configs in `src/open_clip/model_configs` and passing in it's tokenizer as the `--model` and `--hf-tokenizer-name` parameters respectively. Currently we only support RoBERTa ("test-roberta" config), however adding new models should be trivial. You can also determine how many layers, from the end, to leave unfrozen with the `--lock-text-unlocked-layers` parameter. Here's an example command to train CLIP with the RoBERTa LM that has it's last 10 layers unfrozen:

```
python -m open_clip_train.main \
         --train-data="pipe:aws s3 cp s3://s-mas/cc3m/{00000..00329}.tar -" \
         --train-num-samples 3000000 \
         --val-data="pipe:aws s3 cp s3://s-mas/cc3m/{00330..00331}.tar -" \
         --val-num-samples 10000 \
         --dataset-type webdataset \
         --batch-size 256 \
         --warmup 2000 \
         --epochs 10 \
```

```
    --lr 5e-4 \
    --precision amp \
    --workers 6 \
    --model "roberta-ViT-B-32" \
    --lock-text \
    --lock-text-unlocked-layers 10 \
    --name "10_unfrozen" \
    --report-to "tensorboard" \
```

Loss Curves

When run on a machine with 8 GPUs the command should produce the following training curve for Conceptual Captions:



More detailed curves for Conceptual Captions are given at /docs/clip_conceptual_captions.md.

When training a RN50 on YFCC the same hyperparameters as above are used, with the exception of `lr=5e-4` and `epochs=32`.

Note that to use another model, like `ViT-B/32` or `RN50x4` or `RN50x16` or `ViT-B/16`, specify with `--model RN50x4`.

Logging

For tensorboard logging, run:

```
tensorboard --logdir=logs/tensorboard/ --port=7777
```

For wandb logging, we recommend looking at the `step` variable instead of `Step`, since the later was not properly set in earlier versions of this codebase. For older runs with models trained before #613, the `Step` variable should be ignored. For newer runs, after that PR, the two variables are the same.

Evaluation / Zero-Shot

We recommend https://github.com/LAION-AI/CLIP_benchmark#how-to-use for systematic evaluation on 40 datasets.

Evaluating local checkpoint:

```
python -m open_clip_train.main \
    --val-data="/path/to/validation_data.csv"  \
    --model RN101 \
    --pretrained /path/to/checkpoints/epoch_K.pt
```

Evaluating hosted pretrained checkpoint on ImageNet zero-shot prediction:

```
python -m open_clip_train.main \
    --imagenet-val /path/to/imagenet/validation \
    --model ViT-B-32-quickgelu \
    --pretrained laion400m_e32
```

Model distillation

You can distill from a pre-trained by using `--distill-model` and `--distill-pretrained` to specify the model you'd like to distill from. For instance, to distill from OpenAI ViT-L/14 use `--distill-model ViT-L-14 --distill-pretrained openai`.

Gradient accumulation

To simulate larger batches use `--accum-freq k`. If per gpu batch size, `--batch-size`, is `m`, then the effective batch size will be `k * m * num_gpus`.

When increasing `--accum-freq` from its default of 1, samples/s will remain approximately constant (batch size will double, as will time-per-batch). It is recommended to use other features to reduce batch size such as `--grad-checkpointing --local-loss --gather-with-grad` before increasing `--accum-freq`. `--accum-freq` can be used in addition to these features.

Instead of 1 forward pass per example, there are now 2 forward passes per-example. However, the first is done with `torch.no_grad`.

There is some additional GPU memory required --- the features and data from all `m` batches are stored in memory.

There are also `m` loss computations instead of the usual 1.

For more information see Cui et al. (https://arxiv.org/abs/2112.09331) or Pham et al. (https://arxiv.org/abs/2111.10050).

Int8 Support

We have beta support for int8 training and inference. You can enable int8 training with `--use-bnb-linear SwitchBackLinearGlobal` or `--use-bnb-linear SwitchBackLinearGlobalMemEfficient`. Please see the bitsandbytes library for definitions for these layers. For CLIP VIT-Huge this should currently correspond to a 10% training speedup with no accuracy loss. More speedups comin when the attention layer is refactored so that linear layers man be replaced there, too.

See the tutorial https://github.com/mlfoundations/open_clip/blob/main/tutorials/int8_tutorial.ipynb or paper.

Support for remote loading/training

It is always possible to resume directly from a remote file, e.g., a file in an s3 bucket. Just set `--resume s3://<path-to-checkpoint>`. This will work with any filesystem supported by `fsspec`.

It is also possible to train `open_clip` models while continuously backing up to s3. This can help to avoid slow local file systems.

Say that your node has a local ssd `/scratch`, an s3 bucket `s3://<path-to-bucket>`.

In that case, set `--logs /scratch` and `--remote-sync s3://<path-to-bucket>`. Then, a background process will sync `/scratch/<run-name>` to `s3://<path-to-bucket>/<run-name>`. After syncing, the background process will sleep for `--remote-sync-frequency` seconds, which defaults to 5 minutes.

There is also experimental support for syncing to other remote file systems, not just s3. To do so, specify `--remote-sync-protocol fsspec`. However, this is currently very slow and not recommended.

Also, to optionally avoid saving too many checkpoints locally when using these features, you can use `--delete-previous-checkpoint` which deletes the previous checkpoint after saving a new one.

Note: if you are using this feature with `--resume latest`, there are a few warnings. First, use with `--save-most-recent` is not supported. Second, only `s3` is supported. Finally, since the sync happens in the background, it is possible that the most recent checkpoint may not be finished syncing to the remote.

Pushing Models to Hugging Face Hub

The module `open_clip.push_to_hf_hub` includes helpers for pushing models /w weights and config to the HF Hub.

The tool can be run from command line, ex: `python -m open_clip.push_to_hf_hub --model convnext_large_d_320 --pretrained /train/checkpoints/epoch_12.pt --repo-id laion/CLIP-convnext_large_d_320.laion2B-s29B-b131K-ft`

Acknowledgments

We gratefully acknowledge the Gauss Centre for Supercomputing e.V. (www.gauss-centre.eu) for funding this part of work by providing computing time through the John von Neumann Institute for Computing (NIC) on the GCS Supercomputer JUWELS Booster at Jülich Supercomputing Centre (JSC).

The Team

Current development of this repository is led by Ross Wightman, Romain Beaumont, Cade Gordon, and Vaishaal Shankar.

The original version of this repository is from a group of researchers at UW, Google, Stanford, Amazon, Columbia, and Berkeley.

Gabriel Ilharco*, Mitchell Wortsman*, Nicholas Carlini, Rohan Taori, Achal Dave, Vaishaal Shankar, John Miller, Hongseok Namkoong, Hannaneh Hajishirzi, Ali Farhadi, Ludwig Schmidt

Special thanks to Jong Wook Kim and Alec Radford for help with reproducing CLIP!

Citing

If you found this repository useful, please consider citing:

```bibtex
@software{ilharco_gabriel_2021_5143773,
  author       = {Ilharco, Gabriel and
                  Wortsman, Mitchell and
                  Wightman, Ross and
                  Gordon, Cade and
                  Carlini, Nicholas and
                  Taori, Rohan and
                  Dave, Achal and
                  Shankar, Vaishaal and
                  Namkoong, Hongseok and
                  Miller, John and
                  Hajishirzi, Hannaneh and
                  Farhadi, Ali and
                  Schmidt, Ludwig},
  title        = {OpenCLIP},
  month        = jul,
  year         = 2021,
  note         = {If you use this software, please cite it as below.},
  publisher    = {Zenodo},
  version      = {0.1},
  doi          = {10.5281/zenodo.5143773},
  url          = {https://doi.org/10.5281/zenodo.5143773}
}
```

```bibtex
@inproceedings{cherti2023reproducible,
  title={Reproducible scaling laws for contrastive language-image learning},
  author={Cherti, Mehdi and Beaumont, Romain and Wightman, Ross and Wortsman, Mitchell and Ilharc
  booktitle={Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition},
  pages={2818--2829},
  year={2023}
}
```

```bibtex
@inproceedings{Radford2021LearningTV,
  title={Learning Transferable Visual Models From Natural Language Supervision},
  author={Alec Radford and Jong Wook Kim and Chris Hallacy and A. Ramesh and Gabriel Goh and Sanc
  booktitle={ICML},
  year={2021}
}
```

```bibtex
@inproceedings{schuhmann2022laionb,
  title={{LAION}-5B: An open large-scale dataset for training next generation image-text models},
  author={Christoph Schuhmann and
```

```
            Romain Beaumont and
            Richard Vencu and
            Cade W Gordon and
            Ross Wightman and
            Mehdi Cherti and
            Theo Coombes and
            Aarush Katta and
            Clayton Mullis and
            Mitchell Wortsman and
            Patrick Schramowski and
            Srivatsa R Kundurthy and
            Katherine Crowson and
            Ludwig Schmidt and
            Robert Kaczmarczyk and
            Jenia Jitsev},
  booktitle={Thirty-sixth Conference on Neural Information Processing Systems Datasets and Benchm
  year={2022},
  url={https://openreview.net/forum?id=M3Y74vmsMcY}
}
```

DOI 10.5281/zenodo.16754312