Lightning-Bolts Documentation

Release 0.3.2

PyTorchLightning et al.

Mar 29, 2021

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CHAPTER

ONE

INSTALLATION

You can install using pip

```
pip install lightning-bolts
```

Install bleeding-edge (no guarantees)

```
pip install git+https://github.com/PytorchLightning/lightning-bolts.git@master --
↪upgrade
```

In case you want to have full experience you can install all optional packages at once

```
pip install lightning-bolts["extra"]
```

CHAPTER

TWO

INTRODUCTION GUIDE

Welcome to PyTorch Lightning Bolts!

Bolts is a Deep learning research and production toolbox of:

- SOTA pretrained models.
- Model components.
- Callbacks.
- Losses.
- Datasets.

The Main goal of Bolts is to enable trying new ideas as fast as possible!

All models are tested (daily), benchmarked, documented and work on CPUs, TPUs, GPUs and 16-bit precision.

some examples!

```
from pl_bolts.models import VAE
from pl_bolts.models.vision import GPT2, ImageGPT, PixelCNN
from pl_bolts.models.self_supervised import AMDIM, CPC_v2, SimCLR, Moco_v2
from pl_bolts.models import LinearRegression, LogisticRegression
from pl_bolts.models.gans import GAN
from pl_bolts.callbacks import PrintTableMetricsCallback
from pl_bolts.datamodules import FashionMNISTDataModule, CIFAR10DataModule,␣
↪ImagenetDataModule
```

Bolts are built for rapid idea iteration - subclass, override and train!

```
from pl_bolts.models.vision import ImageGPT
from pl_bolts.models.self_supervised import SimCLR

class VideoGPT(ImageGPT):

    def training_step(self, batch, batch_idx):
        x, y = batch
        x = _shape_input(x)

        logits = self.gpt(x)
        simclr_features = self.simclr(x)

        # -----------------
        # do something new with GPT logits + simclr_features
        # -----------------
```

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```
        loss = self.criterion(logits.view(-1, logits.size(-1)), x.view(-1).long())

        logs = {"loss": loss}
        return {"loss": loss, "log": logs}
```

Mix and match data, modules and components as you please!

```
model = GAN(datamodule=ImagenetDataModule(PATH))
model = GAN(datamodule=FashionMNISTDataModule(PATH))
model = ImageGPT(datamodule=FashionMNISTDataModule(PATH))
```

And train on any hardware accelerator

```
import pytorch_lightning as pl

model = ImageGPT(datamodule=FashionMNISTDataModule(PATH))

# cpus
pl.Trainer.fit(model)

# gpus
pl.Trainer(gpus=8).fit(model)

# tpus
pl.Trainer(tpu_cores=8).fit(model)
```

Or pass in any dataset of your choice

```
model = ImageGPT()
Trainer().fit(
    model,
    train_dataloader=DataLoader(...),
    val_dataloader=DataLoader(...)
)
```

2.1 Community Built

Then lightning community builds bolts and contributes them to Bolts. The lightning team guarantees that contributions are:

1. Rigorously tested (CPUs, GPUs, TPUs).
2. Rigorously documented.
3. Standardized via PyTorch Lightning.
4. Optimized for speed.
5. Checked for correctness.

2.1.1 How to contribute

We accept contributions directly to Bolts or via your own repository.

Note: We encourage you to have your own repository so we can link to it via our docs!

To contribute:

1. Submit a pull request to Bolts (we will help you finish it!).
2. We'll help you add tests.
3. We'll help you refactor models to work on (GPU, TPU, CPU)..
4. We'll help you remove bottlenecks in your model.
5. We'll help you write up documentation.
6. We'll help you pretrain expensive models and host weights for you.
7. We'll create proper attribution for you and link to your repo.
8. Once all of this is ready, we will merge into bolts.

After your model or other contribution is in bolts, our team will make sure it maintains compatibility with the other components of the library!

2.1.2 Contribution ideas

Don't have something to contribute? Ping us on Slack or look at our Github issues!

We'll help and guide you through the implementation / conversion

---

2.2 When to use Bolts

2.2.1 For pretrained models

Most bolts have pretrained weights trained on various datasets or algorithms. This is useful when you don't have enough data, time or money to do your own training.

For example, you could use a pretrained VAE to generate features for an image dataset.

```
from pl_bolts.models.autoencoders import VAE
from pl_bolts.models.self_supervised import CPC_v2

model1 = VAE(input_height=32, pretrained='imagenet2012')
encoder = model1.encoder
encoder.eval()

# bolts are pretrained on different datasets
model2 = CPC_v2(encoder='resnet18', pretrained='imagenet128').freeze()
model3 = CPC_v2(encoder='resnet18', pretrained='stl10').freeze()
```

```
for (x, y) in own_data:
    features = encoder(x)
    feat2 = model2(x)
    feat3 = model3(x)

# which is better?
```

2.2.2 To finetune on your data

If you have your own data, finetuning can often increase the performance. Since this is pure PyTorch you can use any finetuning protocol you prefer.

Example 1: Unfrozen finetune

```
# unfrozen finetune
model = CPC_v2(encoder='resnet18', pretrained='imagenet128')
resnet18 = model.encoder
# don't call .freeze()

classifier = LogisticRegression(...)

for (x, y) in own_data:
    feats = resnet18(x)
    y_hat = classifier(feats)
```

Example 2: Freeze then unfreeze

```
# FREEZE!
model = CPC_v2(encoder='resnet18', pretrained='imagenet128')
resnet18 = model.encoder
resnet18.eval()

classifier = LogisticRegression(...)

for epoch in epochs:
    for (x, y) in own_data:
        feats = resnet18(x)
        y_hat = classifier(feats)
        loss = cross_entropy_with_logits(y_hat, y)

    # UNFREEZE after 10 epochs
    if epoch == 10:
        resnet18.unfreeze()
```

2.2.3 For research

Here is where bolts is very different than other libraries with models. It's not just designed for production, but each module is written to be easily extended for research.

```
from pl_bolts.models.vision import ImageGPT
from pl_bolts.models.self_supervised import SimCLR

class VideoGPT(ImageGPT):

```

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```
    def training_step(self, batch, batch_idx):
        x, y = batch
        x = _shape_input(x)

        logits = self.gpt(x)
        simclr_features = self.simclr(x)

        # -----------------
        # do something new with GPT logits + simclr_features
        # -----------------

        loss = self.criterion(logits.view(-1, logits.size(-1)), x.view(-1).long())

        logs = {"loss": loss}
        return {"loss": loss, "log": logs}
```

Or perhaps your research is in self_supervised_learning and you want to do a new SimCLR. In this case, the only thing you want to change is the loss.

By subclassing you can focus on changing a single piece of a system without worrying that the other parts work (because if they are in Bolts, then they do and we've tested it).

```
# subclass SimCLR and change ONLY what you want to try
class ComplexCLR(SimCLR):

    def init_loss(self):
        return self.new_xent_loss

    def new_xent_loss(self):
        out = torch.cat([out_1, out_2], dim=0) n_samples = len(out)

        # Full similarity matrix
        cov = torch.mm(out, out.t().contiguous())
        sim = torch.exp(cov / temperature)

        # Negative similarity
        mask = ~torch.eye(n_samples, device=sim.device).bool()
        neg = sim.masked_select(mask).view(n_samples, -1).sum(dim=-1)

        # ------------------
        # some new thing we want to do
        # ------------------

        # Positive similarity :
        pos = torch.exp(torch.sum(out_1 * out_2, dim=-1) / temperature)
        pos = torch.cat([pos, pos], dim=0)
        loss = -torch.log(pos / neg).mean()

        return loss
```

2.3 Callbacks

Callbacks are arbitrary programs which can run at any points in time within a training loop in Lightning.

Bolts houses a collection of callbacks that are community contributed and can work in any Lightning Module!

```
from pl_bolts.callbacks import PrintTableMetricsCallback
import pytorch_lightning as pl

trainer = pl.Trainer(callbacks=[PrintTableMetricsCallback()])
```

2.4 DataModules

In PyTorch, working with data has these major elements.

1. Downloading, saving and preparing the dataset.
2. Splitting into train, val and test.
3. For each split, applying different transforms

A DataModule groups together those actions into a single reproducible *DataModule* that can be shared around to guarantee:

1. Consistent data preprocessing (download, splits, etc. . .)
2. The same exact splits
3. The same exact transforms

```
from pl_bolts.datamodules import ImagenetDataModule

dm = ImagenetDataModule(data_dir=PATH)

# standard PyTorch!
train_loader = dm.train_dataloader()
val_loader = dm.val_dataloader()
test_loader = dm.test_dataloader()

Trainer().fit(
    model,
    train_loader,
    val_loader
)
```

But when paired with PyTorch LightningModules (all bolts models), you can plug and play full dataset definitions with the same splits, transforms, etc. . .

```
imagenet = ImagenetDataModule(PATH)
model = VAE(datamodule=imagenet)
model = ImageGPT(datamodule=imagenet)
model = GAN(datamodule=imagenet)
```

We even have prebuilt modules to bridge the gap between Numpy, Sklearn and PyTorch

```
from sklearn.datasets import load_boston
from pl_bolts.datamodules import SklearnDataModule

X, y = load_boston(return_X_y=True)
datamodule = SklearnDataModule(X, y)

model = LitModel(datamodule)
```

2.5 Regression Heroes

In case your job or research doesn't need a "hammer", we offer implementations of Classic ML models which benefit from lightning's multi-GPU and TPU support.

So, now you can run huge workloads scalably, without needing to do any engineering. For instance, here we can run logistic Regression on Imagenet (each epoch takes about 3 minutes)!

```
from pl_bolts.models.regression import LogisticRegression

imagenet = ImagenetDataModule(PATH)

# 224 x 224 x 3
pixels_per_image = 150528
model = LogisticRegression(input_dim=pixels_per_image, num_classes=1000)
model.prepare_data = imagenet.prepare_data

trainer = Trainer(gpus=2)
trainer.fit(
    model,
    imagenet.train_dataloader(batch_size=256),
    imagenet.val_dataloader(batch_size=256)
)
```

2.5.1 Linear Regression

Here's an example for Linear regression

```
import pytorch_lightning as pl
from pl_bolts.datamodules import SklearnDataModule
from sklearn.datasets import load_boston

# link the numpy dataset to PyTorch
X, y = load_boston(return_X_y=True)
loaders = SklearnDataModule(X, y)

# training runs training batches while validating against a validation set
model = LinearRegression()
trainer = pl.Trainer(num_gpus=8)
trainer.fit(model, train_dataloader=loaders.train_dataloader(), val_
↪dataloaders=loaders.val_dataloader())
```

Once you're done, you can run the test set if needed.

```
trainer.test(test_dataloaders=loaders.test_dataloader())
```

But more importantly, you can scale up to many GPUs, TPUs or even CPUs

```
# 8 GPUs
trainer = pl.Trainer(num_gpus=8)

# 8 TPU cores
trainer = pl.Trainer(tpu_cores=8)

# 32 GPUs
trainer = pl.Trainer(num_gpus=8, num_nodes=4)

# 128 CPUs
trainer = pl.Trainer(num_processes=128)
```

2.5.2 Logistic Regression

Here's an example for logistic regression

```
from sklearn.datasets import load_iris
from pl_bolts.models.regression import LogisticRegression
from pl_bolts.datamodules import SklearnDataModule
import pytorch_lightning as pl

# use any numpy or sklearn dataset
X, y = load_iris(return_X_y=True)
dm = SklearnDataModule(X, y, batch_size=12)

# build model
model = LogisticRegression(input_dim=4, num_classes=3)

# fit
trainer = pl.Trainer(tpu_cores=8, precision=16)
trainer.fit(model, train_dataloader=dm.train_dataloader(), val_dataloaders=dm.val_
↪dataloader())

trainer.test(test_dataloaders=dm.test_dataloader())
```

Any input will be flattened across all dimensions except the first one (batch). This means images, sound, etc… work out of the box.

```
# create dataset
dm = MNISTDataModule(num_workers=0, data_dir=tmpdir)

model = LogisticRegression(input_dim=28 * 28, num_classes=10, learning_rate=0.001)
model.prepare_data = dm.prepare_data
model.train_dataloader = dm.train_dataloader
model.val_dataloader = dm.val_dataloader
model.test_dataloader = dm.test_dataloader

trainer = pl.Trainer(max_epochs=2)
trainer.fit(model)
trainer.test(model)
# {test_acc: 0.92}
```

But more importantly, you can scale up to many GPUs, TPUs or even CPUs

```
# 8 GPUs
trainer = pl.Trainer(num_gpus=8)

# 8 TPUs
trainer = pl.Trainer(tpu_cores=8)

# 32 GPUs
trainer = pl.Trainer(num_gpus=8, num_nodes=4)

# 128 CPUs
trainer = pl.Trainer(num_processes=128)
```

2.6 Regular PyTorch

Everything in bolts also works with regular PyTorch since they are all just nn.Modules!

However, if you train using Lightning you don't have to deal with engineering code :)

2.7 Command line support

Any bolt module can also be trained from the command line

```
cd pl_bolts/models/autoencoders/basic_vae
python basic_vae_pl_module.py
```

Each script accepts Argparse arguments for both the lightning trainer and the model

```
python basic_vae_pl_module.py --latent_dim 32 --batch_size 32 --gpus 4 --max_epochs 12
```

CHAPTER

THREE

MODEL QUALITY CONTROL

For bolts to be added to the library we have a **rigorous** quality control checklist

3.1 Bolts vs my own repo

We hope you keep your own repo still! We want to link to it to let people know. However, by adding your contribution to bolts you get these **additional** benefits!

1. More visibility! (more people all over the world use your code)
2. We test your code on every PR (CPUs, GPUs, TPUs).
3. We host the docs (and test on every PR).
4. We help you build thorough, beautiful documentation.
5. We help you build robust tests.
6. We'll pretrain expensive models for you and host weights.
7. We will improve the speed of your models!
8. Eligible for invited talks to discuss your implementation.
9. Lightning swag + involvement in the broader contributor community :)

Note: You still get to keep your attribution and be recognized for your work!

Note: Bolts is a community library built by incredible people like you!

3.2 Contribution requirements

3.2.1 Benchmarked

Models have known performance results on common baseline datasets.

3.2.2 Device agnostic

Models must work on CPUs, GPUs and TPUs without changing code. We help authors with this.

```
# bad
encoder.to(device)
```

3.2.3 Fast

We inspect models for computational inefficiencies and help authors meet the bar. Granted, sometimes the approaches are slow for mathematical reasons. But anything related to engineering we help overcome.

```
# bad
mtx = ...
for xi in rows:
    for yi in cols
        mxt[xi, yi] = ...

# good
x = x.item().numpy()
x = np.some_fx(x)
x = torch.tensor(x)
```

3.2.4 Tested

Models are tested on every PR (on CPUs, GPUs and soon TPUs).

- Live build
- Tests

3.2.5 Modular

Models are modularized to be extended and reused easily.

```
# GOOD!
class LitVAE(pl.LightningModule):

    def init_prior(self, ...):
        # enable users to override interesting parts of each model

    def init_posterior(self, ...):
        # enable users to override interesting parts of each model

# BAD
class LitVAE(pl.LightningModule):

    def __init__(self):
        self.prior = ...
        self.posterior = ...
```

3.2.6 Attribution

Any models and weights that are contributed are attributed to you as the author(s).

We request that each contribution have:

- The original paper link
- The list of paper authors
- The link to the original paper code (if available)
- The link to your repo
- Your name and your team's name as the implementation authors.
- Your team's affiliation
- Any generated examples, or result plots.
- Hyperparameter configurations for the results.

Thank you for all your amazing contributions!

3.3 The bar seems high

If your model doesn't yet meet this bar, no worries! Please open the PR and our team of core contributors will help you get there!

3.4 Do you have contribution ideas?

Yes! Check the Github issues for requests from the Lightning team and the community! We'll even work with you to finish your implementation! Then we'll help you pretrain it and cover the compute costs when possible.

CHAPTER

FOUR

BUILD A CALLBACK

This module houses a collection of callbacks that can be passed into the trainer

```
from pl_bolts.callbacks import PrintTableMetricsCallback

trainer = pl.Trainer(callbacks=[PrintTableMetricsCallback()])

# loss│train_loss│val_loss│epoch
# ──────────────────────────────────
# 2.2541470527648926│2.2541470527648926│2.2158432006835938│0
```

4.1 What is a Callback

A callback is a self-contained program that can be intertwined into a training pipeline without polluting the main research logic.

4.2 Create a Callback

Creating a callback is simple:

```
from pytorch_lightning.callbacks import Callback

class MyCallback(Callback)
    def on_epoch_end(self, trainer, pl_module):
        # do something
```

Please refer to Callback docs for a full list of the 20+ hooks available.

CHAPTER

FIVE

INFO CALLBACKS

These callbacks give all sorts of useful information during training.

5.1 Print Table Metrics

This callback prints training metrics to a table. It's very bare-bones for speed purposes.

class pl_bolts.callbacks.printing.**PrintTableMetricsCallback**

Bases: pytorch_lightning.callbacks.

Prints a table with the metrics in columns on every epoch end

Example:

```
from pl_bolts.callbacks import PrintTableMetricsCallback

callback = PrintTableMetricsCallback()
```

Pass into trainer like so:

```
trainer = pl.Trainer(callbacks=[callback])
trainer.fit(...)

# ------------------------------
# at the end of every epoch it will print
# ------------------------------

# loss|train_loss|val_loss|epoch
# ——————————————————————————
# 2.2541470527648926|2.2541470527648926|2.2158432006835938|0
```

5.2 Data Monitoring in LightningModule

The data monitoring callbacks allow you to log and inspect the distribution of data that passes through the training step and layers of the model. When used in combination with a supported logger, the `TrainingDataMonitor` creates a histogram for each *batch* input in `training_step()` and sends it to the logger:

```
from pl_bolts.callbacks import TrainingDataMonitor
from pytorch_lightning import Trainer

# log the histograms of input data sent to LightningModule.training_step
monitor = TrainingDataMonitor(log_every_n_steps=25)

model = YourLightningModule()
trainer = Trainer(callbacks=[monitor])
trainer.fit()
```

The second, more advanced `ModuleDataMonitor` callback tracks histograms for the data that passes through the model itself and its submodules, i.e., it tracks all *.forward()* calls and registers the in- and outputs. You can track all or just a selection of submodules:

```
from pl_bolts.callbacks import ModuleDataMonitor
from pytorch_lightning import Trainer

# log the in- and output histograms of LightningModule's `forward`
monitor = ModuleDataMonitor()

# all submodules in LightningModule
monitor = ModuleDataMonitor(submodules=True)

# specific submodules
monitor = ModuleDataMonitor(submodules=["generator", "generator.conv1"])

model = YourLightningModule()
trainer = Trainer(callbacks=[monitor])
trainer.fit()
```

This is especially useful for debugging the data flow in complex models and to identify numerical instabilities.

5.3 Model Verification

5.3.1 Gradient-Check for Batch-Optimization

Gradient descent over a batch of samples can not only benefit the optimization but also leverages data parallelism. However, one has to be careful not to mix data across the batch dimension. Only a small error in a reshape or permutation operation results in the optimization getting stuck and you won't even get a runtime error. How can one tell if the model mixes data in the batch? A simple trick is to do the following:

1. run the model on an example batch (can be random data)
2. get the output batch and select the n-th sample (choose n)
3. compute a dummy loss value of only that sample and compute the gradient w.r.t the entire input batch
4. observe that only the i-th sample in the input batch has non-zero gradient

If the gradient is non-zero for the other samples in the batch, it means the forward pass of the model is mixing data! The `BatchGradientVerificationCallback` does all of that for you before training begins.

```
from pytorch_lightning import Trainer
from pl_bolts.callbacks import BatchGradientVerificationCallback

model = YourLightningModule()
verification = BatchGradientVerificationCallback()
trainer = Trainer(callbacks=[verification])
trainer.fit(model)
```

This Callback will warn the user with the following message in case data mixing inside the batch is detected:

```
Your model is mixing data across the batch dimension.
This can lead to wrong gradient updates in the optimizer.
Check the operations that reshape and permute tensor dimensions in your model.
```

A non-Callback version `BatchGradientVerification` that works with any PyTorch `Module` is also available:

```
from pl_bolts.utils import BatchGradientVerification

model = YourPyTorchModel()
verification = BatchGradientVerification(model)
valid = verification.check(input_array=torch.rand(2, 3, 4), sample_idx=1)
```

In this example we run the test on a batch size 2 by inspecting gradients on the second sample.

CHAPTER

SIX

SELF-SUPERVISED CALLBACKS

Useful callbacks for self-supervised learning models

6.1 BYOLMAWeightUpdate

The exponential moving average weight-update rule from Bootstrap Your Own Latent (BYOL).

class pl_bolts.callbacks.byol_updates.**BYOLMAWeightUpdate**(*initial_tau=0.996*)

Bases: pytorch_lightning.

Weight update rule from BYOL.

Your model should have:

- self.online_network
- self.target_network

Updates the target_network params using an exponential moving average update rule weighted by tau. BYOL claims this keeps the online_network from collapsing.

Note: Automatically increases tau from initial_tau to 1.0 with every training step

Example:

```
# model must have 2 attributes
model = Model()
model.online_network = ...
model.target_network = ...

trainer = Trainer(callbacks=[BYOLMAWeightUpdate()])
```

Parameters **initial_tau**¶ (float) – starting tau. Auto-updates with every training step

6.2 SSLOnlineEvaluator

Appends a MLP for fine-tuning to the given model. Callback has its own mini-inner loop.

class pl_bolts.callbacks.ssl_online.**SSLOnlineEvaluator**(*dataset*, *drop_p=0.2*, *hidden_dim=None*, *z_dim=None*, *num_classes=None*)

Bases: pytorch_lightning.

Attaches a MLP for fine-tuning using the standard self-supervised protocol.

Example:

```
# your model must have 2 attributes
model = Model()
model.z_dim = ... # the representation dim
model.num_classes = ... # the num of classes in the model

online_eval = SSLOnlineEvaluator(
    z_dim=model.z_dim,
    num_classes=model.num_classes,
    dataset='imagenet'
)
```

Parameters

- **dataset** (str) – if stl10, need to get the labeled batch
- **drop_p** (float) – Dropout probability
- **hidden_dim** (Optional[int]) – Hidden dimension for the fine-tune MLP
- **z_dim** (Optional[int]) – Representation dimension
- **num_classes** (Optional[int]) – Number of classes

CHAPTER

SEVEN

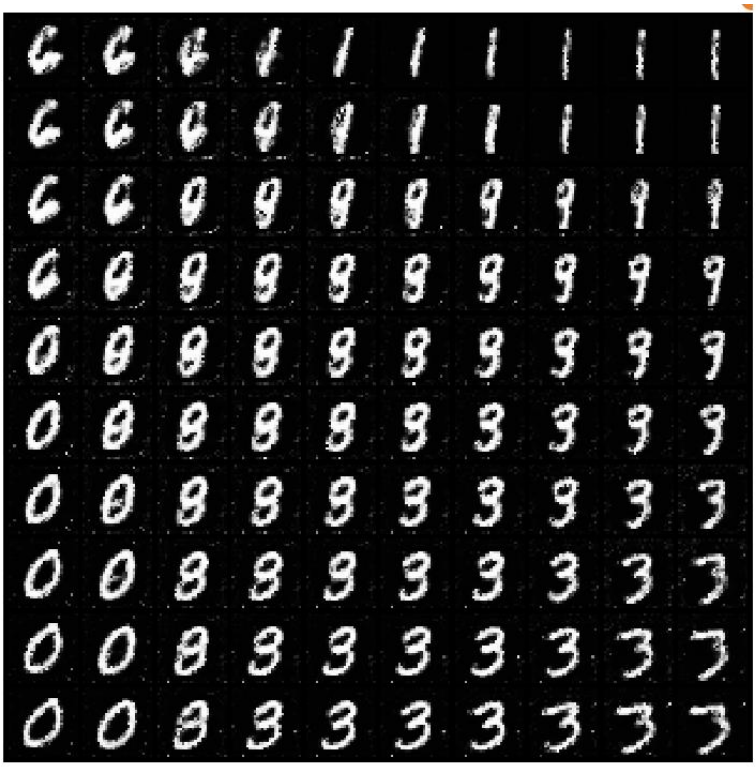
VARIATIONAL CALLBACKS

Useful callbacks for GANs, variational-autoencoders or anything with latent spaces.

7.1 Latent Dim Interpolator

Interpolates latent dims.

Example output:



class pl_bolts.callbacks.variational.**LatentDimInterpolator**(*interpolate_epoch_interval=20*, *range_start=-5*, *range_end=5*, *steps=11*, *num_samples=2*, *normalize=True*)

Bases: pytorch_lightning.callbacks.

Interpolates the latent space for a model by setting all dims to zero and stepping through the first two dims increasing one unit at a time.

Default interpolates between [-5, 5] (-5, -4, -3, . . . , 3, 4, 5)

Example:

```
from pl_bolts.callbacks import LatentDimInterpolator

Trainer(callbacks=[LatentDimInterpolator()])
```

Parameters

- **interpolate_epoch_interval** (int) – default 20
- **range_start** (int) – default -5
- **range_end** (int) – default 5
- **steps** (int) – number of step between start and end
- **num_samples** (int) – default 2
- **normalize** (bool) – default True (change image to (0, 1) range)

CHAPTER

EIGHT

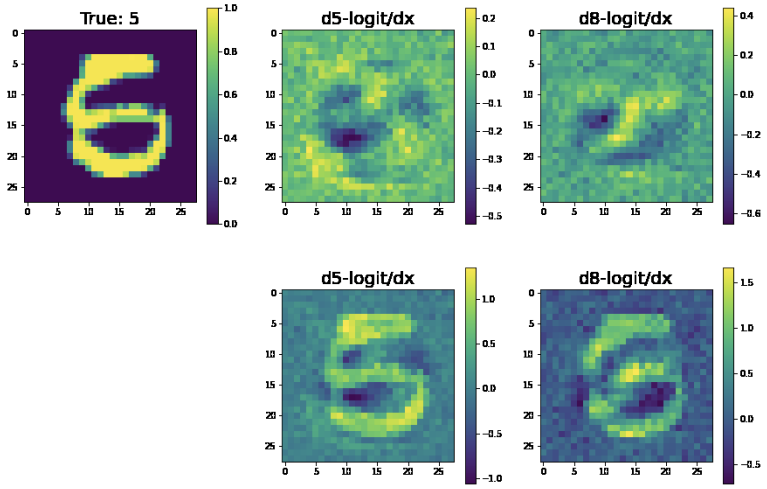
VISION CALLBACKS

Useful callbacks for vision models

8.1 Confused Logit

Shows how the input would have to change to move the prediction from one logit to the other

Example outputs:



class pl_bolts.callbacks.vision.confused_logit.**ConfusedLogitCallback**(*top_k*, *projection_factor=3*, *min_logit_value=5.0*, *logging_batch_interval=20*, *max_logit_difference=0.1*)

Bases: pytorch_lightning.

Takes the logit predictions of a model and when the probabilities of two classes are very close, the model doesn't have high certainty that it should pick one vs the other class.

This callback shows how the input would have to change to swing the model from one label prediction to the other.

In this case, the network predicts a 5... but gives almost equal probability to an 8. The images show what about the original 5 would have to change to make it more like a 5 or more like an 8.

For each confused logit the confused images are generated by taking the gradient from a logit wrt an input for the top two closest logits.

Example:

```
from pl_bolts.callbacks.vision import ConfusedLogitCallback
trainer = Trainer(callbacks=[ConfusedLogitCallback()])
```

Note: Whenever called, this model will look for `self.last_batch` and `self.last_logits` in the LightningModule.

Note: This callback supports tensorboard only right now.

Authored by:

- Alfredo Canziani

Parameters

- **top_k** (int) – How many "offending" images we should plot
- **projection_factor** (int) – How much to multiply the input image to make it look more like this logit label
- **min_logit_value** (float) – Only consider logit values above this threshold
- **logging_batch_interval** (int) – How frequently to inspect/potentially plot something
- **max_logit_difference** (float) – When the top 2 logits are within this threshold we consider them confused

---

8.2 Tensorboard Image Generator

Generates images from a generative model and plots to tensorboard

class pl_bolts.callbacks.vision.image_generation.**TensorboardGenerativeModelImageSampler**(*num nro pad nor mal ize= nor sca pad*

Bases: pytorch_lightning.

Generates images and logs to tensorboard. Your model must implement the `forward` function for generation

Requirements:

```
# model must have img_dim arg
model.img_dim = (1, 28, 28)

# model forward must work for sampling
z = torch.rand(batch_size, latent_dim)
img_samples = your_model(z)
```

Example:

```
from pl_bolts.callbacks import TensorboardGenerativeModelImageSampler

trainer = Trainer(callbacks=[TensorboardGenerativeModelImageSampler()])
```

Parameters

- **num_samples** (int) – Number of images displayed in the grid. Default: 3.
- **nrow** (int) – Number of images displayed in each row of the grid. The final grid size is (B / nrow, nrow). Default: 8.
- **padding** (int) – Amount of padding. Default: 2.
- **normalize** (bool) – If True, shift the image to the range (0, 1), by the min and max values specified by range. Default: False.
- **norm_range** (Optional[Tuple[int, int]]) – Tuple (min, max) where min and max are numbers, then these numbers are used to normalize the image. By default, min and max are computed from the tensor.
- **scale_each** (bool) – If True, scale each image in the batch of images separately rather than the (min, max) over all images. Default: False.
- **pad_value** (int) – Value for the padded pixels. Default: 0.

CHAPTER

NINE

DATAMODULES

DataModules (introduced in PyTorch Lightning 0.9.0) decouple the data from a model. A DataModule is simply a collection of a training dataloder, val dataloader and test dataloader. In addition, it specifies how to:

- Download/prepare data.
- Train/val/test splits.
- Transform

Then you can use it like this:

Example:

```
dm = MNISTDataModule('path/to/data')
model = LitModel()

trainer = Trainer()
trainer.fit(model, datamodule=dm)
```

Or use it manually with plain PyTorch

Example:

```
dm = MNISTDataModule('path/to/data')
for batch in dm.train_dataloader():
    ...
for batch in dm.val_dataloader():
    ...
for batch in dm.test_dataloader():
    ...
```

Please visit the PyTorch Lightning documentation for more details on DataModules

CHAPTER

TEN

SKLEARN DATAMODULE

Utilities to map sklearn or numpy datasets to PyTorch Dataloaders with automatic data splits and GPU/TPU support.

```
from sklearn.datasets import load_boston
from pl_bolts.datamodules import SklearnDataModule

X, y = load_boston(return_X_y=True)
loaders = SklearnDataModule(X, y)

train_loader = loaders.train_dataloader(batch_size=32)
val_loader = loaders.val_dataloader(batch_size=32)
test_loader = loaders.test_dataloader(batch_size=32)
```

Or build your own torch datasets

```
from sklearn.datasets import load_boston
from pl_bolts.datamodules import SklearnDataset

X, y = load_boston(return_X_y=True)
dataset = SklearnDataset(X, y)
loader = DataLoader(dataset)
```

10.1 Sklearn Dataset Class

Transforms a sklearn or numpy dataset to a PyTorch Dataset.

class pl_bolts.datamodules.sklearn_datamodule.**SklearnDataset**(*X*, *y*, *X_transform=None*, *y_transform=None*)

Bases: torch.utils.data.

Mapping between numpy (or sklearn) datasets to PyTorch datasets.

Example

```
>>> from sklearn.datasets import load_boston
>>> from pl_bolts.datamodules import SklearnDataset
...
>>> X, y = load_boston(return_X_y=True)
>>> dataset = SklearnDataset(X, y)
>>> len(dataset)
506
```

Parameters

- **X** (ndarray) – Numpy ndarray
- **y** (ndarray) – Numpy ndarray
- **X_transform** (Optional[Any]) – Any transform that works with Numpy arrays
- **y_transform** (Optional[Any]) – Any transform that works with Numpy arrays

---

10.2 Sklearn DataModule Class

Automatically generates the train, validation and test splits for a Numpy dataset. They are set up as dataloaders for convenience. Optionally, you can pass in your own validation and test splits.

class pl_bolts.datamodules.sklearn_datamodule.**SklearnDataModule**(*X*, *y*, *x_val=None*, *y_val=None*, *x_test=None*, *y_test=None*, *val_split=0.2*, *test_split=0.1*, *num_workers=2*, *random_state=1234*, *shuffle=True*, *batch_size=16*, *pin_memory=False*, *drop_last=False*, **args*, ***kwargs*)

Bases: pytorch_lightning.

Automatically generates the train, validation and test splits for a Numpy dataset. They are set up as dataloaders for convenience. Optionally, you can pass in your own validation and test splits.

Example

```
>>> from sklearn.datasets import load_boston
>>> from pl_bolts.datamodules import SklearnDataModule
...
>>> X, y = load_boston(return_X_y=True)
>>> loaders = SklearnDataModule(X, y, batch_size=32)
...
>>> # train set
>>> train_loader = loaders.train_dataloader()
>>> len(train_loader.dataset)
355
>>> len(train_loader)
12
>>> # validation set
>>> val_loader = loaders.val_dataloader()
>>> len(val_loader.dataset)
100
>>> len(val_loader)
4
>>> # test set
>>> test_loader = loaders.test_dataloader()
>>> len(test_loader.dataset)
51
>>> len(test_loader)
2
```

CHAPTER

ELEVEN

VISION DATAMODULES

The following are pre-built datamodules for computer-vision.

11.1 Supervised learning

These are standard vision datasets with the train, test, val splits pre-generated in DataLoaders with the standard transforms (and Normalization) values

11.1.1 BinaryMNIST

class pl_bolts.datamodules.binary_mnist_datamodule.**BinaryMNISTDataModule**(*data_dir=None*, *val_split=0.2*, *num_workers=16*, *normalize=False*, *batch_size=32*, *seed=42*, *shuffle=False*, *pin_memory=False*, *drop_last=False*, **args*, ***kwargs*)

Bases: pytorch_lightning.

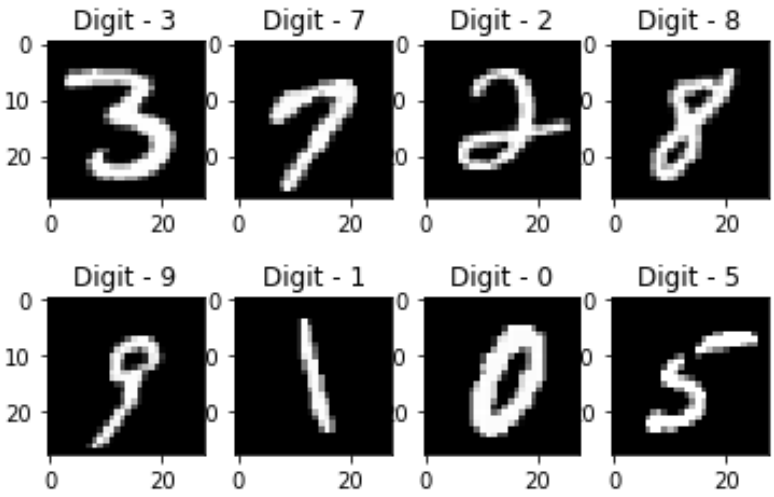
Specs:

- 10 classes (1 per digit)
- Each image is (1 x 28 x 28)

Binary MNIST, train, val, test splits and transforms

Transforms:

```
mnist_transforms = transform_lib.Compose([
    transform_lib.ToTensor()
])
```



Example:

```
from pl_bolts.datamodules import BinaryMNISTDataModule

dm = BinaryMNISTDataModule('.')
model = LitModel()

Trainer().fit(model, datamodule=dm)
```

Parameters

- **data_dir** (Optional[str]) – Where to save/load the data
- **val_split** (Union[int, float]) – Percent (float) or number (int) of samples to use for the validation split
- **num_workers** (int) – How many workers to use for loading data
- **normalize** (bool) – If true applies image normalize
- **batch_size** (int) – How many samples per batch to load
- **seed** (int) – Random seed to be used for train/val/test splits
- **shuffle** (bool) – If true shuffles the train data every epoch
- **pin_memory** (bool) – If true, the data loader will copy Tensors into CUDA pinned memory before returning them
- **drop_last** (bool) – If true drops the last incomplete batch

default_transforms()
Default transform for the dataset

Return type Callable

property num_classes
Return: 10

Return type int

11.1.2 CityScapes

class pl_bolts.datamodules.cityscapes_datamodule.**CityscapesDataModule**(*data_dir*, *quality_mode='fine'*, *target_type='instance'*, *num_workers=16*, *batch_size=32*, *seed=42*, *shuffle=False*, *pin_memory=False*, *drop_last=False*, **args*, ***kwargs*)

Bases: pytorch_lightning.

Standard Cityscapes, train, val, test splits and transforms

Note: You need to have downloaded the Cityscapes dataset first and provide the path to where it is saved.
You can download the dataset here: https://www.cityscapes-dataset.com/

Specs:

- 30 classes (road, person, sidewalk, etc...)
- (image, target) - image dims: (3 x 1024 x 2048), target dims: (1024 x 2048)

Transforms:

```
transforms = transform_lib.Compose([
    transform_lib.ToTensor(),
    transform_lib.Normalize(
        mean=[0.28689554, 0.32513303, 0.28389177],
        std=[0.18696375, 0.19017339, 0.18720214]
    )
])
```

Example:

```
from pl_bolts.datamodules import CityscapesDataModule

dm = CityscapesDataModule(PATH)
```

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```
model = LitModel()

Trainer().fit(model, datamodule=dm)
```

Or you can set your own transforms

Example:

```
dm.train_transforms = ...
dm.test_transforms = ...
dm.val_transforms  = ...
dm.target_transforms = ...
```

Parameters

- **data_dir** (str) – where to load the data from path, i.e. where directory leftImg8bit and gtFine or gtCoarse are located
- **quality_mode** (str) – the quality mode to use, either 'fine' or 'coarse'
- **target_type** (str) – targets to use, either 'instance' or 'semantic'
- **num_workers** (int) – how many workers to use for loading data
- **batch_size** (int) – number of examples per training/eval step
- **seed** (int) – random seed to be used for train/val/test splits
- **shuffle** (bool) – If true shuffles the data every epoch
- **pin_memory** (bool) – If true, the data loader will copy Tensors into CUDA pinned memory before returning them
- **drop_last** (bool) – If true drops the last incomplete batch

test_dataloader()
Cityscapes test set

Return type DataLoader

train_dataloader()
Cityscapes train set

Return type DataLoader

val_dataloader()
Cityscapes val set

Return type DataLoader

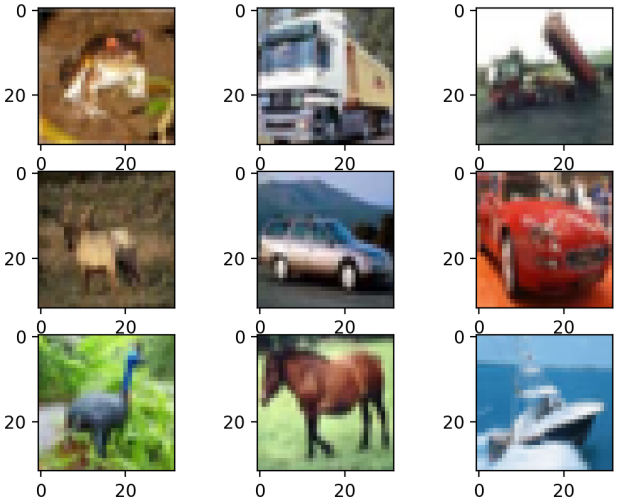
property num_classes
Return: 30

Return type int

11.1.3 CIFAR-10

class pl_bolts.datamodules.cifar10_datamodule.**CIFAR10DataModule**(*data_dir=None*, *val_split=0.2*, *num_workers=16*, *normalize=False*, *batch_size=32*, *seed=42*, *shuffle=False*, *pin_memory=False*, *drop_last=False*, **args*, ***kwargs*)

Bases: pytorch_lightning.



Specs:

- 10 classes (1 per class)
- Each image is (3 x 32 x 32)

Standard CIFAR10, train, val, test splits and transforms

Transforms:

```
mnist_transforms = transform_lib.Compose([
    transform_lib.ToTensor(),
    transforms.Normalize(
        mean=[x / 255.0 for x in [125.3, 123.0, 113.9]],
        std=[x / 255.0 for x in [63.0, 62.1, 66.7]]
    )
])
```

Example:

```
from pl_bolts.datamodules import CIFAR10DataModule

dm = CIFAR10DataModule(PATH)
model = LitModel()

Trainer().fit(model, datamodule=dm)
```

Or you can set your own transforms

Example:

```
dm.train_transforms = ...
dm.test_transforms = ...
dm.val_transforms  = ...
```

Parameters

- **data_dir** (Optional[str]) – Where to save/load the data
- **val_split** (Union[int, float]) – Percent (float) or number (int) of samples to use for the validation split
- **num_workers** (int) – How many workers to use for loading data
- **normalize** (bool) – If true applies image normalize
- **batch_size** (int) – How many samples per batch to load
- **seed** (int) – Random seed to be used for train/val/test splits
- **shuffle** (bool) – If true shuffles the train data every epoch
- **pin_memory** (bool) – If true, the data loader will copy Tensors into CUDA pinned memory before returning them
- **drop_last** (bool) – If true drops the last incomplete batch

default_transforms()

Default transform for the dataset

Return type Callable

property num_classes

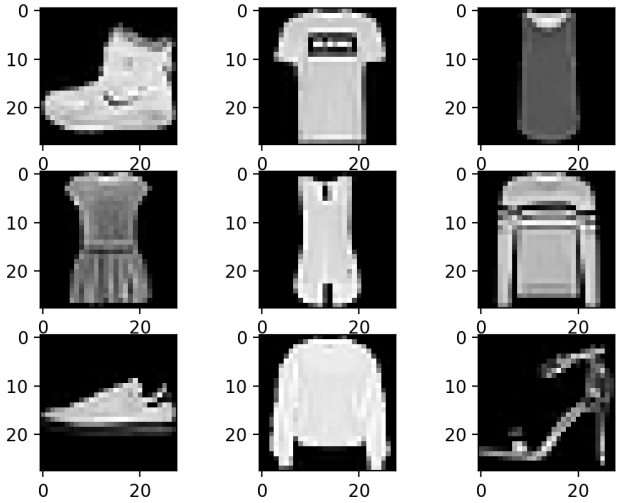
Return: 10

Return type int

11.1.4 FashionMNIST

class pl_bolts.datamodules.fashion_mnist_datamodule.**FashionMNISTDataModule**(*data_dir=None*, *val_split=0.2*, *num_workers=16*, *normalize=False*, *batch_size=32*, *seed=42*, *shuffle=False*, *pin_memory=False*, *drop_last=False*, **args*, ***kwargs*)

Bases: pytorch_lightning.



Specs:

- 10 classes (1 per type)
- Each image is (1 x 28 x 28)

Standard FashionMNIST, train, val, test splits and transforms

Transforms:

```
mnist_transforms = transform_lib.Compose([
    transform_lib.ToTensor()
])
```

Example:

```
from pl_bolts.datamodules import FashionMNISTDataModule

dm = FashionMNISTDataModule('.')
model = LitModel()

Trainer().fit(model, datamodule=dm)
```

Parameters

- **data_dir** (Optional[str]) – Where to save/load the data
- **val_split** (Union[int, float]) – Percent (float) or number (int) of samples to use for the validation split
- **num_workers** (int) – How many workers to use for loading data
- **normalize** (bool) – If true applies image normalize
- **batch_size** (int) – How many samples per batch to load
- **seed** (int) – Random seed to be used for train/val/test splits
- **shuffle** (bool) – If true shuffles the train data every epoch
- **pin_memory** (bool) – If true, the data loader will copy Tensors into CUDA pinned memory before returning them
- **drop_last** (bool) – If true drops the last incomplete batch

default_transforms()
Default transform for the dataset

Return type Callable

property num_classes
Return: 10

Return type int

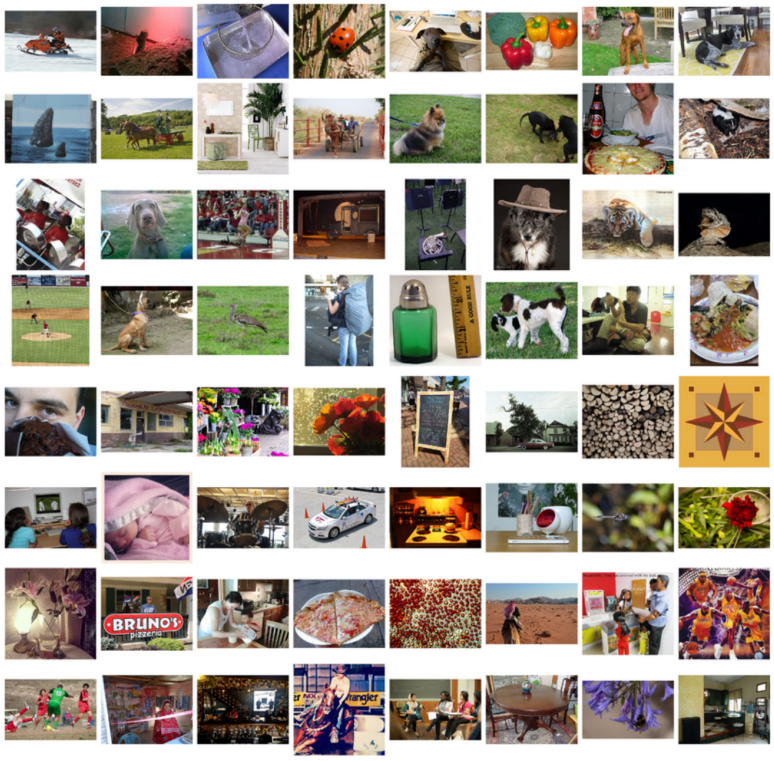
11.1.5 Imagenet

class pl_bolts.datamodules.imagenet_datamodule.**ImagenetDataModule**(*data_dir*, *meta_dir=None*, *num_imgs_per_val_class=50*, *image_size=224*, *num_workers=16*, *batch_size=32*, *shuffle=False*, *pin_memory=False*, *drop_last=False*, **args*, ***kwargs*)

Bases: pytorch_lightning.

Specs:

- 1000 classes



- Each image is (3 x varies x varies) (here we default to 3 x 224 x 224)

Imagenet train, val and test dataloaders.

The train set is the imagenet train.

The val set is taken from the train set with *num_imgs_per_val_class* images per class. For example if *num_imgs_per_val_class=2* then there will be 2,000 images in the validation set.

The test set is the official imagenet validation set.

Example:

```
from pl_bolts.datamodules import ImagenetDataModule

dm = ImagenetDataModule(IMAGENET_PATH)
model = LitModel()

Trainer().fit(model, datamodule=dm)
```

Parameters

- **data_dir** (str) – path to the imagenet dataset file
- **meta_dir** (Optional[str]) – path to meta.bin file
- **num_imgs_per_val_class** (int) – how many images per class for the validation set
- **image_size** (int) – final image size
- **num_workers** (int) – how many data workers
- **batch_size** (int) – batch_size

- **shuffle** (bool) – If true shuffles the data every epoch
- **pin_memory** (bool) – If true, the data loader will copy Tensors into CUDA pinned memory before returning them
- **drop_last** (bool) – If true drops the last incomplete batch

prepare_data()
This method already assumes you have imagenet2012 downloaded. It validates the data using the meta.bin.

> **Warning:** Please download imagenet on your own first.

Return type None

test_dataloader()
Uses the validation split of imagenet2012 for testing

Return type DataLoader

train_dataloader()
Uses the train split of imagenet2012 and puts away a portion of it for the validation split

Return type DataLoader

train_transform()
The standard imagenet transforms

```
transform_lib.Compose([
    transform_lib.RandomResizedCrop(self.image_size),
    transform_lib.RandomHorizontalFlip(),
    transform_lib.ToTensor(),
    transform_lib.Normalize(
        mean=[0.485, 0.456, 0.406],
        std=[0.229, 0.224, 0.225]
    ),
])
```

Return type Callable

val_dataloader()
Uses the part of the train split of imagenet2012 that was not used for training via *num_imgs_per_val_class*

Parameters

- **batch_size** – the batch size
- **transforms** – the transforms

Return type DataLoader

val_transform()
The standard imagenet transforms for validation

```
transform_lib.Compose([
    transform_lib.Resize(self.image_size + 32),
    transform_lib.CenterCrop(self.image_size),
    transform_lib.ToTensor(),
    transform_lib.Normalize(
        mean=[0.485, 0.456, 0.406],
        std=[0.229, 0.224, 0.225]
```

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```
    ),
])
```

Return type Callable

property num_classes

Return:

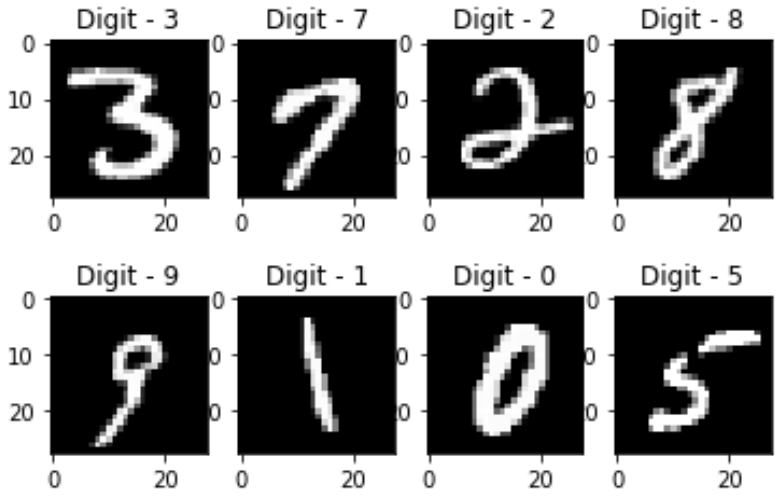
1000

Return type int

11.1.6 MNIST

class pl_bolts.datamodules.mnist_datamodule.**MNISTDataModule**(*data_dir=None*, *val_split=0.2*, *num_workers=16*, *normalize=False*, *batch_size=32*, *seed=42*, *shuffle=False*, *pin_memory=False*, *drop_last=False*, **args*, ***kwargs*)

Bases: pytorch_lightning.



Specs:

- 10 classes (1 per digit)
- Each image is (1 x 28 x 28)

Standard MNIST, train, val, test splits and transforms

Transforms:

```
mnist_transforms = transform_lib.Compose([
    transform_lib.ToTensor()
])
```

Example:

```
from pl_bolts.datamodules import MNISTDataModule

dm = MNISTDataModule('.')
model = LitModel()

Trainer().fit(model, datamodule=dm)
```

Parameters

- **data_dir** (Optional[str]) – Where to save/load the data
- **val_split** (Union[int, float]) – Percent (float) or number (int) of samples to use for the validation split
- **num_workers** (int) – How many workers to use for loading data
- **normalize** (bool) – If true applies image normalize
- **batch_size** (int) – How many samples per batch to load
- **seed** (int) – Random seed to be used for train/val/test splits
- **shuffle** (bool) – If true shuffles the train data every epoch
- **pin_memory** (bool) – If true, the data loader will copy Tensors into CUDA pinned memory before returning them
- **drop_last** (bool) – If true drops the last incomplete batch

default_transforms()
Default transform for the dataset

Return type Callable

property num_classes
Return: 10

Return type int

11.2 Semi-supervised learning

The following datasets have support for unlabeled training and semi-supervised learning where only a few examples are labeled.

11.2.1 Imagenet (ssl)

class pl_bolts.datamodules.ssl_imagenet_datamodule.**SSLImagenetDataModule**(*data_dir*, *meta_dir=None*, *num_workers=16*, *batch_size=32*, *shuffle=False*, *pin_memory=False*, *drop_last=False*, **args*, ***kwargs*)

Bases: pytorch_lightning.

11.2.2 STL-10

class pl_bolts.datamodules.stl10_datamodule.**STL10DataModule**(*data_dir=None*, *unlabeled_val_split=5000*, *train_val_split=500*, *num_workers=16*, *batch_size=32*, *seed=42*, *shuffle=False*, *pin_memory=False*, *drop_last=False*, **args*, ***kwargs*)

Bases: pytorch_lightning.

Specs:

- 10 classes (1 per type)
- Each image is (3 x 96 x 96)

Standard STL-10, train, val, test splits and transforms. STL-10 has support for doing validation splits on the labeled or unlabeled splits

Transforms:

```
mnist_transforms = transform_lib.Compose([
    transform_lib.ToTensor(),
    transforms.Normalize(
        mean=(0.43, 0.42, 0.39),
        std=(0.27, 0.26, 0.27)
    )
])
```

Example:

```
from pl_bolts.datamodules import STL10DataModule

dm = STL10DataModule(PATH)
model = LitModel()

Trainer().fit(model, datamodule=dm)
```

Parameters

- **data_dir** (Optional[str]) – where to save/load the data
- **unlabeled_val_split** (int) – how many images from the unlabeled training split to use for validation
- **train_val_split** (int) – how many images from the labeled training split to use for validation
- **num_workers** (int) – how many workers to use for loading data
- **batch_size** (int) – the batch size
- **seed** (int) – random seed to be used for train/val/test splits
- **shuffle** (bool) – If true shuffles the data every epoch
- **pin_memory** (bool) – If true, the data loader will copy Tensors into CUDA pinned memory before returning them
- **drop_last** (bool) – If true drops the last incomplete batch

prepare_data()
Downloads the unlabeled, train and test split

Return type None

test_dataloader()
Loads the test split of STL10

Parameters

- **batch_size** – the batch size
- **transforms** – the transforms

Return type DataLoader

train_dataloader()
Loads the 'unlabeled' split minus a portion set aside for validation via *unlabeled_val_split*.

Return type DataLoader

train_dataloader_mixed()
Loads a portion of the 'unlabeled' training data and 'train' (labeled) data. both portions have a subset removed for validation via *unlabeled_val_split* and *train_val_split*

Parameters

- **batch_size** – the batch size
- **transforms** – a sequence of transforms

Return type DataLoader

val_dataloader()

Loads a portion of the 'unlabeled' training data set aside for validation The val dataset = (unlabeled - train_val_split)

Parameters

- **batch_size** – the batch size
- **transforms** – a sequence of transforms

Return type DataLoader

val_dataloader_mixed()

Loads a portion of the 'unlabeled' training data set aside for validation along with the portion of the 'train' dataset to be used for validation

unlabeled_val = (unlabeled - train_val_split)

labeled_val = (train- train_val_split)

full_val = unlabeled_val + labeled_val

Parameters

- **batch_size** – the batch size
- **transforms** – a sequence of transforms

Return type DataLoader

CHAPTER

TWELVE

DATASETS

Collection of useful datasets

12.1 Debugging

Use these datasets to debug

12.1.1 DummyDataset

class pl_bolts.datasets.dummy_dataset.**DummyDataset**(**shapes*, *num_samples=10000*)

Bases: torch.utils.data.

Generate a dummy dataset

Example

```
>>> from pl_bolts.datasets import DummyDataset
>>> from torch.utils.data import DataLoader
>>> # mnist dims
>>> ds = DummyDataset((1, 28, 28), (1, ))
>>> dl = DataLoader(ds, batch_size=7)
>>> # get first batch
>>> batch = next(iter(dl))
>>> x, y = batch
>>> x.size()
torch.Size([7, 1, 28, 28])
>>> y.size()
torch.Size([7, 1])
```

Parameters

- ***shapes** – list of shapes
- **num_samples** (int) – how many samples to use in this dataset

12.1.2 DummyDetectionDataset

class pl_bolts.datasets.dummy_dataset.**DummyDetectionDataset**(*img_shape=(3, 256, 256)*, *num_boxes=1*, *num_classes=2*, *num_samples=10000*)

Bases: torch.utils.data.

Generate a dummy dataset for detection

Example

```
>>> from pl_bolts.datasets import DummyDetectionDataset
>>> from torch.utils.data import DataLoader
>>> ds = DummyDetectionDataset()
>>> dl = DataLoader(ds, batch_size=7)
```

Parameters

- ***shapes** – list of shapes
- **num_samples** (int) – how many samples to use in this dataset

12.1.3 RandomDataset

class pl_bolts.datasets.dummy_dataset.**RandomDataset**(*size*, *num_samples=250*)

Bases: torch.utils.data.

Generate a dummy dataset

Example

```
>>> from pl_bolts.datasets import RandomDataset
>>> from torch.utils.data import DataLoader
>>> ds = RandomDataset(10)
>>> dl = DataLoader(ds, batch_size=7)
```

Parameters

- **size** (int) – tuple
- **num_samples** (int) – number of samples

12.1.4 RandomDictDataset

class pl_bolts.datasets.dummy_dataset.**RandomDictDataset**(*size*, *num_samples=250*)

Bases: torch.utils.data.

Generate a dummy dataset with a dict structure

Example

```
>>> from pl_bolts.datasets import RandomDictDataset
>>> from torch.utils.data import DataLoader
>>> ds = RandomDictDataset(10)
>>> dl = DataLoader(ds, batch_size=7)
```

Parameters

- **size** (int) – tuple
- **num_samples** (int) – number of samples

12.1.5 RandomDictStringDataset

class pl_bolts.datasets.dummy_dataset.**RandomDictStringDataset**(*size*, *num_samples=250*)

Bases: torch.utils.data.

Generate a dummy dataset with strings

Example

```
>>> from pl_bolts.datasets import RandomDictStringDataset
>>> from torch.utils.data import DataLoader
>>> ds = RandomDictStringDataset(10)
>>> dl = DataLoader(ds, batch_size=7)
```

Parameters

- **size** (int) – tuple
- **num_samples** (int) – number of samples

CHAPTER

THIRTEEN

ASYNCHRONOUSLOADER

This dataloader behaves identically to the standard pytorch dataloader, but will transfer data asynchronously to the GPU with training. You can also use it to wrap an existing dataloader.

Example:

```
dataloader = AsynchronousLoader(DataLoader(ds, batch_size=16), device=device)

for b in dataloader:
    ...
```

class pl_bolts.datamodules.async_dataloader.**AsynchronousLoader**(*data*, *device=torch.device*, *q_size=10*, *num_batches=None*, ***kwargs*)

Bases: object

Class for asynchronously loading from CPU memory to device memory with DataLoader.

Note that this only works for single GPU training, multiGPU uses PyTorch's DataParallel or DistributedDataParallel which uses its own code for transferring data across GPUs. This could just break or make things slower with DataParallel or DistributedDataParallel.

Parameters

- **data** (Union[DataLoader, Dataset]) – The PyTorch Dataset or DataLoader we're using to load.
- **device** (device) – The PyTorch device we are loading to
- **q_size** (int) – Size of the queue used to store the data loaded to the device
- **num_batches** (Optional[int]) – Number of batches to load. This must be set if the dataloader doesn't have a finite __len__. It will also override DataLoader.__len__ if set and DataLoader has a __len__. Otherwise it can be left as None
- ****kwargs** – Any additional arguments to pass to the dataloader if we're constructing one here

CHAPTER

FOURTEEN

LOSSES

This package lists common losses across research domains (This is a work in progress. If you have any losses you want to contribute, please submit a PR!)

Note: this module is a work in progress

14.1 Your Loss

We're cleaning up many of our losses, but in the meantime, submit a PR to add your loss here!

CHAPTER

FIFTEEN

OBJECT DETECTION

These are common losses used in object detection.

15.1 GIoU Loss

pl_bolts.losses.object_detection.**giou_loss**(*preds*, *target*)

Calculates the generalized intersection over union loss.

It has been proposed in Generalized Intersection over Union: A Metric and A Loss for Bounding Box Regression.

Parameters

- **preds** (Tensor) – an Nx4 batch of prediction bounding boxes with representation `[x_min, y_min, x_max, y_max]`
- **target** (Tensor) – an Mx4 batch of target bounding boxes with representation `[x_min, y_min, x_max, y_max]`

Example

```
>>> import torch
>>> from pl_bolts.losses.object_detection import giou_loss
>>> preds = torch.tensor([[100, 100, 200, 200]])
>>> target = torch.tensor([[150, 150, 250, 250]])
>>> giou_loss(preds, target)
tensor([[1.0794]])
```

Return type Tensor

Returns GIoU loss in an NxM tensor containing the pairwise GIoU loss for every element in preds and target, where N is the number of prediction bounding boxes and M is the number of target bounding boxes

15.2 IoU Loss

pl_bolts.losses.object_detection.**iou_loss**(*preds*, *target*)

Calculates the intersection over union loss.

Parameters

- **preds** (Tensor) – batch of prediction bounding boxes with representation `[x_min, y_min, x_max, y_max]`
- **target** (Tensor) – batch of target bounding boxes with representation `[x_min, y_min, x_max, y_max]`

Example

```
>>> import torch
>>> from pl_bolts.losses.object_detection import iou_loss
>>> preds = torch.tensor([[100, 100, 200, 200]])
>>> target = torch.tensor([[150, 150, 250, 250]])
>>> iou_loss(preds, target)
tensor([[0.8571]])
```

Return type Tensor

Returns IoU loss

CHAPTER

SIXTEEN

REINFORCEMENT LEARNING

These are common losses used in RL.

16.1 DQN Loss

pl_bolts.losses.rl.**dqn_loss**(*batch*, *net*, *target_net*, *gamma=0.99*)

Calculates the mse loss using a mini batch from the replay buffer

Parameters

- **batch** (Tuple[Tensor, Tensor]) – current mini batch of replay data
- **net** (Module) – main training network
- **target_net** (Module) – target network of the main training network
- **gamma** (float) – discount factor

Return type Tensor

Returns loss

16.2 Double DQN Loss

pl_bolts.losses.rl.**double_dqn_loss**(*batch*, *net*, *target_net*, *gamma=0.99*)

Calculates the mse loss using a mini batch from the replay buffer. This uses an improvement to the original DQN loss by using the double dqn. This is shown by using the actions of the train network to pick the value from the target network. This code is heavily commented in order to explain the process clearly

Parameters

- **batch** (Tuple[Tensor, Tensor]) – current mini batch of replay data
- **net** (Module) – main training network
- **target_net** (Module) – target network of the main training network
- **gamma** (float) – discount factor

Return type Tensor

Returns loss

16.3 Per DQN Loss

pl_bolts.losses.rl.**per_dqn_loss**(*batch*, *batch_weights*, *net*, *target_net*, *gamma=0.99*)

Calculates the mse loss with the priority weights of the batch from the PER buffer

Parameters

- **batch** (Tuple[Tensor, Tensor]) – current mini batch of replay data
- **batch_weights** (List) – how each of these samples are weighted in terms of priority
- **net** (Module) – main training network
- **target_net** (Module) – target network of the main training network
- **gamma** (float) – discount factor

Return type Tuple[Tensor, ndarray]

Returns loss and batch_weights

CHAPTER

SEVENTEEN

HOW TO USE MODELS

Models are meant to be "bolted" onto your research or production cases.

Bolts are meant to be used in the following ways

17.1 Predicting on your data

Most bolts have pretrained weights trained on various datasets or algorithms. This is useful when you don't have enough data, time or money to do your own training.

For example, you could use a pretrained VAE to generate features for an image dataset.

```
from pl_bolts.models.self_supervised import SimCLR

weight_path = 'https://pl-bolts-weights.s3.us-east-2.amazonaws.com/simclr/bolts_
↪simclr_imagenet/simclr_imagenet.ckpt'
simclr = SimCLR.load_from_checkpoint(weight_path, strict=False)
encoder = simclr.encoder
encoder.eval()
```

```
for (x, y) in own_data:
    features = encoder(x)
```

The advantage of bolts is that each system can be decomposed and used in interesting ways. For instance, this resnet50 was trained using self-supervised learning (no labels) on Imagenet, and thus might perform better than the same resnet50 trained with labels

```
# trained without labels
from pl_bolts.models.self_supervised import SimCLR

weight_path = 'https://pl-bolts-weights.s3.us-east-2.amazonaws.com/simclr/bolts_
↪simclr_imagenet/simclr_imagenet.ckpt'
simclr = SimCLR.load_from_checkpoint(weight_path, strict=False)
resnet50_unsupervised = simclr.encoder.eval()

# trained with labels
from torchvision.models import resnet50
resnet50_supervised = resnet50(pretrained=True)
```

```
# perhaps the features when trained without labels are much better for classification␣
↪or other tasks
x = image_sample()
unsup_feats = resnet50_unsupervised(x)
sup_feats = resnet50_supervised(x)

# which one will be better?
```

Bolts are often trained on more than just one dataset.

```
from pl_bolts.models.self_supervised import SimCLR

# imagenet weights
weight_path = 'https://pl-bolts-weights.s3.us-east-2.amazonaws.com/simclr/bolts_
↪simclr_imagenet/simclr_imagenet.ckpt'
simclr = SimCLR.load_from_checkpoint(weight_path, strict=False)

simclr.freeze()
```

17.2 Finetuning on your data

If you have a little bit of data and can pay for a bit of training, it's often better to finetune on your own data.

To finetune you have two options unfrozen finetuning or unfrozen later.

17.2.1 Unfrozen Finetuning

In this approach, we load the pretrained model and unfreeze from the beginning

```
from pl_bolts.models.self_supervised import SimCLR

weight_path = 'https://pl-bolts-weights.s3.us-east-2.amazonaws.com/simclr/bolts_
↪simclr_imagenet/simclr_imagenet.ckpt'
simclr = SimCLR.load_from_checkpoint(weight_path, strict=False)
resnet50 = simclr.encoder
# don't call .freeze()
```

```
classifier = LogisticRegression(...)

for (x, y) in own_data:
    feats = resnet50(x)
    y_hat = classifier(feats)
    ...
```

Or as a LightningModule

```
class FineTuner(pl.LightningModule):

    def __init__(self, encoder):
        self.encoder = encoder
        self.classifier = LogisticRegression(...)
```

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```
    def training_step(self, batch, batch_idx):
        (x, y) = batch
        feats = self.encoder(x)
        y_hat = self.classifier(feats)
        loss = cross_entropy_with_logits(y_hat, y)
        return loss

trainer = Trainer(gpus=2)
model = FineTuner(resnet50)
trainer.fit(model)
```

Sometimes this works well, but more often it's better to keep the encoder frozen for a while

17.2.2 Freeze then unfreeze

The approach that works best most often is to freeze first then unfreeze later

```
# freeze!
from pl_bolts.models.self_supervised import SimCLR

weight_path = 'https://pl-bolts-weights.s3.us-east-2.amazonaws.com/simclr/bolts_
↪simclr_imagenet/simclr_imagenet.ckpt'
simclr = SimCLR.load_from_checkpoint(weight_path, strict=False)
resnet50 = simclr.encoder
resnet50.eval()
```

```
classifier = LogisticRegression(...)

for epoch in epochs:
    for (x, y) in own_data:
        feats = resnet50(x)
        y_hat = classifier(feats)
        loss = cross_entropy_with_logits(y_hat, y)

    # unfreeze after 10 epochs
    if epoch == 10:
        resnet50.unfreeze()
```

Note: In practice, unfreezing later works MUCH better.

Or in Lightning as a Callback so you don't pollute your research code.

```
class UnFreezeCallback(Callback):

    def on_epoch_end(self, trainer, pl_module):
        if trainer.current_epoch == 10.
            encoder.unfreeze()

trainer = Trainer(gpus=2, callbacks=[UnFreezeCallback()])
model = FineTuner(resnet50)
trainer.fit(model)
```

Unless you still need to mix it into your research code.

```
class FineTuner(pl.LightningModule):

    def __init__(self, encoder):
        self.encoder = encoder
        self.classifier = LogisticRegression(...)

    def training_step(self, batch, batch_idx):

        # option 1 - (not recommended because it's messy)
        if self.trainer.current_epoch == 10:
            self.encoder.unfreeze()

        (x, y) = batch
        feats = self.encoder(x)
        y_hat = self.classifier(feats)
        loss = cross_entropy_with_logits(y_hat, y)
        return loss

    def on_epoch_end(self, trainer, pl_module):
        # a hook is cleaner (but a callback is much better)
        if self.trainer.current_epoch == 10:
            self.encoder.unfreeze()
```

17.2.3 Hyperparameter search

For finetuning to work well, you should try many versions of the model hyperparameters. Otherwise you're unlikely to get the most value out of your data.

```
from pl_bolts.models.autoencoders import VAE

learning_rates = [0.01, 0.001, 0.0001]
hidden_dim = [128, 256, 512]

for lr in learning_rates:
    for hd in hidden_dim:
        vae = VAE(input_height=32, hidden_dim=hd, learning_rate=lr)
        trainer = Trainer()
        trainer.fit(vae)
```

17.3 Train from scratch

If you do have enough data and compute resources, then you could try training from scratch.

```
# get data
train_data = DataLoader(YourDataset)
val_data = DataLoader(YourDataset)

# use any bolts model without pretraining
model = VAE()

# fit!
```

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```
trainer = Trainer(gpus=2)
trainer.fit(model, train_dataloader=train_data, val_dataloaders=val_data)
```

Note: For this to work well, make sure you have enough data and time to train these models!

17.4 For research

What separates bolts from all the other libraries out there is that bolts is built by and used by AI researchers. This means every single bolt is modularized so that it can be easily extended or mixed with arbitrary parts of the rest of the code-base.

17.4.1 Extending work

Perhaps a research project requires modifying a part of a know approach. In this case, you're better off only changing that part of a system that is already know to perform well. Otherwise, you risk not implementing the work correctly.

Example 1: Changing the prior or approx posterior of a VAE

```
from pl_bolts.models.autoencoders import VAE

class MyVAEFlavor(VAE):

    def init_prior(self, z_mu, z_std):
        P = MyPriorDistribution

        # default is standard normal
        # P = distributions.normal.Normal(loc=torch.zeros_like(z_mu), scale=torch.
↪ones_like(z_std))
        return P

    def init_posterior(self, z_mu, z_std):
        Q = MyPosteriorDistribution
        # default is normal(z_mu, z_sigma)
        # Q = distributions.normal.Normal(loc=z_mu, scale=z_std)
        return Q
```

And of course train it with lightning.

```
model = MyVAEFlavor()
trainer = Trainer()
trainer.fit(model)
```

In just a few lines of code you changed something fundamental about a VAE... This means you can iterate through ideas much faster knowing that the bolt implementation and the training loop are CORRECT and TESTED.

If your model doesn't work with the new P, Q, then you can discard that research idea much faster than trying to figure out if your VAE implementation was correct, or if your training loop was correct.

Example 2: Changing the generator step of a GAN

```
from pl_bolts.models.gans import GAN

class FancyGAN(GAN):

    def generator_step(self, x):
        # sample noise
        z = torch.randn(x.shape[0], self.hparams.latent_dim)
        z = z.type_as(x)

        # generate images
        self.generated_imgs = self(z)

        # ground truth result (ie: all real)
        real = torch.ones(x.size(0), 1)
        real = real.type_as(x)
        g_loss = self.generator_loss(real)

        tqdm_dict = {'g_loss': g_loss}
        output = OrderedDict({
            'loss': g_loss,
            'progress_bar': tqdm_dict,
            'log': tqdm_dict
        })
        return output
```

Example 3: Changing the way the loss is calculated in a contrastive self-supervised learning approach

```
from pl_bolts.models.self_supervised import AMDIM

class MyDIM(AMDIM):

    def validation_step(self, batch, batch_nb):
        [img_1, img_2], labels = batch

        # generate features
        r1_x1, r5_x1, r7_x1, r1_x2, r5_x2, r7_x2 = self.forward(img_1, img_2)

        # Contrastive task
        loss, lgt_reg = self.contrastive_task((r1_x1, r5_x1, r7_x1), (r1_x2, r5_x2,␣
↪r7_x2))
        unsupervised_loss = loss.sum() + lgt_reg

        result = {
            'val_nce': unsupervised_loss
        }
        return result
```

17.4.2 Importing parts

All the bolts are modular. This means you can also arbitrarily mix and match fundamental blocks from across approaches.

Example 1: Use the VAE encoder for a GAN as a generator

```
from pl_bolts.models.gans import GAN
from pl_bolts.models.autoencoders.basic_vae import Encoder

class FancyGAN(GAN):

    def init_generator(self, img_dim):
        generator = Encoder(...)
        return generator

trainer = Trainer(...)
trainer.fit(FancyGAN())
```

Example 2: Use the contrastive task of AMDIM in CPC

```
from pl_bolts.models.self_supervised import AMDIM, CPC_v2

default_amdim_task = AMDIM().contrastive_task
model = CPC_v2(contrastive_task=default_amdim_task, encoder='cpc_default')
# you might need to modify the cpc encoder depending on what you use
```

17.4.3 Compose new ideas

You may also be interested in creating completely new approaches that mix and match all sorts of different pieces together

```
# this model is for illustration purposes, it makes no research sense but it's␣
↪intended to show
# that you can be as creative and expressive as you want.
class MyNewContrastiveApproach(pl.LightningModule):

    def __init__(self):
        suoer().__init_()

        self.gan = GAN()
        self.vae = VAE()
        self.amdim = AMDIM()
        self.cpc = CPC_v2

    def training_step(self, batch, batch_idx):
        (x, y) = batch

        feat_a = self.gan.generator(x)
        feat_b = self.vae.encoder(x)

        unsup_loss = self.amdim(feat_a) + self.cpc(feat_b)

        vae_loss = self.vae._step(batch)
        gan_loss = self.gan.generator_loss(x)
```

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```
        return unsup_loss + vae_loss + gan_loss
```

CHAPTER

EIGHTEEN

CLASSIC ML MODELS

This module implements classic machine learning models in PyTorch Lightning, including linear regression and logistic regression. Unlike other libraries that implement these models, here we use PyTorch to enable multi-GPU, multi-TPU and half-precision training.

18.1 Linear Regression

Linear regression fits a linear model between a real-valued target variable y and one or more features X. We estimate the regression coefficients that minimize the mean squared error between the predicted and true target values.

We formulate the linear regression model as a single-layer neural network. By default we include only one neuron in the output layer, although you can specify the *output_dim* yourself.

Add either L1 or L2 regularization, or both, by specifying the regularization strength (default 0).

```
from pl_bolts.models.regression import LinearRegression
import pytorch_lightning as pl
from pl_bolts.datamodules import SklearnDataModule
from sklearn.datasets import load_boston

X, y = load_boston(return_X_y=True)
loaders = SklearnDataModule(X, y)

model = LinearRegression(input_dim=13)
trainer = pl.Trainer()
trainer.fit(model, train_dataloader=loaders.train_dataloader(), val_
↪dataloaders=loaders.val_dataloader())
trainer.test(test_dataloaders=loaders.test_dataloader())
```

class pl_bolts.models.regression.linear_regression.**LinearRegression**(*input_dim*, *output_dim=1*, *bias=True*, *learning_rate=0.0001*, *optimizer=torch.optim.Adam*, *l1_strength=0.0*, *l2_strength=0.0*, ***kwargs*)

Bases: pytorch_lightning.

Linear regression model implementing - with optional L1/L2 regularization $$min_{W} ||(Wx + b) - y ||_2^2 $$

Parameters

- **input_dim** (int) – number of dimensions of the input (1+)
- **output_dim** (int) – number of dimensions of the output (default=1)
- **bias** (bool) – If false, will not use $+b$
- **learning_rate** (float) – learning_rate for the optimizer
- **optimizer** (Optimizer) – the optimizer to use (default='Adam')
- **l1_strength** (float) – L1 regularization strength (default=None)
- **l2_strength** (float) – L2 regularization strength (default=None)

18.2 Logistic Regression

Logistic regression is a linear model used for classification, i.e. when we have a categorical target variable. This implementation supports both binary and multi-class classification.

In the binary case, we formulate the logistic regression model as a one-layer neural network with one neuron in the output layer and a sigmoid activation function. In the multi-class case, we use a single-layer neural network but now with k neurons in the output, where k is the number of classes. This is also referred to as multinomial logistic regression.

Add either L1 or L2 regularization, or both, by specifying the regularization strength (default 0).

```
from sklearn.datasets import load_iris
from pl_bolts.models.regression import LogisticRegression
from pl_bolts.datamodules import SklearnDataModule
import pytorch_lightning as pl

# use any numpy or sklearn dataset
X, y = load_iris(return_X_y=True)
dm = SklearnDataModule(X, y)

# build model
model = LogisticRegression(input_dim=4, num_classes=3)

# fit
trainer = pl.Trainer(tpu_cores=8, precision=16)
trainer.fit(model, train_dataloader=dm.train_dataloader(), val_dataloaders=dm.val_
↪dataloader())

trainer.test(test_dataloaders=dm.test_dataloader(batch_size=12))
```

Any input will be flattened across all dimensions except the first one (batch). This means images, sound, etc… work out of the box.

```
# create dataset
dm = MNISTDataModule(num_workers=0, data_dir=tmpdir)

model = LogisticRegression(input_dim=28 * 28, num_classes=10, learning_rate=0.001)
```

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```
model.prepare_data = dm.prepare_data
model.train_dataloader = dm.train_dataloader
model.val_dataloader = dm.val_dataloader
model.test_dataloader = dm.test_dataloader

trainer = pl.Trainer(max_epochs=2)
trainer.fit(model)
trainer.test(model)
# {test_acc: 0.92}
```

class pl_bolts.models.regression.logistic_regression.**LogisticRegression**(*input_dim*, *num_classes*, *bias=True*, *learning_rate=0.0001*, *optimizer=torch.optim.Adam*, *l1_strength=0.0*, *l2_strength=0.0*, ***kwargs*)

Bases: pytorch_lightning.

Logistic regression model

Parameters

- **input_dim** (int) – number of dimensions of the input (at least 1)
- **num_classes** (int) – number of class labels (binary: 2, multi-class: >2)
- **bias** (bool) – specifies if a constant or intercept should be fitted (equivalent to fit_intercept in sklearn)
- **learning_rate** (float) – learning_rate for the optimizer
- **optimizer** (Optimizer) – the optimizer to use (default='Adam')
- **l1_strength** (float) – L1 regularization strength (default=None)
- **l2_strength** (float) – L2 regularization strength (default=None)

CHAPTER

NINETEEN

AUTOENCODERS

This section houses autoencoders and variational autoencoders.

19.1 Basic AE

This is the simplest autoencoder. You can use it like so

```
from pl_bolts.models.autoencoders import AE

model = AE()
trainer = Trainer()
trainer.fit(model)
```

You can override any part of this AE to build your own variation.

```
from pl_bolts.models.autoencoders import AE

class MyAEFlavor(AE):

    def init_encoder(self, hidden_dim, latent_dim, input_width, input_height):
        encoder = YourSuperFancyEncoder(...)
        return encoder
```

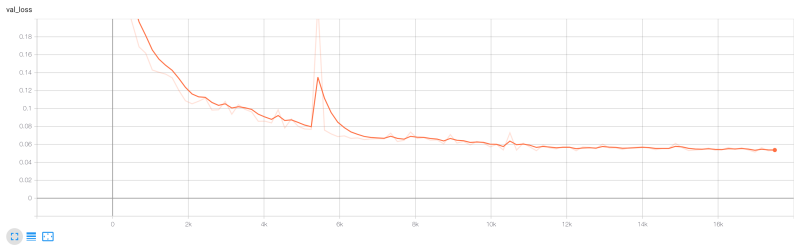
You can use the pretrained models present in bolts.

CIFAR-10 pretrained model:

```
from pl_bolts.models.autoencoders import AE

ae = AE(input_height=32)
print(AE.pretrained_weights_available())
ae = ae.from_pretrained('cifar10-resnet18')

ae.freeze()
```

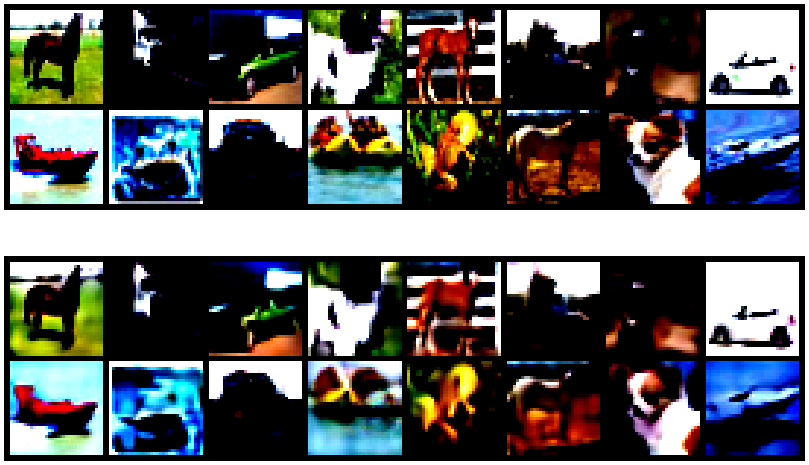
- Tensorboard for AE on CIFAR-10

Training:



Reconstructions:

Both input and generated images are normalized versions as the training was done with such images.



class pl_bolts.models.autoencoders.**AE**(*input_height*, *enc_type='resnet18'*, *first_conv=False*, *maxpool1=False*, *enc_out_dim=512*, *latent_dim=256*, *lr=0.0001*, ***kwargs*)

Bases: pytorch_lightning.

Standard AE

Model is available pretrained on different datasets:

Example:

```
# not pretrained
ae = AE()

# pretrained on cifar10
ae = AE(input_height=32).from_pretrained('cifar10-resnet18')
```

Parameters

- **input_height** (int) – height of the images
- **enc_type** (str) – option between resnet18 or resnet50

- **first_conv** (bool) – use standard kernel_size 7, stride 2 at start or replace it with kernel_size 3, stride 1 conv
- **maxpool1** (bool) – use standard maxpool to reduce spatial dim of feat by a factor of 2
- **enc_out_dim** (int) – set according to the out_channel count of encoder used (512 for resnet18, 2048 for resnet50)
- **latent_dim** (int) – dim of latent space
- **lr** (float) – learning rate for Adam

19.1.1 Variational Autoencoders

19.2 Basic VAE

Use the VAE like so.

```
from pl_bolts.models.autoencoders import VAE

model = VAE()
trainer = Trainer()
trainer.fit(model)
```

You can override any part of this VAE to build your own variation.

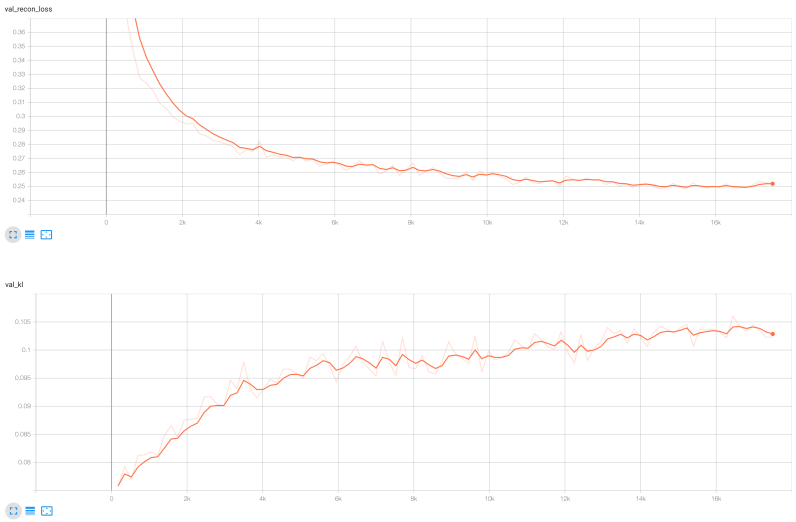
```
from pl_bolts.models.autoencoders import VAE

class MyVAEFlavor(VAE):

    def get_posterior(self, mu, std):
        # do something other than the default
        # P = self.get_distribution(self.prior, loc=torch.zeros_like(mu), scale=torch.
↪ones_like(std))

        return P
```

You can use the pretrained models present in bolts.

CIFAR-10 pretrained model:

```
from pl_bolts.models.autoencoders import VAE

vae = VAE(input_height=32)
print(VAE.pretrained_weights_available())
vae = vae.from_pretrained('cifar10-resnet18')

vae.freeze()
```

- Tensorboard for VAE on CIFAR-10



Training:

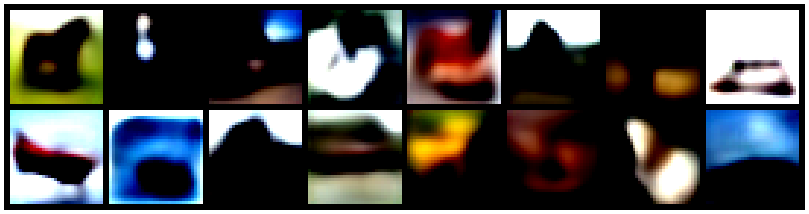
Reconstructions:

Both input and generated images are normalized versions as the training was done with such images.

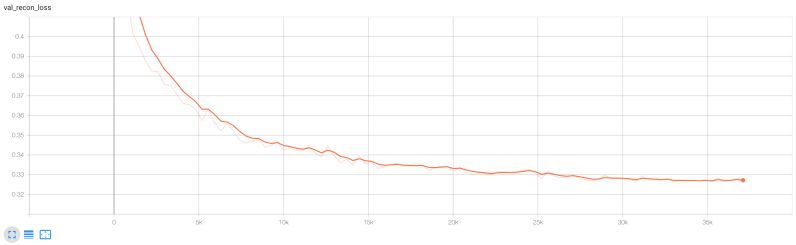
STL-10 pretrained model:

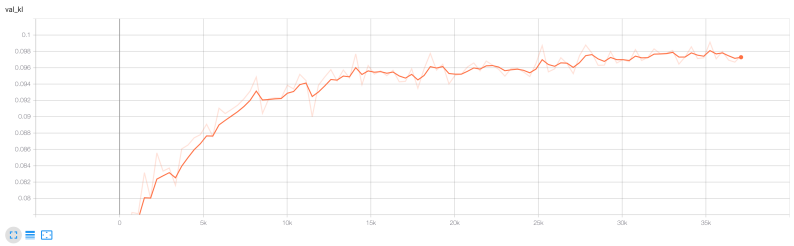
```
from pl_bolts.models.autoencoders import VAE

vae = VAE(input_height=96, first_conv=True)
print(VAE.pretrained_weights_available())
vae = vae.from_pretrained('cifar10-resnet18')

vae.freeze()
```

- Tensorboard for VAE on STL-10



Training:





class pl_bolts.models.autoencoders.**VAE**(*input_height*, *enc_type='resnet18'*, *first_conv=False*, *maxpool1=False*, *enc_out_dim=512*, *kl_coeff=0.1*, *latent_dim=256*, *lr=0.0001*, ***kwargs*)

Bases: pytorch_lightning.

Standard VAE with Gaussian Prior and approx posterior.

Model is available pretrained on different datasets:

Example:

```
# not pretrained
vae = VAE()

# pretrained on cifar10
vae = VAE(input_height=32).from_pretrained('cifar10-resnet18')

# pretrained on stl10
vae = VAE(input_height=32).from_pretrained('stl10-resnet18')
```

Parameters

- **input_height** (int) – height of the images
- **enc_type** (str) – option between resnet18 or resnet50

- **first_conv** (bool) – use standard kernel_size 7, stride 2 at start or replace it with kernel_size 3, stride 1 conv
- **maxpool1** (bool) – use standard maxpool to reduce spatial dim of feat by a factor of 2
- **enc_out_dim** (int) – set according to the out_channel count of encoder used (512 for resnet18, 2048 for resnet50)
- **kl_coeff** (float) – coefficient for kl term of the loss
- **latent_dim** (int) – dim of latent space
- **lr** (float) – learning rate for Adam

CHAPTER

TWENTY

CONVOLUTIONAL ARCHITECTURES

This package lists contributed convolutional architectures.

20.1 GPT-2

class pl_bolts.models.vision.**GPT2**(*embed_dim*, *heads*, *layers*, *num_positions*, *vocab_size*, *num_classes*)

Bases: pytorch_lightning.

GPT-2 from language Models are Unsupervised Multitask Learners

Paper by: Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever

Implementation contributed by:

- Teddy Koker

Example:

```
from pl_bolts.models.vision import GPT2

seq_len = 17
batch_size = 32
vocab_size = 16
x = torch.randint(0, vocab_size, (seq_len, batch_size))
model = GPT2(embed_dim=32, heads=2, layers=2, num_positions=seq_len, vocab_
↪size=vocab_size, num_classes=4)
results = model(x)
```

forward(*x*, *classify=False*)

Expect input as shape [sequence len, batch] If classify, return classification logits

20.2 Image GPT

class pl_bolts.models.vision.**ImageGPT**(*embed_dim=16*, *heads=2*, *layers=2*, *pixels=28*, *vocab_size=16*, *num_classes=10*, *classify=False*, *batch_size=64*, *learning_rate=0.01*, *steps=25000*, *data_dir='.'*, *num_workers=8*, ***kwargs*)

Bases: pytorch_lightning.

Paper: Generative Pretraining from Pixels [original paper code].

Paper by: Mark Che, Alec Radford, Rewon Child, Jeff Wu, Heewoo Jun, Prafulla Dhariwal, David Luan, Ilya Sutskever

Implementation contributed by:

- Teddy Koker

Original repo with results and more implementation details:

- https://github.com/teddykoker/image-gpt

Example Results (Photo credits: Teddy Koker):

Default arguments:

Table 1: Argument Defaults

Argument	Default	iGPT-S (Chen et al.)
–embed_dim	16	512
–heads	2	8
–layers	8	24
–pixels	28	32
–vocab_size	16	512
–num_classes	10	10
–batch_size	64	128
–learning_rate	0.01	0.01
–steps	25000	1000000

Example:

```
import pytorch_lightning as pl
from pl_bolts.models.vision import ImageGPT

dm = MNISTDataModule('.')
model = ImageGPT(dm)

pl.Trainer(gpu=4).fit(model)
```

As script:

```
cd pl_bolts/models/vision/image_gpt
python igpt_module.py --learning_rate 1e-2 --batch_size 32 --gpus 4
```

Parameters

- **embed_dim** (int) – the embedding dim
- **heads** (int) – number of attention heads
- **layers** (int) – number of layers
- **pixels** (int) – number of input pixels
- **vocab_size** (int) – vocab size
- **num_classes** (int) – number of classes in the input
- **classify** (bool) – true if should classify
- **batch_size** (int) – the batch size
- **learning_rate** (float) – learning rate
- **steps** (int) – number of steps for cosine annealing
- **data_dir** (str) – where to store data
- **num_workers** (int) – num_data workers

20.3 Pixel CNN

class pl_bolts.models.vision.**PixelCNN**(*input_channels*, *hidden_channels=256*, *num_blocks=5*)

Bases: torch.nn.

Implementation of Pixel CNN.

Paper authors: Aaron van den Oord, Nal Kalchbrenner, Oriol Vinyals, Lasse Espeholt, Alex Graves, Koray Kavukcuoglu

Implemented by:

- William Falcon

Example:

```
>>> from pl_bolts.models.vision import PixelCNN
>>> import torch
...
>>> model = PixelCNN(input_channels=3)
>>> x = torch.rand(5, 3, 64, 64)
>>> out = model(x)
...
>>> out.shape
torch.Size([5, 3, 64, 64])
```

20.4 UNet

class pl_bolts.models.vision.**UNet**(*num_classes*, *input_channels=3*, *num_layers=5*, *features_start=64*, *bilinear=False*)

Bases: torch.nn.

Paper: U-Net: Convolutional Networks for Biomedical Image Segmentation

Paper authors: Olaf Ronneberger, Philipp Fischer, Thomas Brox

Implemented by:

- Annika Brundyn
- Akshay Kulkarni

Parameters

- **num_classes** (int) – Number of output classes required
- **input_channels** (int) – Number of channels in input images (default 3)
- **num_layers** (int) – Number of layers in each side of U-net (default 5)
- **features_start** (int) – Number of features in first layer (default 64)
- **bilinear** (bool) – Whether to use bilinear interpolation or transposed convolutions (default) for upsampling.

20.5 Semantic Segmentation

Model template to use for semantic segmentation tasks. The model uses a UNet architecture by default. Override any part of this model to build your own variation.

```
from pl_bolts.models.vision import SemSegment
from pl_bolts.datamodules import KittiDataModule
import pytorch_lightning as pl

dm = KittiDataModule('path/to/kitt/dataset/', batch_size=4)
model = SemSegment(datamodule=dm)
trainer = pl.Trainer()
trainer.fit(model)
```

class pl_bolts.models.vision.**SemSegment**(*lr=0.01*, *num_classes=19*, *num_layers=5*, *features_start=64*, *bilinear=False*)

Bases: pytorch_lightning.

Basic model for semantic segmentation. Uses UNet architecture by default.

The default parameters in this model are for the KITTI dataset. Note, if you'd like to use this model as is, you will first need to download the KITTI dataset yourself. You can download the dataset here.

Implemented by:

- Annika Brundyn

Parameters

- **num_layers** (int) – number of layers in each side of U-net (default 5)
- **features_start** (int) – number of features in first layer (default 64)
- **bilinear** (bool) – whether to use bilinear interpolation (True) or transposed convolutions (default) for upsampling.
- **lr** (float) – learning (default 0.01)

CHAPTER

TWENTYONE

GANS

Collection of Generative Adversarial Networks

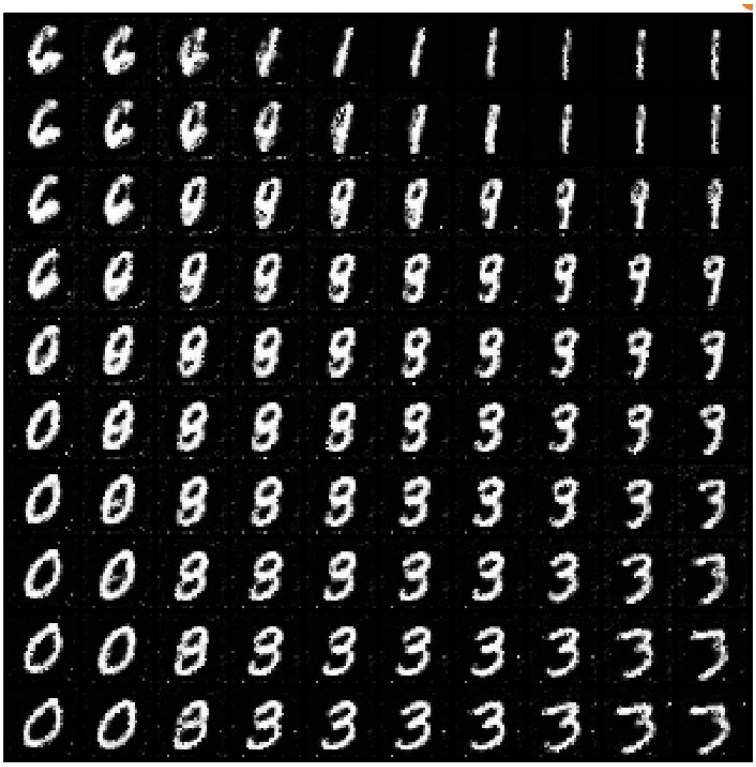
21.1 Basic GAN

This is a vanilla GAN. This model can work on any dataset size but results are shown for MNIST. Replace the encoder, decoder or any part of the training loop to build a new method, or simply finetune on your data.

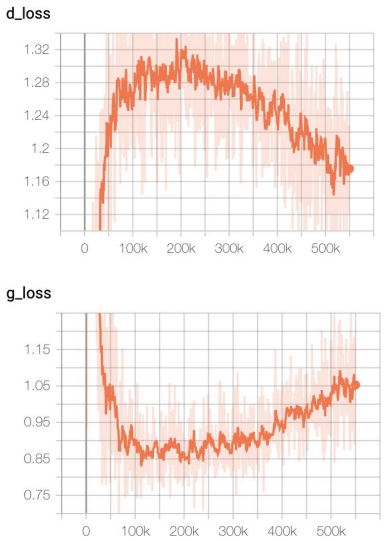
Implemented by:

- William Falcon

Example outputs:



Loss curves:




```
from pl_bolts.models.gans import GAN
...
gan = GAN()
trainer = Trainer()
trainer.fit(gan)
```

class pl_bolts.models.gans.**GAN**(*input_channels*, *input_height*, *input_width*, *latent_dim=32*, *learning_rate=0.0002*, ***kwargs*)

Bases: pytorch_lightning.

Vanilla GAN implementation.

Example:

```
from pl_bolts.models.gans import GAN

m = GAN()
Trainer(gpus=2).fit(m)
```

Example CLI:

```
# mnist
python  basic_gan_module.py --gpus 1

# imagenet
python  basic_gan_module.py --gpus 1 --dataset 'imagenet2012'
--data_dir /path/to/imagenet/folder/ --meta_dir ~/path/to/meta/bin/folder
--batch_size 256 --learning_rate 0.0001
```

Parameters

- **input_channels** (int) – number of channels of an image
- **input_height** (int) – image height
- **input_width** (int) – image width
- **latent_dim** (int) – emb dim for encoder
- **learning_rate** (float) – the learning rate

forward(*z*)

Generates an image given input noise z

Example:

```
z = torch.rand(batch_size, latent_dim)
gan = GAN.load_from_checkpoint(PATH)
img = gan(z)
```

21.2 DCGAN

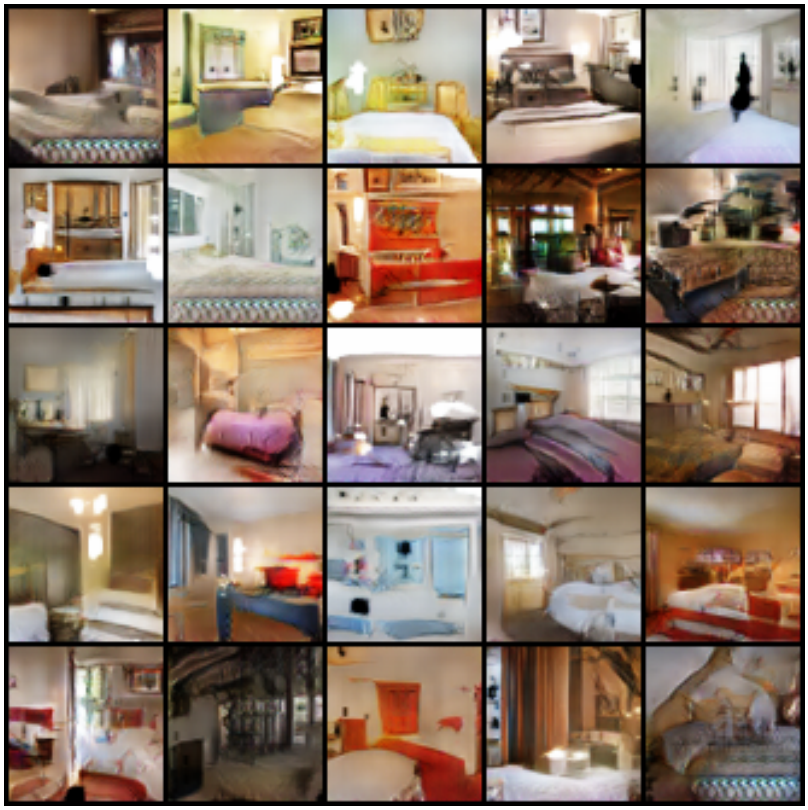
DCGAN implementation from the paper Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks. The implementation is based on the version from PyTorch's examples.

Implemented by:

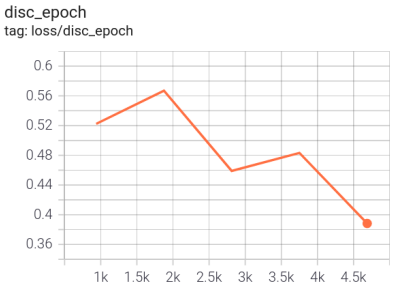
- Christoph Clement

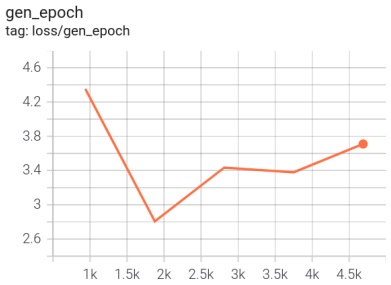
Example MNIST outputs:

Example LSUN bedroom outputs:

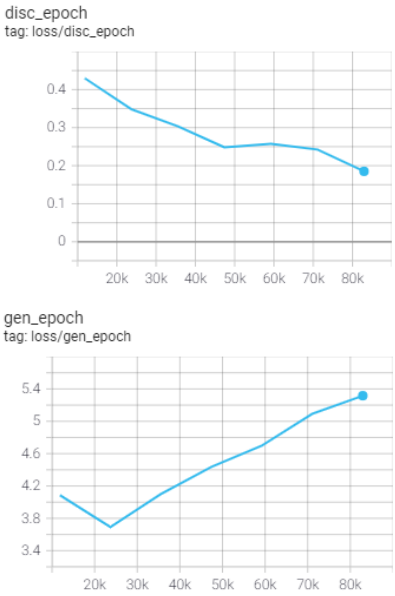


MNIST Loss curves:





LSUN Loss curves:



class pl_bolts.models.gans.**DCGAN**(*beta1=0.5*, *feature_maps_gen=64*, *feature_maps_disc=64*, *image_channels=1*, *latent_dim=100*, *learning_rate=0.0002*, ***kwargs*)

Bases: pytorch_lightning.

DCGAN implementation.

Example:

```
from pl_bolts.models.gans import DCGAN

m = DCGAN()
Trainer(gpus=2).fit(m)
```

Example CLI:

```
# mnist
python dcgan_module.py --gpus 1

# cifar10
python dcgan_module.py --gpus 1 --dataset cifar10 --image_channels 3
```

Parameters

- **beta1** (float) – Beta1 value for Adam optimizer
- **feature_maps_gen** (int) – Number of feature maps to use for the generator
- **feature_maps_disc** (int) – Number of feature maps to use for the discriminator
- **image_channels** (int) – Number of channels of the images from the dataset
- **latent_dim** (int) – Dimension of the latent space
- **learning_rate** (float) – Learning rate

forward(*noise*)

Generates an image given input noise

Example:

```
noise = torch.rand(batch_size, latent_dim)
gan = GAN.load_from_checkpoint(PATH)
img = gan(noise)
```

Return type Tensor

CHAPTER

TWENTYTWO

REINFORCEMENT LEARNING

This module is a collection of common RL approaches implemented in Lightning.

22.1 Module authors

Contributions by: Donal Byrne

- DQN
- Double DQN
- Dueling DQN
- Noisy DQN
- NStep DQN
- Prioritized Experience Replay DQN
- Reinforce
- Vanilla Policy Gradient

Note: RL models currently only support CPU and single GPU training with *distributed_backend=dp*. Full GPU support will be added in later updates.

22.2 DQN Models

The following models are based on DQN. DQN uses value based learning where it is deciding what action to take based on the model's current learned value (V), or the state action value (Q) of the current state. These values are defined as the discounted total reward of the agents state or state action pair.

22.2.1 Deep-Q-Network (DQN)

DQN model introduced in Playing Atari with Deep Reinforcement Learning. Paper authors: Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra, Martin Riedmiller.

Original implementation by: Donal Byrne

The DQN was introduced in Playing Atari with Deep Reinforcement Learning by researchers at DeepMind. This took the concept of tabular Q learning and scaled it to much larger problems by approximating the Q function using a deep neural network.

The goal behind DQN was to take the simple control method of Q learning and scale it up in order to solve complicated tasks. As well as this, the method needed to be stable. The DQN solves these issues with the following additions.

Approximated Q Function

Storing Q values in a table works well in theory, but is completely unscalable. Instead, the authors approximate the Q function using a deep neural network. This allows the DQN to be used for much more complicated tasks

Replay Buffer

Similar to supervised learning, the DQN learns on randomly sampled batches of previous data stored in an Experience Replay Buffer. The 'target' is calculated using the Bellman equation

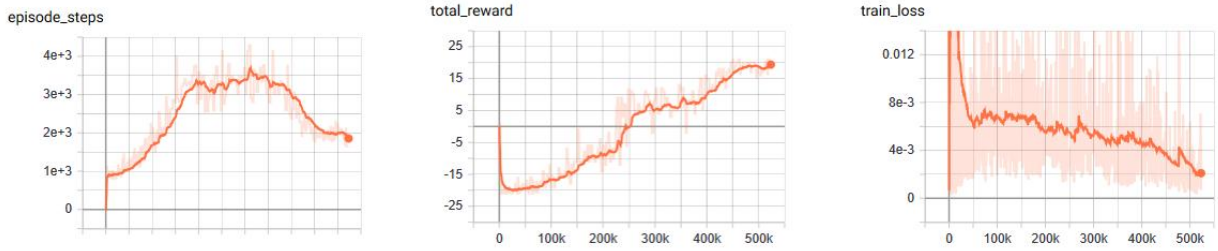
$$Q(s,a) < -(r + \gamma \max_{a' \in A} Q(s',a'))^2$$

and then we optimize using SGD just like a standard supervised learning problem.

$$L = (Q(s,a) - (r + \gamma \max_{a' \in A} Q(s',a'))^2$$

DQN Results

DQN: Pong



Example:

```
from pl_bolts.models.rl import DQN
dqn = DQN("PongNoFrameskip-v4")
trainer = Trainer()
trainer.fit(dqn)
```

class pl_bolts.models.rl.dqn_model.**DQN**(*env*, *eps_start=1.0*, *eps_end=0.02*, *eps_last_frame=150000*, *sync_rate=1000*, *gamma=0.99*, *learning_rate=0.0001*, *batch_size=32*, *replay_size=100000*, *warm_start_size=10000*, *avg_reward_len=100*, *min_episode_reward=-21*, *seed=123*, *batches_per_epoch=1000*, *n_steps=1*, ***kwargs*)

Bases: pytorch_lightning.

Basic DQN Model

PyTorch Lightning implementation of DQN Paper authors: Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra, Martin Riedmiller. Model implemented by:

- *Donal Byrne <https://github.com/djbyrne>*

Example

```
>>> from pl_bolts.models.rl.dqn_model import DQN
...
>>> model = DQN("PongNoFrameskip-v4")
```

Train:

```
trainer = Trainer()
trainer.fit(model)
```

Note: This example is based on: https://github.com/PacktPublishing/Deep-Reinforcement-Learning-Hands-On-Second-Edition/blob/master/Chapter06/02_dqn_pong.py

Note: Currently only supports CPU and single GPU training with *distributed_backend=dp*

Parameters

- **env** (str) – gym environment tag
- **eps_start** (float) – starting value of epsilon for the epsilon-greedy exploration
- **eps_end** (float) – final value of epsilon for the epsilon-greedy exploration
- **eps_last_frame** (int) – the final frame in for the decrease of epsilon. At this frame espilon = eps_end
- **sync_rate** (int) – the number of iterations between syncing up the target network with the train network
- **gamma** (float) – discount factor
- **learning_rate** (float) – learning rate
- **batch_size** (int) – size of minibatch pulled from the DataLoader
- **replay_size** (int) – total capacity of the replay buffer
- **warm_start_size** (int) – how many random steps through the environment to be carried out at the start of training to fill the buffer with a starting point
- **avg_reward_len** (int) – how many episodes to take into account when calculating the avg reward
- **min_episode_reward** (int) – the minimum score that can be achieved in an episode. Used for filling the avg buffer before training begins
- **seed** (int) – seed value for all RNG used
- **batches_per_epoch** (int) – number of batches per epoch
- **n_steps** (int) – size of n step look ahead

static add_model_specific_args(*arg_parser*)
Adds arguments for DQN model

Note: These params are fine tuned for Pong env.

Parameters **arg_parser**¶ (ArgumentParser) – parent parser

Return type ArgumentParser

build_networks()
Initializes the DQN train and target networks

Return type None

configure_optimizers()
Initialize Adam optimizer

Return type List[Optimizer]

forward(*x*)
Passes in a state x through the network and gets the q_values of each action as an output

Parameters **x**¶ (Tensor) – environment state

Return type Tensor

Returns q values

static make_environment(*env_name*, *seed=None*)
Initialise gym environment

Parameters

- **env_name**¶ (str) – environment name or tag
- **seed**¶ (Optional[int]) – value to seed the environment RNG for reproducibility

Return type object

Returns gym environment

populate(*warm_start*)
Populates the buffer with initial experience

Return type None

run_n_episodes(*env*, *n_epsiodes=1*, *epsilon=1.0*)
Carries out N episodes of the environment with the current agent

Parameters

- **env**¶ – environment to use, either train environment or test environment
- **n_epsiodes**¶ (int) – number of episodes to run
- **epsilon**¶ (float) – epsilon value for DQN agent

Return type List[int]

test_dataloader()
Get test loader

Return type DataLoader

test_epoch_end(*outputs*)
Log the avg of the test results

Return type Dict[str, Tensor]

test_step(**args*, ***kwargs*)
Evaluate the agent for 10 episodes

Return type Dict[str, Tensor]

train_batch()
Contains the logic for generating a new batch of data to be passed to the DataLoader

Return type Tuple[Tensor, Tensor, Tensor, Tensor, Tensor]

Returns yields a Experience tuple containing the state, action, reward, done and next_state.

train_dataloader()
Get train loader

Return type DataLoader

training_step(*batch*, *_*)
Carries out a single step through the environment to update the replay buffer. Then calculates loss based on the minibatch recieved

Parameters

- **batch** (Tuple[Tensor, Tensor]) – current mini batch of replay data
- **_** – batch number, not used

Return type OrderedDict

Returns Training loss and log metrics

22.2.2 Double DQN

Double DQN model introduced in Deep Reinforcement Learning with Double Q-learning Paper authors: Hado van Hasselt, Arthur Guez, David Silver

Original implementation by: Donal Byrne

The original DQN tends to overestimate Q values during the Bellman update, leading to instability and is harmful to training. This is due to the max operation in the Bellman equation.

We are constantly taking the max of our agents estimates during our update. This may seem reasonable, if we could trust these estimates. However during the early stages of training, the estimates for these values will be off center and can lead to instability in training until our estimates become more reliable

The Double DQN fixes this overestimation by choosing actions for the next state using the main trained network but uses the values of these actions from the more stable target network. So we are still going to take the greedy action, but the value will be less "optimisitc" because it is chosen by the target network.

DQN expected return

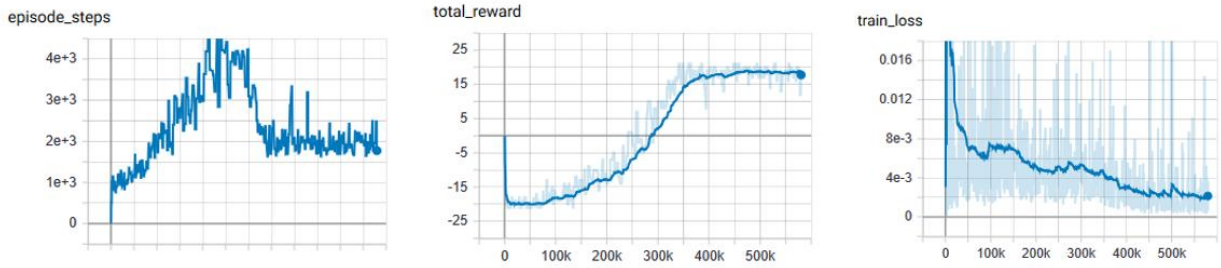
$$Q(s_t, a_t) = r_t + \gamma * \max_{Q'}(S_{t+1}, a)$$

Double DQN expected return

$$Q(s_t, a_t) = r_t + \gamma * \max Q'(S_{t+1}, \arg\max_{Q}(S_{t+1}, a))$$

Double DQN Results

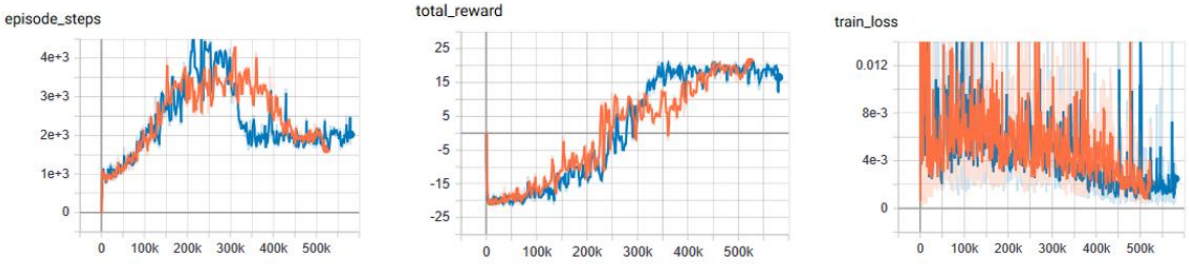
Double DQN: Pong



DQN vs Double DQN: Pong

orange: DQN

blue: Double DQN



Example:

```
from pl_bolts.models.rl import DoubleDQN
ddqn = DoubleDQN("PongNoFrameskip-v4")
trainer = Trainer()
trainer.fit(ddqn)
```

class pl_bolts.models.rl.double_dqn_model.**DoubleDQN**(*env*, *eps_start=1.0*, *eps_end=0.02*, *eps_last_frame=150000*, *sync_rate=1000*, *gamma=0.99*, *learning_rate=0.0001*, *batch_size=32*, *replay_size=100000*, *warm_start_size=10000*, *avg_reward_len=100*, *min_episode_reward=-21*, *seed=123*, *batches_per_epoch=1000*, *n_steps=1*, ***kwargs*)

Bases: pytorch_lightning.

Double Deep Q-network (DDQN) PyTorch Lightning implementation of Double DQN

Paper authors: Hado van Hasselt, Arthur Guez, David Silver

Model implemented by:

- *Donal Byrne <https://github.com/djbyrne>*

Example

```
>>> from pl_bolts.models.rl.double_dqn_model import DoubleDQN
...
>>> model = DoubleDQN("PongNoFrameskip-v4")
```

Train:

```
trainer = Trainer()
trainer.fit(model)
```

Note: This example is based on https://github.com/PacktPublishing/Deep-Reinforcement-Learning-Hands-On-Second-Edition/blob/master/Chapter08/03_dqn_double.py

Note: Currently only supports CPU and single GPU training with *distributed_backend=dp*

Parameters

- **env** (str) – gym environment tag
- **eps_start** (float) – starting value of epsilon for the epsilon-greedy exploration
- **eps_end** (float) – final value of epsilon for the epsilon-greedy exploration
- **eps_last_frame** (int) – the final frame in for the decrease of epsilon. At this frame espilon = eps_end
- **sync_rate** (int) – the number of iterations between syncing up the target network with the train network
- **gamma** (float) – discount factor
- **learning_rate** (float) – learning rate
- **batch_size** (int) – size of minibatch pulled from the DataLoader
- **replay_size** (int) – total capacity of the replay buffer
- **warm_start_size** (int) – how many random steps through the environment to be carried out at the start of training to fill the buffer with a starting point
- **avg_reward_len** (int) – how many episodes to take into account when calculating the avg reward
- **min_episode_reward** (int) – the minimum score that can be achieved in an episode. Used for filling the avg buffer before training begins
- **seed** (int) – seed value for all RNG used
- **batches_per_epoch** (int) – number of batches per epoch
- **n_steps** (int) – size of n step look ahead

training_step(*batch*, _)

Carries out a single step through the environment to update the replay buffer. Then calculates loss based on the minibatch recieved

Parameters

- **batch** (Tuple[Tensor, Tensor]) – current mini batch of replay data
- **_** – batch number, not used

Return type OrderedDict

Returns Training loss and log metrics

22.2.3 Dueling DQN

Dueling DQN model introduced in Dueling Network Architectures for Deep Reinforcement Learning Paper authors: Ziyu Wang, Tom Schaul, Matteo Hessel, Hado van Hasselt, Marc Lanctot, Nando de Freitas

Original implementation by: Donal Byrne

The Q value that we are trying to approximate can be divided into two parts, the value state V(s) and the 'advantage' of actions in that state A(s, a). Instead of having one full network estimate the entire Q value, Dueling DQN uses two estimator heads in order to separate the estimation of the two parts.

The value is the same as in value iteration. It is the discounted expected reward achieved from state s. Think of the value as the 'base reward' from being in state s.

The advantage tells us how much 'extra' reward we get from taking action a while in state s. The advantage bridges the gap between Q(s, a) and V(s) as Q(s, a) = V(s) + A(s, a).

In the paper *Dueling Network Architectures for Deep Reinforcement Learning <https://arxiv.org/abs/1511.06581>* the network uses two heads, one outputs the value state and the other outputs the advantage. This leads to better training stability, faster convergence and overall better results. The V head outputs a single scalar (the state value), while the advantage head outputs a tensor equal to the size of the action space, containing an advantage value for each action in state s.

Changing the network architecture is not enough, we also need to ensure that the advantage mean is 0. This is done by subtracting the mean advantage from the Q value. This essentially pulls the mean advantage to 0.

$$Q(s,a) = V(s) + A(s,a) - 1/N * \sum_{k}(A(s,k)$$

Dueling DQN Benefits

- Ability to efficiently learn the state value function. In the dueling network, every Q update also updates the value stream, where as in DQN only the value of the chosen action is updated. This provides a better approximation of the values
- The differences between total Q values for a given state are quite small in relation to the magnitude of Q. The difference in the Q values between the best action and the second best action can be very small, while the average state value can be much larger. The differences in scale can introduce noise, which may lead to the greedy policy switching the priority of these actions. The seperate estimators for state value and advantage makes the Dueling DQN robust to this type of scenario

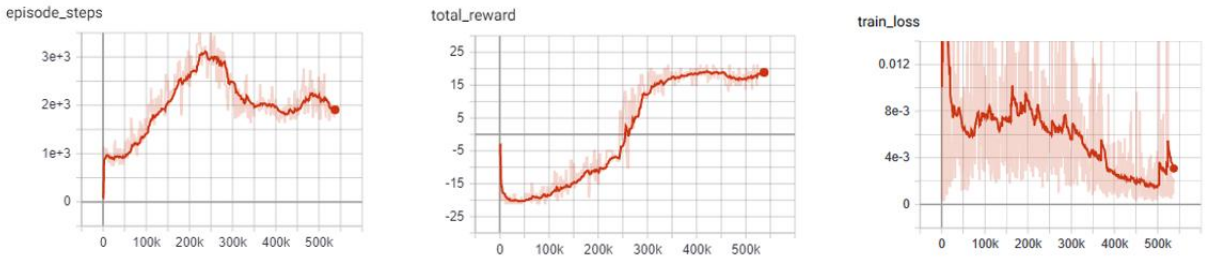
Dueling DQN Results

The results below a noticeable improvement from the original DQN network.

Dueling DQN baseline: Pong

Similar to the results of the DQN baseline, the agent has a period where the number of steps per episodes increase as it begins to hold its own against the heuristic oppoent, but then the steps per episode quickly begins to drop as it gets better and starts to beat its opponent faster and faster. There is a noticable point at step ~250k where the agent goes from losing to winning.

As you can see by the total rewards, the dueling network's training progression is very stable and continues to trend upward until it finally plateus.

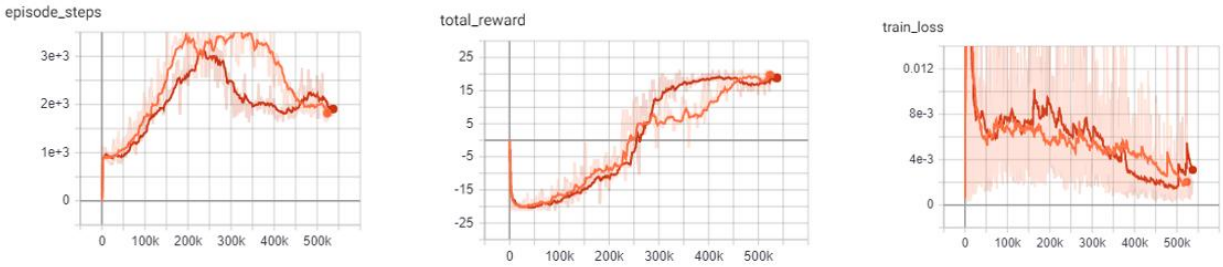


DQN vs Dueling DQN: Pong

In comparison to the base DQN, we see that the Dueling network's training is much more stable and is able to reach a score in the high teens faster than the DQN agent. Even though the Dueling network is more stable and out performs DQN early in training, by the end of training the two networks end up at the same point.

This could very well be due to the simplicity of the Pong environment.

- Orange: DQN
- Red: Dueling DQN



Example:

```
from pl_bolts.models.rl import DuelingDQN
dueling_dqn = DuelingDQN("PongNoFrameskip-v4")
trainer = Trainer()
trainer.fit(dueling_dqn)
```

class pl_bolts.models.rl.dueling_dqn_model.**DuelingDQN**(*env*, *eps_start=1.0*, *eps_end=0.02*, *eps_last_frame=150000*, *sync_rate=1000*, *gamma=0.99*, *learning_rate=0.0001*, *batch_size=32*, *replay_size=100000*, *warm_start_size=10000*, *avg_reward_len=100*, *min_episode_reward=-21*, *seed=123*, *batches_per_epoch=1000*, *n_steps=1*, ***kwargs*)

Bases: pytorch_lightning.

PyTorch Lightning implementation of Dueling DQN

Paper authors: Ziyu Wang, Tom Schaul, Matteo Hessel, Hado van Hasselt, Marc Lanctot, Nando de Freitas

Model implemented by:

- *Donal Byrne <https://github.com/djbyrne>*

Example

```
>>> from pl_bolts.models.rl.dueling_dqn_model import DuelingDQN
...
>>> model = DuelingDQN("PongNoFrameskip-v4")
```

Train:

```
trainer = Trainer()
trainer.fit(model)
```

Note: Currently only supports CPU and single GPU training with *distributed_backend=dp*

Parameters

- **env** (str) – gym environment tag
- **eps_start** (float) – starting value of epsilon for the epsilon-greedy exploration
- **eps_end** (float) – final value of epsilon for the epsilon-greedy exploration
- **eps_last_frame** (int) – the final frame in for the decrease of epsilon. At this frame espilon = eps_end
- **sync_rate** (int) – the number of iterations between syncing up the target network with the train network
- **gamma** (float) – discount factor
- **learning_rate** (float) – learning rate
- **batch_size** (int) – size of minibatch pulled from the DataLoader
- **replay_size** (int) – total capacity of the replay buffer

- **warm_start_size** (int) – how many random steps through the environment to be carried out at the start of training to fill the buffer with a starting point
- **avg_reward_len** (int) – how many episodes to take into account when calculating the avg reward
- **min_episode_reward** (int) – the minimum score that can be achieved in an episode. Used for filling the avg buffer before training begins
- **seed** (int) – seed value for all RNG used
- **batches_per_epoch** (int) – number of batches per epoch
- **n_steps** (int) – size of n step look ahead

build_networks()
Initializes the Dueling DQN train and target networks

Return type None

22.2.4 Noisy DQN

Noisy DQN model introduced in Noisy Networks for Exploration Paper authors: Meire Fortunato, Mohammad Gheshlaghi Azar, Bilal Piot, Jacob Menick, Ian Osband, Alex Graves, Vlad Mnih, Remi Munos, Demis Hassabis, Olivier Pietquin, Charles Blundell, Shane Legg

Original implementation by: Donal Byrne

Up until now the DQN agent uses a seperate exploration policy, generally epsilon-greedy where start and end values are set for its exploration. *Noisy Networks For Exploration <https://arxiv.org/abs/1706.10295>* introduces a new exploration strategy by adding noise parameters to the weights of the fully connect layers which get updated during backpropagation of the network. The noise parameters drive the exploration of the network instead of simply taking random actions more frequently at the start of training and less frequently towards the end. The of authors of propose two ways of doing this.

During the optimization step a new set of noisy parameters are sampled. During training the agent acts according to the fixed set of parameters. At the next optimization step, the parameters are updated with a new sample. This ensures the agent always acts based on the parameters that are drawn from the current noise distribution.

The authors propose two methods of injecting noise to the network.

1) Independent Gaussian Noise: This injects noise per weight. For each weight a random value is taken from the distribution. Noise parameters are stored inside the layer and are updated during backpropagation. The output of the layer is calculated as normal.

2) Factorized Gaussian Noise: This injects nosier per input/ouput. In order to minimize the number of random values this method stores two random vectors, one with the size of the input and the other with the size of the output. Using these two vectors, a random matrix is generated for the layer by calculating the outer products of the vector

Noisy DQN Benefits

- Improved exploration function. Instead of just performing completely random actions, we add decreasing amount of noise and uncertainty to our policy allowing to explore while still utilising its policy.
- The fact that this method is automatically tuned means that we do not have to tune hyper parameters for epsilon-greedy!

Note: For now I have just implemented the Independant Gaussian as it has been reported there isn't much difference in results for these benchmark environments.

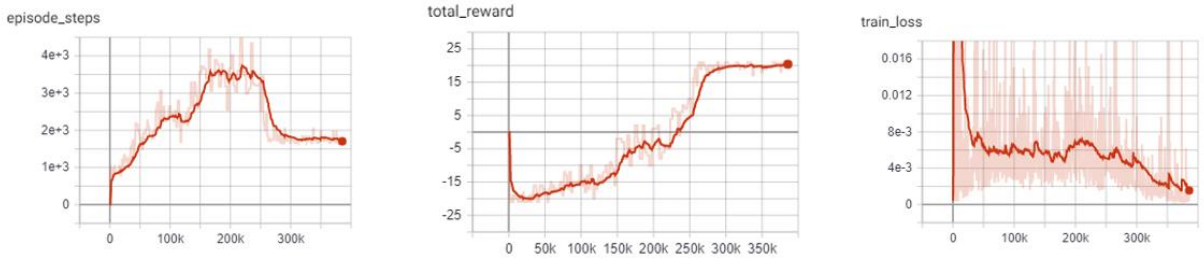
In order to update the basic DQN to a Noisy DQN we need to do the following

Noisy DQN Results

The results below improved stability and faster performance growth.

Noisy DQN baseline: Pong

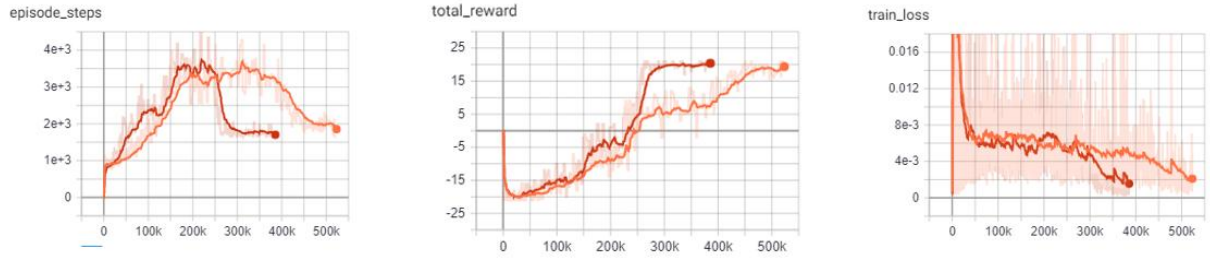
Similar to the other improvements, the average score of the agent reaches positive numbers around the 250k mark and steadily increases till convergence.



DQN vs Noisy DQN: Pong

In comparison to the base DQN, the Noisy DQN is more stable and is able to converge on an optimal policy much faster than the original. It seems that the replacement of the epsilon-greedy strategy with network noise provides a better form of exploration.

- Orange: DQN
- Red: Noisy DQN



Example:

```
from pl_bolts.models.rl import NoisyDQN
noisy_dqn = NoisyDQN("PongNoFrameskip-v4")
trainer = Trainer()
trainer.fit(noisy_dqn)
```

class pl_bolts.models.rl.noisy_dqn_model.**NoisyDQN**(*env*, *eps_start=1.0*, *eps_end=0.02*, *eps_last_frame=150000*, *sync_rate=1000*, *gamma=0.99*, *learning_rate=0.0001*, *batch_size=32*, *replay_size=100000*, *warm_start_size=10000*, *avg_reward_len=100*, *min_episode_reward=-21*, *seed=123*, *batches_per_epoch=1000*, *n_steps=1*, ***kwargs*)

Bases: pytorch_lightning.

PyTorch Lightning implementation of Noisy DQN

Paper authors: Meire Fortunato, Mohammad Gheshlaghi Azar, Bilal Piot, Jacob Menick, Ian Osband, Alex Graves, Vlad Mnih, Remi Munos, Demis Hassabis, Olivier Pietquin, Charles Blundell, Shane Legg

Model implemented by:

- *Donal Byrne <https://github.com/djbyrne>*

Example

```
>>> from pl_bolts.models.rl.noisy_dqn_model import NoisyDQN
...
>>> model = NoisyDQN("PongNoFrameskip-v4")
```

Train:

```
trainer = Trainer()
trainer.fit(model)
```

Note: Currently only supports CPU and single GPU training with *distributed_backend=dp*

Parameters

- **env** (str) – gym environment tag
- **eps_start** (float) – starting value of epsilon for the epsilon-greedy exploration
- **eps_end** (float) – final value of epsilon for the epsilon-greedy exploration
- **eps_last_frame** (int) – the final frame in for the decrease of epsilon. At this frame espilon = eps_end
- **sync_rate** (int) – the number of iterations between syncing up the target network with the train network
- **gamma** (float) – discount factor

- **learning_rate** (float) – learning rate
- **batch_size** (int) – size of minibatch pulled from the DataLoader
- **replay_size** (int) – total capacity of the replay buffer
- **warm_start_size** (int) – how many random steps through the environment to be carried out at the start of training to fill the buffer with a starting point
- **avg_reward_len** (int) – how many episodes to take into account when calculating the avg reward
- **min_episode_reward** (int) – the minimum score that can be achieved in an episode. Used for filling the avg buffer before training begins
- **seed** (int) – seed value for all RNG used
- **batches_per_epoch** (int) – number of batches per epoch
- **n_steps** (int) – size of n step look ahead

build_networks()
Initializes the Noisy DQN train and target networks

Return type None

on_train_start()
Set the agents epsilon to 0 as the exploration comes from the network

Return type None

train_batch()
Contains the logic for generating a new batch of data to be passed to the DataLoader. This is the same function as the standard DQN except that we dont update epsilon as it is always 0. The exploration comes from the noisy network.

Return type Tuple[Tensor, Tensor, Tensor, Tensor, Tensor]

Returns yields a Experience tuple containing the state, action, reward, done and next_state.

22.2.5 N-Step DQN

N-Step DQN model introduced in Learning to Predict by the Methods of Temporal Differences Paper authors: Richard S. Sutton

Original implementation by: Donal Byrne

N Step DQN was introduced in Learning to Predict by the Methods of Temporal Differences. This method improves upon the original DQN by updating our Q values with the expected reward from multiple steps in the future as opposed to the expected reward from the immediate next state. When getting the Q values for a state action pair using a single step which looks like this

$$Q(s_t, a_t) = r_t + \gamma \max_a Q(s_{t+1}, a_{t+1})$$

but because the Q function is recursive we can continue to roll this out into multiple steps, looking at the expected return for each step into the future.

$$Q(s_t, a_t) = r_t + \gamma r_{t+1} + \gamma^2 \max_{a'} Q(s_{t+2}, a')$$

The above example shows a 2-Step look ahead, but this could be rolled out to the end of the episode, which is just Monte Carlo learning. Although we could just do a monte carlo update and look forward to the end of the episode,

it wouldn't be a good idea. Every time we take another step into the future, we are basing our approximation off our current policy. For a large portion of training, our policy is going to be less than optimal. For example, at the start of training, our policy will be in a state of high exploration, and will be little better than random.

Note: For each rollout step you must scale the discount factor accordingly by the number of steps. As you can see from the equation above, the second gamma value is to the power of 2. If we rolled this out one step further, we would use gamma to the power of 3 and so.

So if we are aproximating future rewards off a bad policy, chances are those approximations are going to be pretty bad and every time we unroll our update equation, the worse it will get. The fact that we are using an off policy method like DQN with a large replay buffer will make this even worse, as there is a high chance that we will be training on experiences using an old policy that was worse than our current policy.

So we need to strike a balance between looking far enough ahead to improve the convergence of our agent, but not so far that are updates become unstable. In general, small values of 2-4 work best.

N-Step Benefits

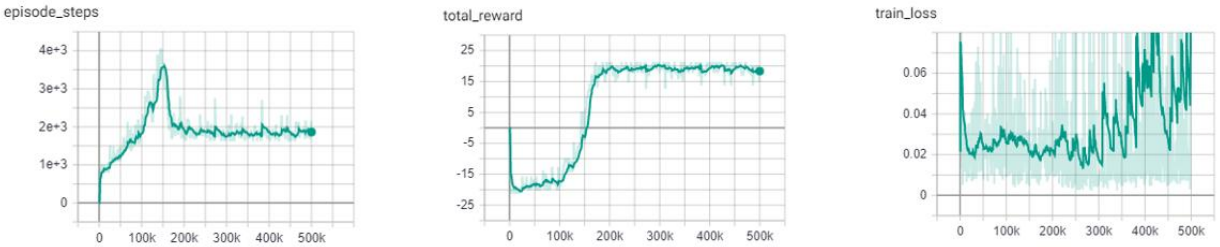
- Multi-Step learning is capable of learning faster than typical 1 step learning methods.
- Note that this method introduces a new hyperparameter n. Although n=4 is generally a good starting point and provides good results across the board.

N-Step Results

As expected, the N-Step DQN converges much faster than the standard DQN, however it also adds more instability to the loss of the agent. This can be seen in the following experiments.

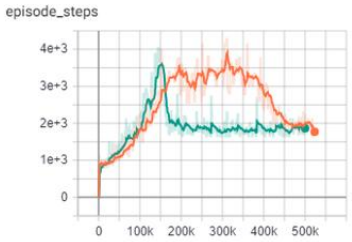
N-Step DQN: Pong

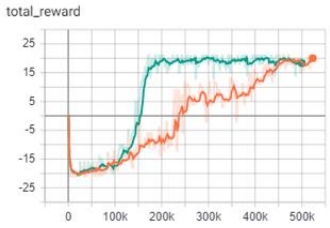
The N-Step DQN shows the greatest increase in performance with respect to the other DQN variations. After less than 150k steps the agent begins to consistently win games and achieves the top score after ~170K steps. This is reflected in the sharp peak of the total episode steps and of course, the total episode rewards.

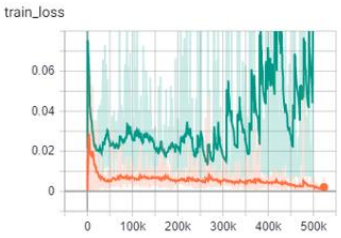


DQN vs N-Step DQN: Pong

This improvement is shown in stark contrast to the base DQN, which only begins to win games after 250k steps and requires over twice as many steps (450k) as the N-Step agent to achieve the high score of 21. One important thing to notice is the large increase in the loss of the N-Step agent. This is expected as the agent is building its expected reward off approximations of the future states. The large the size of N, the greater the instability. Previous literature, listed below, shows the best results for the Pong environment with an N step between 3-5. For these experiments I opted with an N step of 4.







Example:

```
from pl_bolts.models.rl import DQN
n_step_dqn = DQN("PongNoFrameskip-v4", n_steps=4)
trainer = Trainer()
trainer.fit(n_step_dqn)
```

22.2.6 Prioritized Experience Replay DQN

Double DQN model introduced in Prioritized Experience Replay Paper authors: Tom Schaul, John Quan, Ioannis Antonoglou, David Silver

Original implementation by: Donal Byrne

The standard DQN uses a buffer to break up the correlation between experiences and uniform random samples for each batch. Instead of just randomly sampling from the buffer prioritized experience replay (PER) prioritizes these samples based on training loss. This concept was introduced in the paper Prioritized Experience Replay

Essentially we want to train more on the samples that sunrise the agent.

The priority of each sample is defined below where

$$P(i) = P_i^\alpha / \sum_k P_k^\alpha$$

where pi is the priority of the ith sample in the buffer and is the number that shows how much emphasis we give to the priority. If = 0 , our sampling will become uniform as in the classic DQN method. Larger values for put more stress on samples with higher priority

Its important that new samples are set to the highest priority so that they are sampled soon. This however introduces bias to new samples in our dataset. In order to compensate for this bias, the value of the weight is defined as

$$w_i = (N.P(i))^{-\beta}$$

Where beta is a hyper parameter between 0-1. When beta is 1 the bias is fully compensated. However authors noted that in practice it is better to start beta with a small value near 0 and slowly increase it to 1.

PER Benefits

- The benefits of this technique are that the agent sees more samples that it struggled with and gets more chances to improve upon it.

Memory Buffer

First step is to replace the standard experience replay buffer with the prioritized experience replay buffer. This is pretty large (100+ lines) so I wont go through it here. There are two buffers implemented. The first is a naive list based buffer found in memory.PERBuffer and the second is more efficient buffer using a Sum Tree datastructure.

The list based version is simpler, but has a sample complexity of O(N). The Sum Tree in comparison has a complexity of O(1) for sampling and O(logN) for updating priorities.

Update loss function

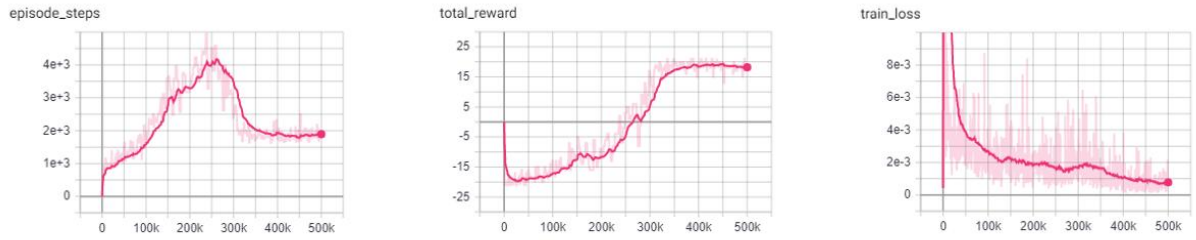
The next thing we do is to use the sample weights that we get from PER. Add the following code to the end of the loss function. This applies the weights of our sample to the batch loss. Then we return the mean loss and weighted loss for each datum, with the addition of a small epsilon value.

PER Results

The results below show improved stability and faster performance growth.

PER DQN: Pong

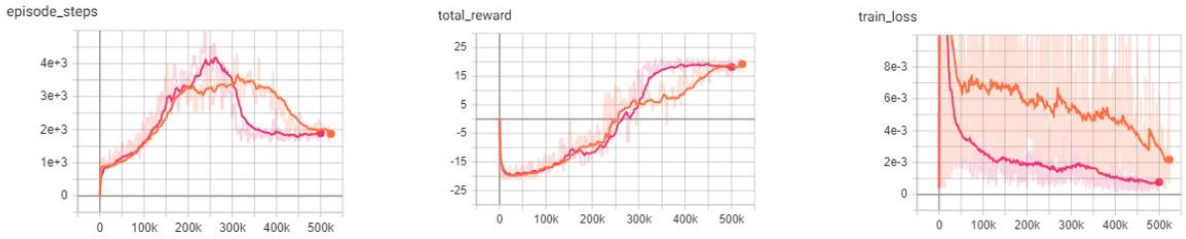
Similar to the other improvements, we see that PER improves the stability of the agents training and shows to converged on an optimal policy faster.



DQN vs PER DQN: Pong

In comparison to the base DQN, the PER DQN does show improved stability and performance. As expected, the loss of the PER DQN is siginificantly lower. This is the main objective of PER by focusing on experiences with high loss.

It is important to note that loss is not the only metric we should be looking at. Although the agent may have very low loss during training, it may still perform poorly due to lack of exploration.



- Orange: DQN
- Pink: PER DQN

Example:

```
from pl_bolts.models.rl import PERDQN
per_dqn = PERDQN("PongNoFrameskip-v4")
trainer = Trainer()
trainer.fit(per_dqn)
```

class pl_bolts.models.rl.per_dqn_model.**PERDQN**(*env*, *eps_start=1.0*, *eps_end=0.02*, *eps_last_frame=150000*, *sync_rate=1000*, *gamma=0.99*, *learning_rate=0.0001*, *batch_size=32*, *replay_size=100000*, *warm_start_size=10000*, *avg_reward_len=100*, *min_episode_reward=-21*, *seed=123*, *batches_per_epoch=1000*, *n_steps=1*, ***kwargs*)

Bases: pytorch_lightning.

PyTorch Lightning implementation of DQN With Prioritized Experience Replay

Paper authors: Tom Schaul, John Quan, Ioannis Antonoglou, David Silver

Model implemented by:

- *Donal Byrne <https://github.com/djbyrne>*

Example

```
>>> from pl_bolts.models.rl.per_dqn_model import PERDQN
...
>>> model = PERDQN("PongNoFrameskip-v4")
```

Train:

```
trainer = Trainer()
trainer.fit(model)
```

Note:

This example is based on: https://github.com/PacktPublishing/Deep-Reinforcement-Learning-Hands-On-Second-Edition/blob/master/Chapter08/05_dqn_prio_replay.py

---

Note: Currently only supports CPU and single GPU training with *distributed_backend=dp*

Parameters

- **env** (str) – gym environment tag
- **eps_start** (float) – starting value of epsilon for the epsilon-greedy exploration
- **eps_end** (float) – final value of epsilon for the epsilon-greedy exploration
- **eps_last_frame** (int) – the final frame in for the decrease of epsilon. At this frame espilon = eps_end
- **sync_rate** (int) – the number of iterations between syncing up the target network with the train network
- **gamma** (float) – discount factor
- **learning_rate** (float) – learning rate
- **batch_size** (int) – size of minibatch pulled from the DataLoader

- **replay_size**¶ (int) – total capacity of the replay buffer
- **warm_start_size**¶ (int) – how many random steps through the environment to be carried out at the start of training to fill the buffer with a starting point
- **avg_reward_len**¶ (int) – how many episodes to take into account when calculating the avg reward
- **min_episode_reward**¶ (int) – the minimum score that can be achieved in an episode. Used for filling the avg buffer before training begins
- **seed**¶ (int) – seed value for all RNG used
- **batches_per_epoch**¶ (int) – number of batches per epoch
- **n_steps**¶ (int) – size of n step look ahead

train_batch()

Contains the logic for generating a new batch of data to be passed to the DataLoader

Return type Tuple[Tensor, Tensor, Tensor, Tensor, Tensor]

Returns yields a Experience tuple containing the state, action, reward, done and next_state.

training_step(*batch*, *_*)

Carries out a single step through the environment to update the replay buffer. Then calculates loss based on the minibatch recieved

Parameters

- **batch**¶ – current mini batch of replay data
- *_*¶ – batch number, not used

Return type OrderedDict

Returns Training loss and log metrics

22.3 Policy Gradient Models

The following models are based on Policy Gradients. Unlike the Q learning models shown before, Policy based models do not try and learn the specifc values of state or state action pairs. Instead it cuts out the middle man and directly learns the policy distribution. In Policy Gradient models we update our network parameters in the direction suggested by our policy gradient in order to find a policy that produces the highest results.

Policy Gradient Key Points:

- Outputs a distribution of actions instead of discrete Q values
- Optimizes the policy directly, instead of indirectly through the optimization of Q values
- The policy distribution of actions allows the model to handle more complex action spaces, such as continuous actions
- The policy distribution introduces stochasticity, providing natural exploration to the model
- The policy distribution provides a more stable update as a change in weights will only change the total distribution slightly, as opposed to changing weights based on the Q value of state S will change all Q values with similar states.
- Policy gradients tend to converge faste, however they are not as sample efficient and generally require more interactions with the environment.

22.3.1 REINFORCE

REINFORCE model introduced in Policy Gradient Methods For Reinforcement Learning With Function Approximation Paper authors: Richard S. Sutton, David McAllester, Satinder Singh, Yishay Mansour

Original implementation by: Donal Byrne

REINFORCE is one of the simplest forms of the Policy Gradient method of RL. This method uses a Monte Carlo rollout, where its steps through entire episodes of the environment to build up trajectories computing the total rewards. The algorithm is as follows:

1. Initialize our network.
2. Play N full episodes saving the transitions through the environment.
3. For every step *t* in each episode *k* we calculate the discounted reward of the subsequent steps.

$$Q_{k,t} = \sum_{i=0} \gamma^i r_i$$

4. Calculate the loss for all transitions.

$$L = -\sum_{k,t} Q_{k,t} \log(\pi(S_{k,t}, A_{k,t}))$$

5. Perform SGD on the loss and repeat.

What this loss function is saying is simply that we want to take the log probability of action A at state S given our policy (network output). This is then scaled by the discounted reward that we calculated in the previous step. We then take the negative of our sum. This is because the loss is minimized during SGD, but we want to maximize our policy.

Note: The current implementation does not actually wait for the batch episodes the complete every time as we pass in a fixed batch size. For the time being we simply use a large batch size to accomodate this. This approach still works well for simple tasks as it still manages to get an accurate Q value by using a large batch size, but it is not as accurate or completely correct. This will be updated in a later version.

REINFORCE Benefits

- Simple and straightforward
- Computationally more efficient for simple tasks such as Cartpole than the Value Based methods.

REINFORCE Results

Hyperparameters:

- Batch Size: 800
- Learning Rate: 0.01
- Episodes Per Batch: 4
- Gamma: 0.99

TODO: Add results graph

Example:

```
from pl_bolts.models.rl import Reinforce
reinforce = Reinforce("CartPole-v0")
trainer = Trainer()
trainer.fit(reinforce)
```

class pl_bolts.models.rl.reinforce_model.**Reinforce**(*env*, *gamma=0.99*, *lr=0.01*, *batch_size=8*, *n_steps=10*, *avg_reward_len=100*, *entropy_beta=0.01*, *epoch_len=1000*, *num_batch_episodes=4*, ***kwargs*)

Bases: pytorch_lightning.

PyTorch Lightning implementation of REINFORCE Paper authors: Richard S. Sutton, David McAllester, Satinder Singh, Yishay Mansour Model implemented by:

- *Donal Byrne <https://github.com/djbyrne>*

Example

```
>>> from pl_bolts.models.rl.reinforce_model import Reinforce
...
>>> model = Reinforce("CartPole-v0")
```

Train:

```
trainer = Trainer()
trainer.fit(model)
```

Note: This example is based on: https://github.com/PacktPublishing/Deep-Reinforcement-Learning-Hands-On-Second-Edition/blob/master/Chapter11/02_cartpole_reinforce.py

Note: Currently only supports CPU and single GPU training with *distributed_backend=dp*

Parameters

- **env** (str) – gym environment tag
- **gamma** (float) – discount factor
- **lr** (float) – learning rate
- **batch_size** (int) – size of minibatch pulled from the DataLoader
- **n_steps** (int) – number of stakes per discounted experience
- **entropy_beta** (float) – entropy coefficient
- **epoch_len** (int) – how many batches before pseudo epoch
- **num_batch_episodes** (int) – how many episodes to rollout for each batch of training
- **avg_reward_len** (int) – how many episodes to take into account when calculating the avg reward

static add_model_specific_args(*arg_parser*)
Adds arguments for DQN model

Note: These params are fine tuned for Pong env.

Parameters **arg_parser¶** – the current argument parser to add to

Return type ArgumentParser

Returns arg_parser with model specific cargs added

calc_qvals(*rewards*)
Calculate the discounted rewards of all rewards in list

Parameters **rewards¶** (List[float]) – list of rewards from latest batch

Return type List[float]

Returns list of discounted rewards

configure_optimizers()
Initialize Adam optimizer

Return type List[Optimizer]

discount_rewards(*experiences*)
Calculates the discounted reward over N experiences

Parameters **experiences¶** (Tuple[Experience]) – Tuple of Experience

Return type float

Returns total discounted reward

forward(*x*)
Passes in a state x through the network and gets the q_values of each action as an output

Parameters **x¶** (Tensor) – environment state

Return type Tensor

Returns q values

get_device(*batch*)
Retrieve device currently being used by minibatch

Return type str

train_batch()
Contains the logic for generating a new batch of data to be passed to the DataLoader

Yields yields a tuple of Lists containing tensors for states, actions and rewards of the batch.

Return type Tuple[List[Tensor], List[Tensor], List[Tensor]]

train_dataloader()
Get train loader

Return type DataLoader

training_step(*batch*, _)
Carries out a single step through the environment to update the replay buffer. Then calculates loss based on the minibatch recieved

Parameters

- **batch** (Tuple[Tensor, Tensor]) – current mini batch of replay data
- _ – batch number, not used

Return type OrderedDict

Returns Training loss and log metrics

22.3.2 Vanilla Policy Gradient

Vanilla Policy Gradient model introduced in Policy Gradient Methods For Reinforcement Learning With Function Approximation Paper authors: Richard S. Sutton, David McAllester, Satinder Singh, Yishay Mansour

Original implementation by: Donal Byrne

Vanilla Policy Gradient (VPG) expands upon the REINFORCE algorithm and improves some of its major issues. The major issue with REINFORCE is that it has high variance. This can be improved by subtracting a baseline value from the Q values. For this implementation we use the average reward as our baseline.

Although Policy Gradients are able to explore naturally due to the stochastic nature of the model, the agent can still frequently be stuck in a local optima. In order to improve this, VPG adds an entropy term to improve exploration.

$$H(\pi) = -\sum \pi(a|s) \log \pi(a|s)$$

To further control the amount of additional entropy in our model we scale the entropy term by a small beta value. The scaled entropy is then subtracted from the policy loss.

VPG Benefits

- Addition of the baseline reduces variance in the model
- Improved exploration due to entropy bonus

VPG Results

Hyperparameters:

- Batch Size: 8
- Learning Rate: 0.001
- N Steps: 10
- N environments: 4
- Entropy Beta: 0.01
- Gamma: 0.99

Example:

```
from pl_bolts.models.rl import VanillaPolicyGradient
vpg = VanillaPolicyGradient("CartPole-v0")
trainer = Trainer()
trainer.fit(vpg)
```

class pl_bolts.models.rl.vanilla_policy_gradient_model.**VanillaPolicyGradient**(*env*, *gamma=0.99*, *lr=0.01*, *batch_size=8*, *n_steps=10*, *avg_reward_len=10*, *entropy_beta=0.01*, *epoch_len=1000*, ***kwargs*)

Bases: pytorch_lightning.

PyTorch Lightning implementation of Vanilla Policy Gradient

Paper authors: Richard S. Sutton, David McAllester, Satinder Singh, Yishay Mansour

Model implemented by:

- *Donal Byrne <https://github.com/djbyrne>*

Example

```
>>> from pl_bolts.models.rl.vanilla_policy_gradient_model import␣
↪VanillaPolicyGradient
...
>>> model = VanillaPolicyGradient("CartPole-v0")
```

Train:

```
trainer = Trainer()
trainer.fit(model)
```

Note: This example is based on: https://github.com/PacktPublishing/Deep-Reinforcement-Learning-Hands-On-Second-Edition/blob/master/Chapter11/04_cartpole_pg.py

Note: Currently only supports CPU and single GPU training with *distributed_backend=dp*

Parameters

- **env**¶ (str) – gym environment tag
- **gamma**¶ (float) – discount factor
- **lr**¶ (float) – learning rate
- **batch_size**¶ (int) – size of minibatch pulled from the DataLoader
- **batch_episodes**¶ – how many episodes to rollout for each batch of training
- **entropy_beta**¶ (float) – dictates the level of entropy per batch
- **avg_reward_len**¶ (int) – how many episodes to take into account when calculating the avg reward
- **epoch_len**¶ (int) – how many batches before pseudo epoch

static add_model_specific_args(*arg_parser*)
Adds arguments for DQN model

Note: These params are fine tuned for Pong env.

Parameters **arg_parser**¶ – the current argument parser to add to

Return type ArgumentParser

Returns arg_parser with model specific cargs added

compute_returns(*rewards*)
Calculate the discounted rewards of the batched rewards

Parameters **rewards**¶ – list of batched rewards

Returns list of discounted rewards

configure_optimizers()
Initialize Adam optimizer

Return type List[Optimizer]

forward(*x*)
Passes in a state x through the network and gets the q_values of each action as an output

Parameters **x**¶ (Tensor) – environment state

Return type Tensor

Returns q values

get_device(*batch*)
Retrieve device currently being used by minibatch

Return type str

loss(*states*, *actions*, *scaled_rewards*)
Calculates the loss for VPG

Parameters

- **states**¶ – batched states
- **actions**¶ – batch actions
- **scaled_rewards**¶ – batche Q values

Return type Tensor

Returns loss for the current batch

train_batch()
Contains the logic for generating a new batch of data to be passed to the DataLoader

Return type Tuple[List[Tensor], List[Tensor], List[Tensor]]

Returns yields a tuple of Lists containing tensors for states, actions and rewards of the batch.

train_dataloader()
Get train loader

Return type DataLoader

training_step(*batch*, *_*)

Carries out a single step through the environment to update the replay buffer. Then calculates loss based on the minibatch recieved

Parameters

- **batch** (Tuple[Tensor, Tensor]) – current mini batch of replay data
- **_** – batch number, not used

Return type OrderedDict

Returns Training loss and log metrics

CHAPTER

TWENTYTHREE

SELF-SUPERVISED LEARNING

This bolts module houses a collection of all self-supervised learning models.

Self-supervised learning extracts representations of an input by solving a pretext task. In this package, we implement many of the current state-of-the-art self-supervised algorithms.

Self-supervised models are trained with unlabeled datasets

23.1 Use cases

Here are some use cases for the self-supervised package.

23.1.1 Extracting image features

The models in this module are trained unsupervised and thus can capture better image representations (features).

In this example, we'll load a resnet 18 which was pretrained on imagenet using CPC as the pretext task.

```
from pl_bolts.models.self_supervised import SimCLR

# load resnet50 pretrained using SimCLR on imagenet
weight_path = 'https://pl-bolts-weights.s3.us-east-2.amazonaws.com/simclr/bolts_
↪simclr_imagenet/simclr_imagenet.ckpt'
simclr = SimCLR.load_from_checkpoint(weight_path, strict=False)

simclr_resnet50 = simclr.encoder
simclr_resnet50.eval()
```

This means you can now extract image representations that were pretrained via unsupervised learning.

Example:

```
my_dataset = SomeDataset()
for batch in my_dataset:
    x, y = batch
    out = simclr_resnet50(x)
```

23.1.2 Train with unlabeled data

These models are perfect for training from scratch when you have a huge set of unlabeled images

```
from pl_bolts.models.self_supervised import SimCLR
from pl_bolts.models.self_supervised.simclr import SimCLREvalDataTransform,␣
↪SimCLRTrainDataTransform


train_dataset = MyDataset(transforms=SimCLRTrainDataTransform())
val_dataset = MyDataset(transforms=SimCLREvalDataTransform())

# simclr needs a lot of compute!
model = SimCLR()
trainer = Trainer(tpu_cores=128)
trainer.fit(
    model,
    DataLoader(train_dataset),
    DataLoader(val_dataset),
)
```

23.1.3 Research

Mix and match any part, or subclass to create your own new method

```
from pl_bolts.models.self_supervised import CPC_v2
from pl_bolts.losses.self_supervised_learning import FeatureMapContrastiveTask

amdim_task = FeatureMapContrastiveTask(comparisons='01, 11, 02', bidirectional=True)
model = CPC_v2(contrastive_task=amdim_task)
```

23.2 Contrastive Learning Models

Contrastive self-supervised learning (CSL) is a self-supervised learning approach where we generate representations of instances such that similar instances are near each other and far from dissimilar ones. This is often done by comparing triplets of positive, anchor and negative representations.

In this section, we list Lightning implementations of popular contrastive learning approaches.

23.2.1 AMDIM

class pl_bolts.models.self_supervised.**AMDIM**(*datamodule='cifar10'*, *encoder='amdim_encoder'*, *contrastive_task=torch.nn.Module*, *image_channels=3*, *image_height=32*, *encoder_feature_dim=320*, *embedding_fx_dim=1280*, *conv_block_depth=10*, *use_bn=False*, *tclip=20.0*, *learning_rate=0.0002*, *data_dir=''*, *num_classes=10*, *batch_size=200*, *num_workers=16*, ***kwargs*)

Bases: pytorch_lightning.

PyTorch Lightning implementation of Augmented Multiscale Deep InfoMax (AMDIM).

Paper authors: Philip Bachman, R Devon Hjelm, William Buchwalter.

Model implemented by: William Falcon

This code is adapted to Lightning using the original author repo (the original repo).

Example

```
>>> from pl_bolts.models.self_supervised import AMDIM
...
>>> model = AMDIM(encoder='resnet18')
```

Train:

```
trainer = Trainer()
trainer.fit(model)
```

Parameters

- **datamodule** (Union[str, LightningDataModule]) – A LightningDatamodule
- **encoder** (Union[str, Module, LightningModule]) – an encoder string or model
- **image_channels** (int) – 3
- **image_height** (int) – pixels
- **encoder_feature_dim** (int) – Called *ndf* in the paper, this is the representation size for the encoder.
- **embedding_fx_dim** (int) – Output dim of the embedding function (*nrkhs* in the paper) (Reproducing Kernel Hilbert Spaces).
- **conv_block_depth** (int) – Depth of each encoder block,
- **use_bn** (bool) – If true will use batchnorm.
- **tclip** (int) – soft clipping non-linearity to the scores after computing the regularization term and before computing the log-softmax. This is the 'second trick' used in the paper
- **learning_rate** (int) – The learning rate
- **data_dir** (str) – Where to store data
- **num_classes** (int) – How many classes in the dataset
- **batch_size** (int) – The batch size

23.2.2 BYOL

class pl_bolts.models.self_supervised.**BYOL**(*num_classes*, *learning_rate=0.2*, *weight_decay=1.5e-06*, *input_height=32*, *batch_size=32*, *num_workers=0*, *warmup_epochs=10*, *max_epochs=1000*, ***kwargs*)

Bases: pytorch_lightning.

PyTorch Lightning implementation of Bootstrap Your Own Latent (BYOL)

Paper authors: Jean-Bastien Grill, Florian Strub, Florent Altché, Corentin Tallec, Pierre H. Richemond, Elena Buchatskaya, Carl Doersch, Bernardo Avila Pires, Zhaohan Daniel Guo, Mohammad Gheshlaghi Azar, Bilal Piot, Koray Kavukcuoglu, Rémi Munos, Michal Valko.

Model implemented by:

- Annika Brundyn

> **Warning:** Work in progress. This implementation is still being verified.

TODOs:

- verify on CIFAR-10
- verify on STL-10
- pre-train on imagenet

Example:

```
model = BYOL(num_classes=10)

dm = CIFAR10DataModule(num_workers=0)
dm.train_transforms = SimCLRTrainDataTransform(32)
dm.val_transforms = SimCLREvalDataTransform(32)

trainer = pl.Trainer()
trainer.fit(model, datamodule=dm)
```

Train:

```
trainer = Trainer()
trainer.fit(model)
```

CLI command:

```
# cifar10
python byol_module.py --gpus 1

# imagenet
python byol_module.py
    --gpus 8
    --dataset imagenet2012
    --data_dir /path/to/imagenet/
    --meta_dir /path/to/folder/with/meta.bin/
    --batch_size 32
```

Parameters

- **datamodule** – The datamodule
- **learning_rate** (float) – the learning rate
- **weight_decay** (float) – optimizer weight decay
- **input_height** (int) – image input height
- **batch_size** (int) – the batch size
- **num_workers** (int) – number of workers

- **warmup_epochs** (int) – num of epochs for scheduler warm up
- **max_epochs** (int) – max epochs for scheduler

23.2.3 CPC (V2)

PyTorch Lightning implementation of Data-Efficient Image Recognition with Contrastive Predictive Coding

Paper authors: (Olivier J. Hénaff, Aravind Srinivas, Jeffrey De Fauw, Ali Razavi, Carl Doersch, S. M. Ali Eslami, Aaron van den Oord).

Model implemented by:

- William Falcon
- Tullie Murrell

To Train:

```
import pytorch_lightning as pl
from pl_bolts.models.self_supervised import CPC_v2
from pl_bolts.datamodules import CIFAR10DataModule
from pl_bolts.models.self_supervised.cpc import (
    CPCTrainTransformsCIFAR10, CPCEvalTransformsCIFAR10)

# data
dm = CIFAR10DataModule(num_workers=0)
dm.train_transforms = CPCTrainTransformsCIFAR10()
dm.val_transforms = CPCEvalTransformsCIFAR10()

# model
model = CPC_v2()

# fit
trainer = pl.Trainer()
trainer.fit(model, datamodule=dm)
```

To finetune:

```
python cpc_finetuner.py
    --ckpt_path path/to/checkpoint.ckpt
    --dataset cifar10
    --gpus 1
```

CIFAR-10 and STL-10 baselines

CPCv2 does not report baselines on CIFAR-10 and STL-10 datasets. Results in table are reported from the YADIM paper.

Table 1: CPCv2 implementation results

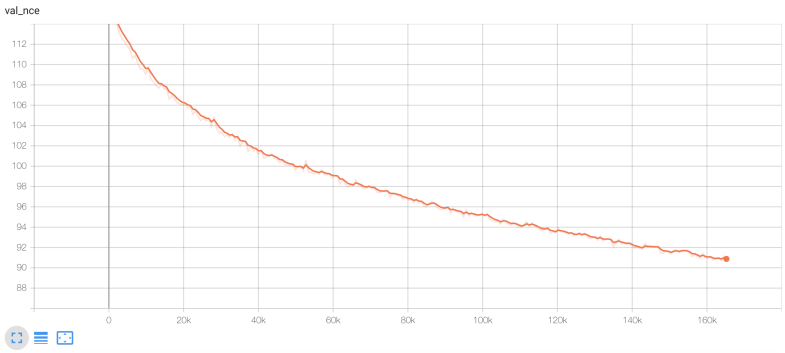
Dataset	test acc	Encoder	Optimizer	Batch	Epochs	Hardware	LR
CIFAR-10	84.52	CPCresnet101	Adam	64	1000 (upto 24 hours)	1 V100 (32GB)	4e-5
STL-10	78.36	CPCresnet101	Adam	144	1000 (upto 72 hours)	4 V100 (32GB)	1e-4
ImageNet	54.82	CPCresnet101	Adam	3072	1000 (upto 21 days)	64 V100 (32GB)	4e-5

CIFAR-10 pretrained model:

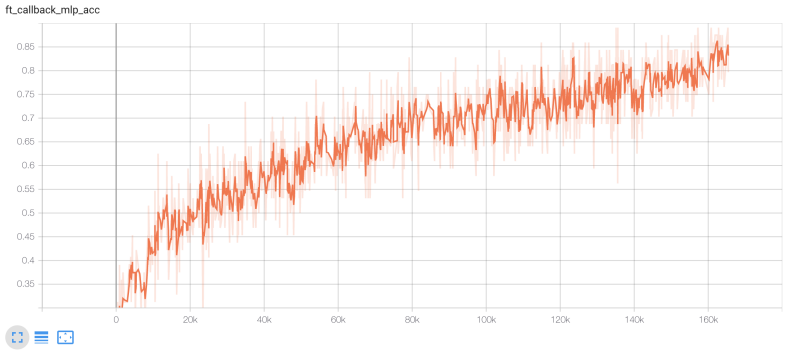
```
from pl_bolts.models.self_supervised import CPC_v2

weight_path = 'https://pl-bolts-weights.s3.us-east-2.amazonaws.com/cpc/cpc-cifar10-v4-
↪exp3/epoch%3D474.ckpt'
cpc_v2 = CPC_v2.load_from_checkpoint(weight_path, strict=False)

cpc_v2.freeze()
```

- Tensorboard for CIFAR10

Pre-training:



Fine-tuning:

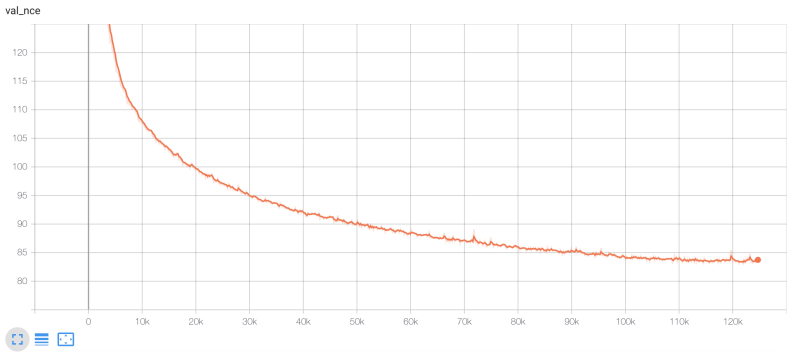


STL-10 pretrained model:

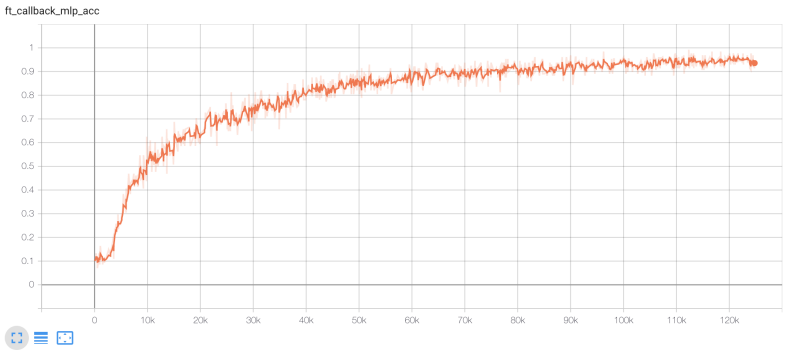
```
from pl_bolts.models.self_supervised import CPC_v2

weight_path = 'https://pl-bolts-weights.s3.us-east-2.amazonaws.com/cpc/cpc-stl10-v0-
↪exp3/epoch%3D624.ckpt'
cpc_v2 = CPC_v2.load_from_checkpoint(weight_path, strict=False)

cpc_v2.freeze()
```

- Tensorboard for STL10

Pre-training:



Fine-tuning:



23.2.4 CPC (v2) API

class pl_bolts.models.self_supervised.**CPC_v2**(*encoder_name='cpc_encoder'*, *patch_size=8*, *patch_overlap=4*, *online_ft=True*, *task='cpc'*, *num_workers=4*, *num_classes=10*, *learning_rate=0.0001*, *pretrained=None*, ***kwargs*)

Bases: pytorch_lightning.

Parameters

- **encoder_name** (str) – A string for any of the resnets in torchvision, or the original CPC encoder, or a custon nn.Module encoder
- **patch_size** (int) – How big to make the image patches
- **patch_overlap** (int) – How much overlap each patch should have
- **online_ft** (bool) – If True, enables a 1024-unit MLP to fine-tune online
- **task** (str) – Which self-supervised task to use ('cpc', 'amdim', etc...)
- **num_workers** (int) – number of dataloader workers
- **num_classes** (int) – number of classes
- **learning_rate** (float) – learning rate
- **pretrained** (Optional[str]) – If true, will use the weights pretrained (using CPC) on Imagenet

23.2.5 Moco (v2) API

class pl_bolts.models.self_supervised.**Moco_v2**(*base_encoder='resnet18'*, *emb_dim=128*, *num_negatives=65536*, *encoder_momentum=0.999*, *softmax_temperature=0.07*, *learning_rate=0.03*, *momentum=0.9*, *weight_decay=0.0001*, *data_dir='./'*, *batch_size=256*, *use_mlp=False*, *num_workers=8*, **args*, ***kwargs*)

Bases: pytorch_lightning.

PyTorch Lightning implementation of Moco

Paper authors: Xinlei Chen, Haoqi Fan, Ross Girshick, Kaiming He.

Code adapted from facebookresearch/moco to Lightning by:

- William Falcon

Example:: from pl_bolts.models.self_supervised import Moco_v2 model = Moco_v2() trainer = Trainer() trainer.fit(model)

CLI command:

```
# cifar10
python moco2_module.py --gpus 1

# imagenet
python moco2_module.py
    --gpus 8
    --dataset imagenet2012
    --data_dir /path/to/imagenet/
    --meta_dir /path/to/folder/with/meta.bin/
    --batch_size 32
```

Parameters

- **base_encoder** (Union[str, Module]) – torchvision model name or torch.nn.Module
- **emb_dim** (int) – feature dimension (default: 128)
- **num_negatives** (int) – queue size; number of negative keys (default: 65536)
- **encoder_momentum** (float) – moco momentum of updating key encoder (default: 0.999)
- **softmax_temperature** (float) – softmax temperature (default: 0.07)
- **learning_rate** (float) – the learning rate
- **momentum** (float) – optimizer momentum
- **weight_decay** (float) – optimizer weight decay
- **datamodule** – the DataModule (train, val, test dataloaders)
- **data_dir** (str) – the directory to store data
- **batch_size** (int) – batch size
- **use_mlp** (bool) – add an mlp to the encoders
- **num_workers** (int) – workers for the loaders

forward(*img_q*, *img_k*)

Input: im_q: a batch of query images im_k: a batch of key images

Output: logits, targets

init_encoders(*base_encoder*)
Override to add your own encoders

23.2.6 SimCLR

PyTorch Lightning implementation of SimCLR

Paper authors: Ting Chen, Simon Kornblith, Mohammad Norouzi, Geoffrey Hinton.

Model implemented by:

- William Falcon
- Tullie Murrell
- Ananya Harsh Jha

To Train:

```
import pytorch_lightning as pl
from pl_bolts.models.self_supervised import SimCLR
from pl_bolts.datamodules import CIFAR10DataModule
from pl_bolts.models.self_supervised.simclr.transforms import (
    SimCLREvalDataTransform, SimCLRTrainDataTransform)

# data
dm = CIFAR10DataModule(num_workers=0)
dm.train_transforms = SimCLRTrainDataTransform(32)
dm.val_transforms = SimCLREvalDataTransform(32)

# model
model = SimCLR(num_samples=dm.num_samples, batch_size=dm.batch_size, dataset='cifar10
↪')

# fit
trainer = pl.Trainer()
trainer.fit(model, datamodule=dm)
```

CIFAR-10 baseline

Table 2: Cifar-10 implementation results

Implementation	test acc	Encoder	Optimizer	Batch	Epochs	Hardware	LR
Original	~94.00	resnet50	LARS	2048	800	TPUs	1.0/1.5
Ours	88.50	resnet50	LARS-SGD	2048	800 (4 hours)	8 V100 (16GB)	1.5

CIFAR-10 pretrained model:

```
from pl_bolts.models.self_supervised import SimCLR

weight_path = 'https://pl-bolts-weights.s3.us-east-2.amazonaws.com/simclr/bolts_
↪simclr_imagenet/simclr_imagenet.ckpt'
simclr = SimCLR.load_from_checkpoint(weight_path, strict=False)
```

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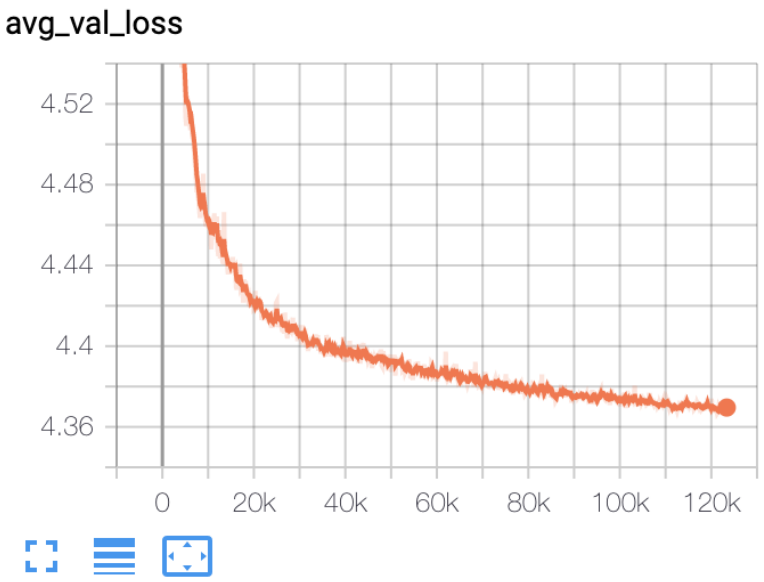
```
simclr.freeze()
```

Pre-training:



Fine-tuning (Single layer MLP, 1024 hidden units):

To reproduce:

```
# pretrain
python simclr_module.py
    --gpus 8
    --dataset cifar10
    --batch_size 256
    -- num_workers 16
    --optimizer sgd
    --learning_rate 1.5
    --lars_wrapper
    --exclude_bn_bias
    --max_epochs 800
    --online_ft
```

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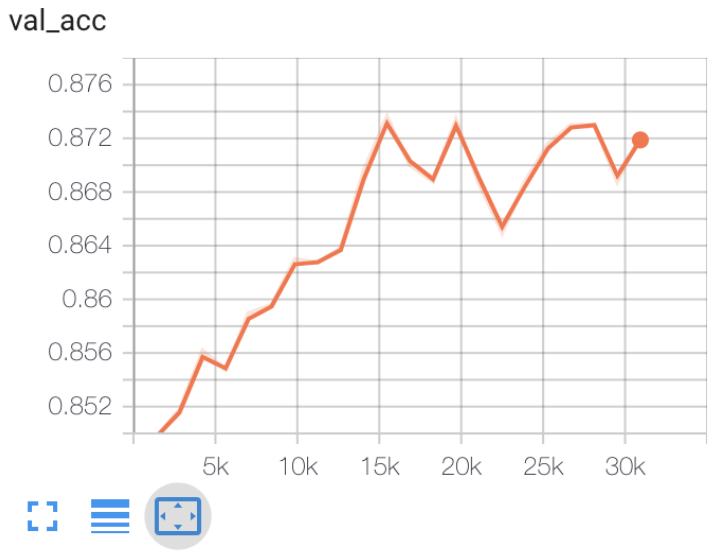
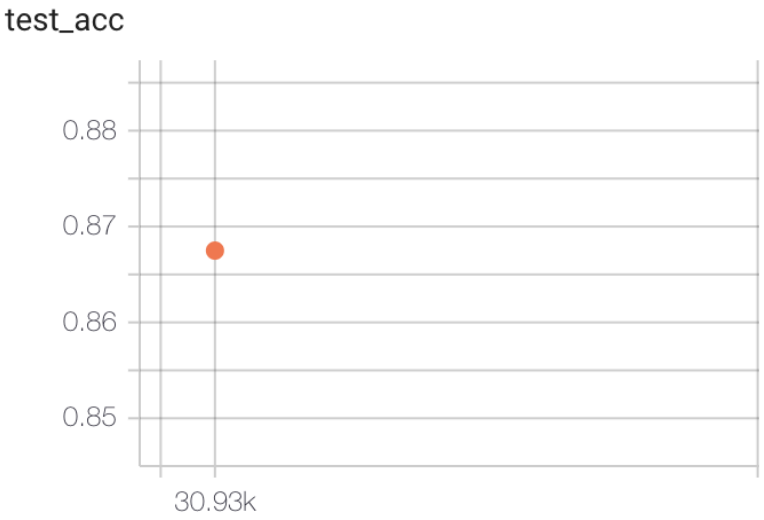

val_acc
0.876
0.872
0.868
0.864
0.86
0.856
0.852
5k
10k
15k
20k
25k
30k


test_acc
0.88
0.87
0.86
0.85
30.93k

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```
# finetune
python simclr_finetuner.py
    --gpus 4
    --ckpt_path path/to/simclr/ckpt
    --dataset cifar10
    --batch_size 64
    --num_workers 8
    --learning_rate 0.3
    --num_epochs 100
```

Imagenet baseline for SimCLR

Table 3: Cifar-10 implementation results

Implementation	test acc	Encoder	Optimizer	Batch	Epochs	Hardware	LR
Original	~69.3	resnet50	LARS	4096	800	TPUs	4.8
Ours	68.4	resnet50	LARS-SGD	4096	800	64 V100 (16GB)	4.8

Imagenet pretrained model:

```
from pl_bolts.models.self_supervised import SimCLR

weight_path = 'https://pl-bolts-weights.s3.us-east-2.amazonaws.com/simclr/bolts_
↪simclr_imagenet/simclr_imagenet.ckpt'
simclr = SimCLR.load_from_checkpoint(weight_path, strict=False)

simclr.freeze()
```

To reproduce:

```
# pretrain
python simclr_module.py
    --dataset imagenet
    --data_path path/to/imagenet

# finetune
python simclr_finetuner.py
    --gpus 8
    --ckpt_path path/to/simclr/ckpt
    --dataset imagenet
    --data_dir path/to/imagenet/dataset
    --batch_size 256
```

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```
    --num_workers 16
    --learning_rate 0.8
    --nesterov True
    --num_epochs 90
```

SimCLR API

class pl_bolts.models.self_supervised.**SimCLR**(*gpus*, *num_samples*, *batch_size*, *dataset*, *num_nodes=1*, *arch='resnet50'*, *hidden_mlp=2048*, *feat_dim=128*, *warmup_epochs=10*, *max_epochs=100*, *temperature=0.1*, *first_conv=True*, *maxpool1=True*, *optimizer='adam'*, *lars_wrapper=True*, *exclude_bn_bias=False*, *start_lr=0.0*, *learning_rate=0.001*, *final_lr=0.0*, *weight_decay=1e-06*, ***kwargs*)

Bases: pytorch_lightning.

Parameters

- **batch_size** (int) – the batch size
- **num_samples** (int) – num samples in the dataset
- **warmup_epochs** (int) – epochs to warmup the lr for
- **lr** – the optimizer learning rate
- **opt_weight_decay** – the optimizer weight decay
- **loss_temperature** – the loss temperature

nt_xent_loss(*out_1*, *out_2*, *temperature*, *eps=1e-06*)

assume out_1 and out_2 are normalized out_1: [batch_size, dim] out_2: [batch_size, dim]

23.2.7 SwAV

PyTorch Lightning implementation of SwAV Adapted from the official implementation

Paper authors: Mathilde Caron, Ishan Misra, Julien Mairal, Priya Goyal, Piotr Bojanowski, Armand Joulin.

Implementation adapted by:

- Ananya Harsh Jha

To Train:

```
import pytorch_lightning as pl
from pl_bolts.models.self_supervised import SwAV
from pl_bolts.datamodules import STL10DataModule
from pl_bolts.models.self_supervised.swav.transforms import (
    SwAVTrainDataTransform, SwAVEvalDataTransform
)
from pl_bolts.transforms.dataset_normalizations import stl10_normalization

# data
```

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```
batch_size = 128
dm = STL10DataModule(data_dir='.', batch_size=batch_size)
dm.train_dataloader = dm.train_dataloader_mixed
dm.val_dataloader = dm.val_dataloader_mixed

dm.train_transforms = SwAVTrainDataTransform(
    normalize=stl10_normalization()
)

dm.val_transforms = SwAVEvalDataTransform(
    normalize=stl10_normalization()
)

# model
model = SwAV(
    gpus=1,
    num_samples=dm.num_unlabeled_samples,
    dataset='stl10',
    batch_size=batch_size
)

# fit
trainer = pl.Trainer(precision=16)
trainer.fit(model)
```

Pre-trained ImageNet

We have included an option to directly load ImageNet weights provided by FAIR into bolts.

You can load the pretrained model using:

ImageNet pretrained model:

```
from pl_bolts.models.self_supervised import SwAV

weight_path = 'https://pl-bolts-weights.s3.us-east-2.amazonaws.com/swav/swav_imagenet/
↪swav_imagenet.pth.tar'
swav = SwAV.load_from_checkpoint(weight_path, strict=True)

swav.freeze()
```

STL-10 baseline

The original paper does not provide baselines on STL10.

Table 4: STL-10 implementation results

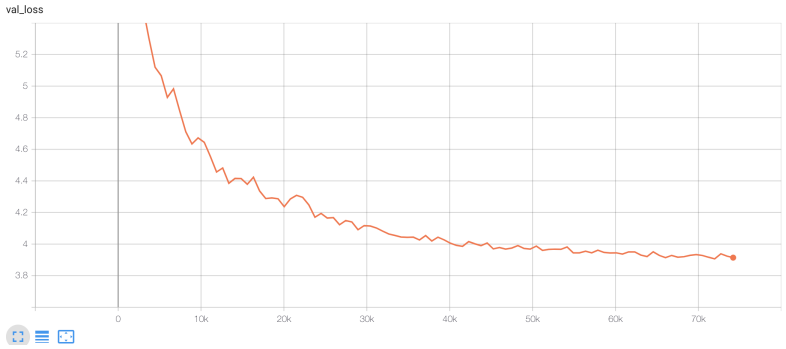
Imple-menta-tion	test acc	Encoder	Opti-mizer	Batch	Queue used	Epochs	Hardware	LR
Ours	86.72	SwAV resnet50	LARS	128	No	100 (~9 hr)	1 V100 (16GB)	1e-3

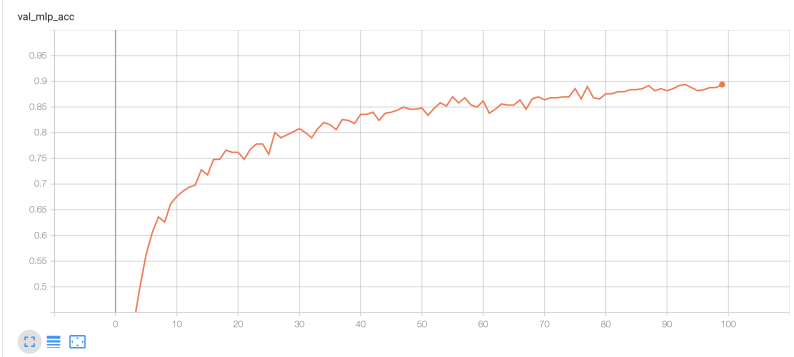
- Pre-training tensorboard link

STL-10 pretrained model:

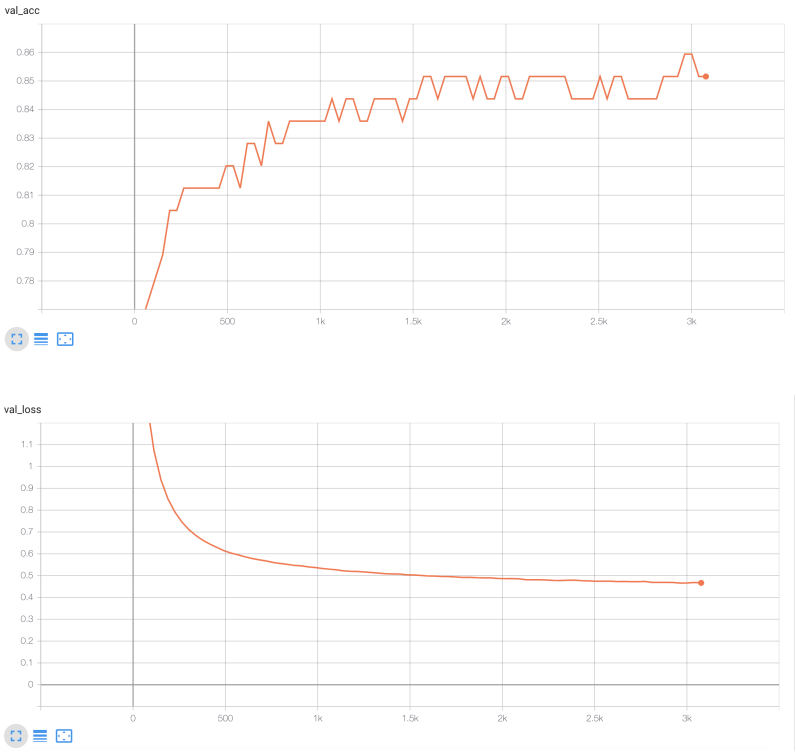
```
from pl_bolts.models.self_supervised import SwAV

weight_path = 'https://pl-bolts-weights.s3.us-east-2.amazonaws.com/swav/checkpoints/
↪swav_stl10.pth.tar'
swav = SwAV.load_from_checkpoint(weight_path, strict=False)

swav.freeze()
```

Pre-training:





Fine-tuning (Single layer MLP, 1024 hidden units):



To reproduce:

```
# pretrain
python swav_module.py
    --online_ft
    --gpus 1
    --lars_wrapper
    --batch_size 128
    --learning_rate 1e-3
    --gaussian_blur
    --queue_length 0
    --jitter_strength 1.
    --nmb_prototypes 512

# finetune
python swav_finetuner.py
--gpus 8
--ckpt_path path/to/simclr/ckpt
--dataset imagenet
--data_dir path/to/imagenet/dataset
--batch_size 256
```

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```
--num_workers 16
--learning_rate 0.8
--nesterov True
--num_epochs 90
```

Imagenet baseline for SwAV

Table 5: Cifar-10 implementation results

Implementation	test acc	Encoder	Optimizer	Batch	Epochs	Hardware	LR
Original	75.3	resnet50	LARS	4096	800	64 V100s	4.8
Ours	74	resnet50	LARS-SGD	4096	800	64 V100 (16GB)	4.8

Imagenet pretrained model:

```
from pl_bolts.models.self_supervised import SwAV

weight_path = 'https://pl-bolts-weights.s3.us-east-2.amazonaws.com/swav/bolts_swav_
↪imagenet/swav_imagenet.ckpt'
swav = SwAV.load_from_checkpoint(weight_path, strict=False)

swav.freeze()
```

SwAV API

class pl_bolts.models.self_supervised.**SwAV**(*gpus*, *num_samples*, *batch_size*, *dataset*, *num_nodes=1*, *arch='resnet50'*, *hidden_mlp=2048*, *feat_dim=128*, *warmup_epochs=10*, *max_epochs=100*, *nmb_prototypes=3000*, *freeze_prototypes_epochs=1*, *temperature=0.1*, *sinkhorn_iterations=3*, *queue_length=0*, *queue_path='queue'*, *epoch_queue_starts=15*, *crops_for_assign=[0, 1]*, *nmb_crops=[2, 6]*, *first_conv=True*, *maxpool1=True*, *optimizer='adam'*, *lars_wrapper=True*, *exclude_bn_bias=False*, *start_lr=0.0*, *learning_rate=0.001*, *final_lr=0.0*, *weight_decay=1e-06*, *epsilon=0.05*, ***kwargs*)

Bases: pytorch_lightning.

Parameters

- **gpus**¶ (int) – number of gpus per node used in training, passed to SwAV module to manage the queue and select distributed sinkhorn
- **num_nodes**¶ (int) – number of nodes to train on
- **num_samples**¶ (int) – number of image samples used for training
- **batch_size**¶ (int) – batch size per GPU in ddp
- **dataset**¶ (str) – dataset being used for train/val
- **arch**¶ (str) – encoder architecture used for pre-training
- **hidden_mlp**¶ (int) – hidden layer of non-linear projection head, set to 0 to use a linear projection head
- **feat_dim**¶ (int) – output dim of the projection head
- **warmup_epochs**¶ (int) – apply linear warmup for this many epochs
- **max_epochs**¶ (int) – epoch count for pre-training
- **nmb_prototypes**¶ (int) – count of prototype vectors
- **freeze_prototypes_epochs**¶ (int) – epoch till which gradients of prototype layer are frozen
- **temperature**¶ (float) – loss temperature
- **sinkhorn_iterations**¶ (int) – iterations for sinkhorn normalization
- **queue_length**¶ (int) – set queue when batch size is small, must be divisible by total batch-size (i.e. total_gpus * batch_size), set to 0 to remove the queue
- **queue_path**¶ (str) – folder within the logs directory
- **epoch_queue_starts**¶ (int) – start uing the queue after this epoch
- **crops_for_assign**¶ (list) – list of crop ids for computing assignment
- **nmb_crops**¶ (list) – number of global and local crops, ex: [2, 6]
- **first_conv**¶ (bool) – keep first conv same as the original resnet architecture, if set to false it is replace by a kernel 3, stride 1 conv (cifar-10)
- **maxpool1**¶ (bool) – keep first maxpool layer same as the original resnet architecture, if set to false, first maxpool is turned off (cifar10, maybe stl10)
- **optimizer**¶ (str) – optimizer to use
- **lars_wrapper**¶ (bool) – use LARS wrapper over the optimizer
- **exclude_bn_bias**¶ (bool) – exclude batchnorm and bias layers from weight decay in optimizers
- **start_lr**¶ (float) – starting lr for linear warmup
- **learning_rate**¶ (float) – learning rate
- **final_lr**¶ (float) – float = final learning rate for cosine weight decay
- **weight_decay**¶ (float) – weight decay for optimizer
- **epsilon**¶ (float) – epsilon val for swav assignments

CHAPTER

TWENTYFOUR

LEARNING RATE SCHEDULERS

This package lists common learning rate schedulers across research domains (This is a work in progress. If you have any learning rate schedulers you want to contribute, please submit a PR!)

Note: this module is a work in progress

24.1 Your Learning Rate Scheduler

We're cleaning up many of our learning rate schedulers, but in the meantime, submit a PR to add yours here!

24.2 Linear Warmup Cosine Annealing Learning Rate Scheduler

class pl_bolts.optimizers.lr_scheduler.**LinearWarmupCosineAnnealingLR**(*optimizer*, *warmup_epochs*, *max_epochs*, *warmup_start_lr=0.0*, *eta_min=0.0*, *last_epoch=-1*)

Bases: torch.optim.lr_scheduler.

Sets the learning rate of each parameter group to follow a linear warmup schedule between warmup_start_lr and base_lr followed by a cosine annealing schedule between base_lr and eta_min.

Warning: It is recommended to call `step()` for `LinearWarmupCosineAnnealingLR` after each iteration as calling it after each epoch will keep the starting lr at warmup_start_lr for the first epoch which is 0 in most cases.

Warning: passing epoch to `step()` is being deprecated and comes with an EPOCH_DEPRECATION_WARNING. It calls the `_get_closed_form_lr()` method for this scheduler instead of `get_lr()`. Though this does not change the behavior of the scheduler, when passing epoch param to `step()`, the user should call the `step()` function before calling train and validation methods.

Example

```
>>> layer = nn.Linear(10, 1)
>>> optimizer = Adam(layer.parameters(), lr=0.02)
>>> scheduler = LinearWarmupCosineAnnealingLR(optimizer, warmup_epochs=10, max_
↪epochs=40)
>>> #
>>> # the default case
>>> for epoch in range(40):
...     # train(...)
...     # validate(...)
...     scheduler.step()
>>> #
>>> # passing epoch param case
>>> for epoch in range(40):
...     scheduler.step(epoch)
...     # train(...)
...     # validate(...)
```

Parameters

- **optimizer** (*Optimizer*) – Wrapped optimizer.
- **warmup_epochs** (*int*) – Maximum number of iterations for linear warmup
- **max_epochs** (*int*) – Maximum number of iterations
- **warmup_start_lr** (*float*) – Learning rate to start the linear warmup. Default: 0.
- **eta_min** (*float*) – Minimum learning rate. Default: 0.
- **last_epoch** (*int*) – The index of last epoch. Default: -1.

get_lr()

Compute learning rate using chainable form of the scheduler

Return type List[float]

CHAPTER

TWENTYFIVE

SELF-SUPERVISED LEARNING TRANSFORMS

These transforms are used in various self-supervised learning approaches.

25.1 CPC transforms

Transforms used for CPC

25.1.1 CIFAR-10 Train (c)

class pl_bolts.models.self_supervised.cpc.transforms.**CPCTrainTransformsCIFAR10**(*patch_size=8*, *overlap=4*)

Bases: object

Transforms used for CPC:

Transforms:

```
random_flip
img_jitter
col_jitter
rnd_gray
transforms.ToTensor()
normalize
Patchify(patch_size=patch_size, overlap_size=patch_size // 2)
```

Example:

```
# in a regular dataset
CIFAR10(..., transforms=CPCTrainTransformsCIFAR10())

# in a DataModule
module = CIFAR10DataModule(PATH)
train_loader = module.train_dataloader(batch_size=32,␣
↪transforms=CPCTrainTransformsCIFAR10())
```

Parameters

- **patch_size** – size of patches when cutting up the image into overlapping patches
- **overlap** – how much to overlap patches

__call__(*inp*)
Call self as a function.

25.1.2 CIFAR-10 Eval (c)

class pl_bolts.models.self_supervised.cpc.transforms.**CPCEvalTransformsCIFAR10**(*patch_size=8*, *overlap=4*)

Bases: object

Transforms used for CPC:

Transforms:

```
random_flip
transforms.ToTensor()
normalize
Patchify(patch_size=patch_size, overlap_size=overlap)
```

Example:

```
# in a regular dataset
CIFAR10(..., transforms=CPCEvalTransformsCIFAR10())

# in a DataModule
module = CIFAR10DataModule(PATH)
train_loader = module.train_dataloader(batch_size=32,␣
↪transforms=CPCEvalTransformsCIFAR10())
```

Parameters

- **patch_size** (int) – size of patches when cutting up the image into overlapping patches
- **overlap** (int) – how much to overlap patches

__call__(*inp*)
Call self as a function.

25.1.3 Imagenet Train (c)

class pl_bolts.models.self_supervised.cpc.transforms.**CPCTrainTransformsImageNet128**(*patch_size=32*, *overlap=16*)

Bases: object

Transforms used for CPC:

Transforms:

```
random_flip
transforms.ToTensor()
normalize
Patchify(patch_size=patch_size, overlap_size=patch_size // 2)
```

Example:

```
# in a regular dataset
Imagenet(..., transforms=CPCTrainTransformsImageNet128())

# in a DataModule
module = ImagenetDataModule(PATH)
train_loader = module.train_dataloader(batch_size=32,␣
↪transforms=CPCTrainTransformsImageNet128())
```

Parameters

- **patch_size** (int) – size of patches when cutting up the image into overlapping patches
- **overlap** (int) – how much to overlap patches

__call__(*inp*)
Call self as a function.

25.1.4 Imagenet Eval (c)

class pl_bolts.models.self_supervised.cpc.transforms.**CPCEvalTransformsImageNet128**(*patch_size=*, *overlap=16*)

Bases: object

Transforms used for CPC:

Transforms:

```
random_flip
transforms.ToTensor()
normalize
Patchify(patch_size=patch_size, overlap_size=patch_size // 2)
```

Example:

```
# in a regular dataset
Imagenet(..., transforms=CPCEvalTransformsImageNet128())

# in a DataModule
module = ImagenetDataModule(PATH)
train_loader = module.train_dataloader(batch_size=32,␣
↪transforms=CPCEvalTransformsImageNet128())
```

Parameters

- **patch_size** (int) – size of patches when cutting up the image into overlapping patches
- **overlap** (int) – how much to overlap patches

__call__(*inp*)
Call self as a function.

25.1.5 STL-10 Train (c)

class pl_bolts.models.self_supervised.cpc.transforms.**CPCTrainTransformsSTL10**(*patch_size=16*, *overlap=8*)

Bases: object

Transforms used for CPC:

Transforms:

```
random_flip
img_jitter
col_jitter
rnd_gray
transforms.ToTensor()
normalize
Patchify(patch_size=patch_size, overlap_size=patch_size // 2)
```

Example:

```
# in a regular dataset
STL10(..., transforms=CPCTrainTransformsSTL10())

# in a DataModule
module = STL10DataModule(PATH)
train_loader = module.train_dataloader(batch_size=32,␣
↪transforms=CPCTrainTransformsSTL10())
```

Parameters

- **patch_size** (int) – size of patches when cutting up the image into overlapping patches
- **overlap** (int) – how much to overlap patches

__call__(*inp*)

Call self as a function.

25.1.6 STL-10 Eval (c)

class pl_bolts.models.self_supervised.cpc.transforms.**CPCEvalTransformsSTL10**(*patch_size=16*, *overlap=8*)

Bases: object

Transforms used for CPC:

Transforms:

```
random_flip
transforms.ToTensor()
normalize
Patchify(patch_size=patch_size, overlap_size=patch_size // 2)
```

Example:

```
# in a regular dataset
STL10(..., transforms=CPCEvalTransformsSTL10())

# in a DataModule
module = STL10DataModule(PATH)
train_loader = module.train_dataloader(batch_size=32,␣
↪transforms=CPCEvalTransformsSTL10())
```

Parameters

- **patch_size** (int) – size of patches when cutting up the image into overlapping patches
- **overlap** (int) – how much to overlap patches

__call__(*inp*)
Call self as a function.

25.2 AMDIM transforms

Transforms used for AMDIM

25.2.1 CIFAR-10 Train (a)

class pl_bolts.models.self_supervised.amdim.transforms.**AMDIMTrainTransformsCIFAR10**
Bases: object

Transforms applied to AMDIM

Transforms:

```
img_jitter,
col_jitter,
rnd_gray,
transforms.ToTensor(),
normalize
```

Example:

```
x = torch.rand(5, 3, 32, 32)

transform = AMDIMTrainTransformsCIFAR10()
(view1, view2) = transform(x)
```

__call__(*inp*)
Call self as a function.

25.2.2 CIFAR-10 Eval (a)

class pl_bolts.models.self_supervised.amdim.transforms.**AMDIMEvalTransformsCIFAR10**
Bases: object

Transforms applied to AMDIM

Transforms:

```
transforms.ToTensor(),
normalize
```

Example:

```
x = torch.rand(5, 3, 32, 32)

transform = AMDIMEvalTransformsCIFAR10()
(view1, view2) = transform(x)
```

__call__(*inp*)
Call self as a function.

25.2.3 Imagenet Train (a)

class pl_bolts.models.self_supervised.amdim.transforms.**AMDIMTrainTransformsImageNet128**(*heigh*
Bases: object

Transforms applied to AMDIM

Transforms:

```
img_jitter,
col_jitter,
rnd_gray,
transforms.ToTensor(),
normalize
```

Example:

```
x = torch.rand(5, 3, 128, 128)

transform = AMDIMTrainTransformsSTL10()
(view1, view2) = transform(x)
```

__call__(*inp*)
Call self as a function.

25.2.4 Imagenet Eval (a)

class pl_bolts.models.self_supervised.amdim.transforms.**AMDIMEvalTransformsImageNet128**(*height*
Bases: object

Transforms applied to AMDIM

Transforms:

```
transforms.Resize(height + 6, interpolation=3),
transforms.CenterCrop(height),
transforms.ToTensor(),
normalize
```

Example:

```
x = torch.rand(5, 3, 128, 128)

transform = AMDIMEvalTransformsImageNet128()
view1 = transform(x)
```

__call__(*inp*)
Call self as a function.

25.2.5 STL-10 Train (a)

class pl_bolts.models.self_supervised.amdim.transforms.**AMDIMTrainTransformsSTL10**(*height=64*)
Bases: object

Transforms applied to AMDIM

Transforms:

```
img_jitter,
col_jitter,
rnd_gray,
transforms.ToTensor(),
normalize
```

Example:

```
x = torch.rand(5, 3, 64, 64)

transform = AMDIMTrainTransformsSTL10()
(view1, view2) = transform(x)
```

__call__(*inp*)
Call self as a function.

25.2.6 STL-10 Eval (a)

class pl_bolts.models.self_supervised.amdim.transforms.**AMDIMEvalTransformsSTL10**(*height=64*)
Bases: object

Transforms applied to AMDIM

Transforms:

```
transforms.Resize(height + 6, interpolation=3),
transforms.CenterCrop(height),
transforms.ToTensor(),
normalize
```

Example:

```
x = torch.rand(5, 3, 64, 64)

transform = AMDIMTrainTransformsSTL10()
view1 = transform(x)
```

__call__(*inp*)
Call self as a function.

25.3 MOCO V2 transforms

Transforms used for MOCO V2

25.3.1 CIFAR-10 Train (m2)

class pl_bolts.models.self_supervised.moco.transforms.**Moco2TrainCIFAR10Transforms**(*height=32*)
Bases: object

Moco 2 augmentation: https://arxiv.org/pdf/2003.04297.pdf

__call__(*inp*)
Call self as a function.

25.3.2 CIFAR-10 Eval (m2)

class pl_bolts.models.self_supervised.moco.transforms.**Moco2EvalCIFAR10Transforms**(*height=32*)
Bases: object

Moco 2 augmentation: https://arxiv.org/pdf/2003.04297.pdf

__call__(*inp*)
Call self as a function.

25.3.3 Imagenet Train (m2)

class pl_bolts.models.self_supervised.moco.transforms.**Moco2TrainSTL10Transforms**(*height=64*)
Bases: object

Moco 2 augmentation: https://arxiv.org/pdf/2003.04297.pdf

__call__(*inp*)
Call self as a function.

25.3.4 Imagenet Eval (m2)

class pl_bolts.models.self_supervised.moco.transforms.**Moco2EvalSTL10Transforms**(*height=64*)
Bases: object

Moco 2 augmentation: https://arxiv.org/pdf/2003.04297.pdf

__call__(*inp*)
Call self as a function.

25.3.5 STL-10 Train (m2)

class pl_bolts.models.self_supervised.moco.transforms.**Moco2TrainImagenetTransforms**(*height=128*)
Bases: object

Moco 2 augmentation: https://arxiv.org/pdf/2003.04297.pdf

__call__(*inp*)
Call self as a function.

25.3.6 STL-10 Eval (m2)

class pl_bolts.models.self_supervised.moco.transforms.**Moco2EvalImagenetTransforms**(*height=128*)
Bases: object

Moco 2 augmentation: https://arxiv.org/pdf/2003.04297.pdf

__call__(*inp*)
Call self as a function.

25.4 SimCLR transforms

Transforms used for SimCLR

25.4.1 Train (sc)

class pl_bolts.models.self_supervised.simclr.transforms.**SimCLRTrainDataTransform**(*input_height=*
gaus-
sian_blur=Tru
jit-
ter_strength=
nor-
mal-
ize=None)

Bases: object

Transforms for SimCLR

Transform:

```
RandomResizedCrop(size=self.input_height)
RandomHorizontalFlip()
RandomApply([color_jitter], p=0.8)
RandomGrayscale(p=0.2)
GaussianBlur(kernel_size=int(0.1 * self.input_height))
transforms.ToTensor()
```

Example:

```
from pl_bolts.models.self_supervised.simclr.transforms import␣
↪SimCLRTrainDataTransform

transform = SimCLRTrainDataTransform(input_height=32)
x = sample()
(xi, xj) = transform(x)
```

__call__(*sample*)
Call self as a function.

25.4.2 Eval (sc)

class pl_bolts.models.self_supervised.simclr.transforms.**SimCLREvalDataTransform**(*input_height=2*
gaus-
sian_blur=True
jit-
ter_strength=1.
nor-
mal-
ize=None)

Bases: pl_bolts.models.self_supervised.simclr.transforms.SimCLRTrainDataTransform

Transforms for SimCLR

Transform:

```
Resize(input_height + 10, interpolation=3)
transforms.CenterCrop(input_height),
transforms.ToTensor()
```

Example:

```
from pl_bolts.models.self_supervised.simclr.transforms import␣
↪SimCLREvalDataTransform

transform = SimCLREvalDataTransform(input_height=32)
x = sample()
(xi, xj) = transform(x)
```

CHAPTER

TWENTYSIX

SELF-SUPERVISED LEARNING

Collection of useful functions for self-supervised learning

26.1 Identity class

Example:

```
from pl_bolts.utils import Identity
```

class pl_bolts.utils.self_supervised.**Identity**

Bases: torch.nn.

An identity class to replace arbitrary layers in pretrained models

Example:

```
from pl_bolts.utils import Identity

model = resnet18()
model.fc = Identity()
```

26.2 SSL-ready resnets

Torchvision resnets with the fc layers removed and with the ability to return all feature maps instead of just the last one.

Example:

```
from pl_bolts.utils.self_supervised import torchvision_ssl_encoder

resnet = torchvision_ssl_encoder('resnet18', pretrained=False, return_all_feature_
↪maps=True)
x = torch.rand(3, 3, 32, 32)

feat_maps = resnet(x)
```

pl_bolts.utils.self_supervised.**torchvision_ssl_encoder**(*name*, *pretrained=False*, *return_all_feature_maps=False*)

Return type Module

26.3 SSL backbone finetuner

class pl_bolts.models.self_supervised.ssl_finetuner.**SSLFineTuner**(*backbone*, *in_features=2048*, *num_classes=1000*, *epochs=100*, *hidden_dim=None*, *dropout=0.0*, *learning_rate=0.1*, *weight_decay=1e-06*, *nesterov=False*, *scheduler_type='cosine'*, *decay_epochs=[60, 80]*, *gamma=0.1*, *final_lr=0.0*)

Bases: pytorch_lightning.

Finetunes a self-supervised learning backbone using the standard evaluation protocol of a singler layer MLP with 1024 units

Example:

```
from pl_bolts.utils.self_supervised import SSLFineTuner
from pl_bolts.models.self_supervised import CPC_v2
from pl_bolts.datamodules import CIFAR10DataModule
from pl_bolts.models.self_supervised.cpc.transforms import␣
↪CPCEvalTransformsCIFAR10,

↪CPCTrainTransformsCIFAR10

# pretrained model
backbone = CPC_v2.load_from_checkpoint(PATH, strict=False)

# dataset + transforms
dm = CIFAR10DataModule(data_dir='.')
dm.train_transforms = CPCTrainTransformsCIFAR10()
dm.val_transforms = CPCEvalTransformsCIFAR10()

# finetuner
finetuner = SSLFineTuner(backbone, in_features=backbone.z_dim, num_
↪classes=backbone.num_classes)

# train
trainer = pl.Trainer()
trainer.fit(finetuner, dm)
```

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```
# test
trainer.test(datamodule=dm)
```

Parameters

- **backbone** (Module) – a pretrained model
- **in_features** (int) – feature dim of backbone outputs
- **num_classes** (int) – classes of the dataset
- **hidden_dim** (Optional[int]) – dim of the MLP (1024 default used in self-supervised literature)

CHAPTER

TWENTYSEVEN

SEMI-SUPERVISED LEARNING

Collection of utilities for semi-supervised learning where some part of the data is labeled and the other part is not.

27.1 Balanced classes

Example:

```
from pl_bolts.utils.semi_supervised import balance_classes
```

pl_bolts.utils.semi_supervised.**balance_classes**(*X*, *Y*, *batch_size*)

Makes sure each batch has an equal amount of data from each class. Perfect balance

Parameters

- **X** (Union[Tensor, ndarray]) – input features
- **Y** (Union[Tensor, ndarray, Sequence[int]]) – mixed labels (ints)
- **batch_size** (int) – the ultimate batch size

Return type Tuple[ndarray, ndarray]

27.2 half labeled batches

Example:

```
from pl_bolts.utils.semi_supervised import balance_classes
```

pl_bolts.utils.semi_supervised.**generate_half_labeled_batches**(*smaller_set_X*, *smaller_set_Y*, *larger_set_X*, *larger_set_Y*, *batch_size*)

Given a labeled dataset and an unlabeled dataset, this function generates a joint pair where half the batches are labeled and the other half is not

Return type Tuple[ndarray, ndarray]

CHAPTER

TWENTYEIGHT

SELF-SUPERVISED LEARNING CONTRASTIVE TASKS

This section implements popular contrastive learning tasks used in self-supervised learning.

28.1 FeatureMapContrastiveTask

This task compares sets of feature maps.

In general the feature map comparison pretext task uses triplets of features. Here are the abstract steps of comparison.

Generate multiple views of the same image

```
x1_view_1 = data_augmentation(x1)
x1_view_2 = data_augmentation(x1)
```

Use a different example to generate additional views (usually within the same batch or a pool of candidates)

```
x2_view_1 = data_augmentation(x2)
x2_view_2 = data_augmentation(x2)
```

Pick 3 views to compare, these are the anchor, positive and negative features

```
anchor = x1_view_1
positive = x1_view_2
negative = x2_view_1
```

Generate feature maps for each view

```
(a0, a1, a2) = encoder(anchor)
(p0, p1, p2) = encoder(positive)
```

Make a comparison for a set of feature maps

```
phi = some_score_function()

# the '01' comparison
score = phi(a0, p1)

# and can be bidirectional
score = phi(p0, a1)
```

In practice the contrastive task creates a BxB matrix where B is the batch size. The diagonals for set 1 of feature maps are the anchors, the diagonals of set 2 of the feature maps are the positives, the non-diagonals of set 1 are the negatives.

class pl_bolts.losses.self_supervised_learning.**FeatureMapContrastiveTask**(*comparisons='00, 11', tclip=10.0, bidirectional=True*)

Bases: torch.nn.

Performs an anchor, positive negative pair comparison for each each tuple of feature maps passed.

```
# extract feature maps
pos_0, pos_1, pos_2 = encoder(x_pos)
anc_0, anc_1, anc_2 = encoder(x_anchor)

# compare only the 0th feature maps
task = FeatureMapContrastiveTask('00')
loss, regularizer = task((pos_0), (anc_0))

# compare (pos_0 to anc_1) and (pos_0, anc_2)
task = FeatureMapContrastiveTask('01, 02')
losses, regularizer = task((pos_0, pos_1, pos_2), (anc_0, anc_1, anc_2))
loss = losses.sum()

# compare (pos_1 vs a anc_random)
task = FeatureMapContrastiveTask('0r')
loss, regularizer = task((pos_0, pos_1, pos_2), (anc_0, anc_1, anc_2))
```

```
# with bidirectional the comparisons are done both ways
task = FeatureMapContrastiveTask('01, 02')

# will compare the following:
# 01: (pos_0, anc_1), (anc_0, pos_1)
# 02: (pos_0, anc_2), (anc_0, pos_2)
```

Parameters

- **comparisons** (str) – groupings of feature map indices to compare (zero indexed, 'r' means random) ex: '00, 1r'
- **tclip** (float) – stability clipping value
- **bidirectional** (bool) – if true, does the comparison both ways

forward(*anchor_maps*, *positive_maps*)

Takes in a set of tuples, each tuple has two feature maps with all matching dimensions

Example

```
>>> import torch
>>> from pytorch_lightning import seed_everything
>>> seed_everything(0)
0
>>> a1 = torch.rand(3, 5, 2, 2)
>>> a2 = torch.rand(3, 5, 2, 2)
>>> b1 = torch.rand(3, 5, 2, 2)
>>> b2 = torch.rand(3, 5, 2, 2)
...
```

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```
>>> task = FeatureMapContrastiveTask('01, 11')
...
>>> losses, regularizer = task((a1, a2), (b1, b2))
>>> losses
tensor([2.2351, 2.1902])
>>> regularizer
tensor(0.0324)
```

static parse_map_indexes(*comparisons*)

Example:

```
>>> FeatureMapContrastiveTask.parse_map_indexes('11')
[(1, 1)]
>>> FeatureMapContrastiveTask.parse_map_indexes('11,59')
[(1, 1), (5, 9)]
>>> FeatureMapContrastiveTask.parse_map_indexes('11,59, 2r')
[(1, 1), (5, 9), (2, -1)]
```

28.2 Context prediction tasks

The following tasks aim to predict a target using a context representation.

28.2.1 CPCContrastiveTask

This is the predictive task from CPC (v2).

```
task = CPCTask(num_input_channels=32)

# (batch, channels, rows, cols)
# this should be thought of as 49 feature vectors, each with 32 dims
Z = torch.random.rand(3, 32, 7, 7)

loss = task(Z)
```

class pl_bolts.losses.self_supervised_learning.**CPCTask**(**args: Any*, ***kwargs: Any*)

Bases: torch.nn.

Loss used in CPC

CHAPTER

TWENTYNINE

CONTRIBUTING

Welcome to the PyTorch Lightning community! We're building the most advanced research platform on the planet to implement the latest, best practices that the amazing PyTorch team rolls out!

29.1 Bolts Design Principles

We encourage all sorts of contributions you're interested in adding! When coding for Bolts, please follow these principles.

29.1.1 Simple Internal Code

It's useful for users to look at the code and understand very quickly what's happening. Many users won't be engineers. Thus we need to value clear, simple code over condensed ninja moves. While that's super cool, this isn't the project for that :)

29.1.2 Force User Decisions To Best Practices

There are 1,000 ways to do something. However, eventually one popular solution becomes standard practice, and everyone follows. We try to find the best way to solve a particular problem, and then force our users to use it for readability and simplicity.

When something becomes a best practice, we add it to the framework. This is usually something like bits of code in utils or in the model file that everyone keeps adding over and over again across projects. When this happens, bring that code inside the trainer and add a flag for it.

29.1.3 Backward-compatible API

We all hate updating our deep learning packages because we don't want to refactor a bunch of stuff. In bolts, we make sure every change we make which could break an API is backward compatible with good deprecation warnings.

29.1.4 Gain User Trust

As a researcher, you can't have any part of your code going wrong. So, make thorough tests to ensure that every implementation of a new trick or subtle change is correct.

29.1.5 Interoperability

PyTorch Lightning Bolts is highly interoperable with PyTorch Lightning and PyTorch.

29.2 Contribution Types

We are always looking for help implementing new features or fixing bugs.

A lot of good work has already been done in project mechanics (requirements/base.txt, setup.py, pep8, badges, ci, etc. . .) so we're in a good state there thanks to all the early contributors (even pre-beta release)!

29.2.1 Bug Fixes:

1. If you find a bug please submit a GitHub issue.
    - Make sure the title explains the issue.
    - Describe your setup, what you are trying to do, expected vs. actual behaviour. Please add configs and code samples.
    - Add details on how to reproduce the issue - a minimal test case is always best, colab is also great. Note, that the sample code shall be minimal and if needed with publicly available data.
2. Try to fix it or recommend a solution. We highly recommend to use test-driven approach:
    - Convert your minimal code example to a unit/integration test with assert on expected results.
    - Start by debugging the issue. . . You can run just this particular test in your IDE and draft a fix.
    - Verify that your test case fails on the master branch and only passes with the fix applied.
3. Submit a PR!

***Note**, even if you do not find the solution, sending a PR with a test covering the issue is a valid contribution and we can help you or finish it with you :]*

29.2.2 New Features:

1. Submit a GitHub issue - describe what is the motivation of such feature (adding the use case or an example is helpful).
2. Let's discuss to determine the feature scope.
3. Submit a PR! We recommend test driven approach to adding new features as well:
    - Write a test for the functionality you want to add.
    - Write the functional code until the test passes.
4. Add/update the relevant tests!

- This PR is a good example for adding a new metric, and this one for a new logger.

29.2.3 New Models:

PyTorch Lightning Bolts makes several research models for ready usage. Following are general guidelines for adding new models.

1. Models which are standard baselines
2. Whose results are reproduced properly either by us or by authors.
3. Top models which are not SOTA but highly cited for production usage / for other uses. (E.g. Mobile BERT, MobileNets, FBNets).
4. Do not reinvent the wheel, natively support torchvision, torchtext, torchaudio models.
5. Use open source licensed models.

Please raise an issue before adding a new model. Please let us know why the particular model is important for bolts. There are tons of models that keep coming. It is very difficult to support every model.

29.2.4 Test cases:

Want to keep Lightning Bolts healthy? Love seeing those green tests? So do we! How to we keep it that way? We write tests! We value tests contribution even more than new features.

Tests are written using pytest. Tests in PyTorch Lightning bolts train model on a datamodule. Datamodule is lightning abstraction of representing dataloader and dataset. Model is checked by simply calling `.fit()` function over the datamodule.

Along with these we have tests for losses, callbacks and transforms as well.

Have a look at sample tests here.

After you have added the respective tests, you can run the tests locally with make script:

```
make test
```

Want to add a new test case and not sure how? Talk to us!

29.3 Note before submitting the PR, make sure you have run `make isort`.

29.4 Guidelines

For this section, we refer to read the parent PL guidelines

Reminder

All added or edited code shall be the own original work of the particular contributor. If you use some third-party implementation, all such blocks/functions/modules shall be properly referred and if possible also agreed by code's author. For example - `This code is inspired from http://...`. In case you adding new dependencies, make sure that they are compatible with the actual PyTorch Lightning license (ie. dependencies should be *at least* as permissive as the PyTorch Lightning license).

29.4.1 Question & Answer

1. **How can I help/contribute?**

   All help is extremely welcome - reporting bugs, fixing documentation, adding test cases, solving issues and preparing bug fixes. To solve some issues you can start with label good first issue or chose something close to your domain with label help wanted. Before you start to implement anything check that the issue description that it is clear and self-assign the task to you (if it is not possible, just comment that you take it and we assign it to you...).

2. **Is there a recommendation for branch names?**

   We do not rely on the name convention so far you are working with your own fork. Anyway it would be nice to follow this convention `<type>/<issue-id>_<short-name>` where the types are: `bugfix`, `feature`, `docs`, `tests`, ...

3. **I have a model in other framework than PyTorch, how do I add it here?**

   Since PyTorch Lightning is written on top of PyTorch. We need models in PyTorch only. Also, we would need same or equivalent results with PyTorch Lightning after converting the models from other frameworks.

CHAPTER

THIRTY

PL BOLTS GOVERNANCE | PERSONS OF INTEREST

30.1 Core Maintainers

- William Falcon (williamFalcon) (Lightning founder)
- Jirka Borovec (Borda)
- Annika Brundyn (annikabrundyn)
- Ananya Harsh Jha (ananyahjha93)
- Teddy Koker (teddykoker)
- Akihiro Nitta (akihironitta)

CHAPTER

THIRTYONE

CHANGELOG

All notable changes to this project will be documented in this file.

The format is based on Keep a Changelog, and this project adheres to Semantic Versioning.

31.1 [0.3.2] - 2021-03-20

31.1.1 [0.3.2] - Changed

- Renamed SSL modules: `CPCV2` >> `CPC_v2` and `MocoV2` >> `Moco_v2` (#585)
- Refactored *setup.py* to be typing friendly (#601)

31.2 [0.3.1] - 2021-03-09

31.2.1 [0.3.1] - Added

- Added Pix2Pix model (#533)

31.2.2 [0.3.1] - Changed

- Moved vision models (`GPT2`, `ImageGPT`, `SemSegment`, `UNet`) to `pl_bolts.models.vision` (#561)

31.2.3 [0.3.1] - Fixed

- Fixed BYOL moving average update (#574)
- Fixed custom gamma in rl (#550)
- Fixed PyTorch 1.8 compatibility issue (#580, #579)
- Fixed handling batchnorms in `BatchGradientVerification` (#569)
- Corrected `num_rows` calculation in `LatentDimInterpolator` callback (#573)

31.3 [0.3.0] - 2021-01-20

31.3.1 [0.3.0] - Added

- Added `input_channels` argument to UNet (#297)
- Added SwAV (#239, #348, #323)
- Added data monitor callbacks `ModuleDataMonitor` and `TrainingDataMonitor` (#285)
- Added DCGAN module (#403)
- Added `VisionDataModule` as parent class for `BinaryMNISTDataModule`, `CIFAR10DataModule`, `FashionMNISTDataModule`, and `MNISTDataModule` (#400)
- Added GIoU loss (#347)
- Added IoU loss (#469)
- Added semantic segmentation model `SemSegment` with `UNet` backend (#259)
- Added pption to normalize latent interpolation images (#438)
- Added flags to datamodules (#388)
- Added metric GIoU (#347)
- Added Intersection over Union Metric/Loss (#469)
- Added SimSiam model (#407)
- Added gradient verification callback (#465)
- Added Backbones to FRCNN (#475)

31.3.2 [0.3.0] - Changed

- Decoupled datamodules from models (#332, #270)
- Set PyTorch Lightning 1.0 as the minimum requirement (#274)
- Moved `pl_bolts.callbacks.self_supervised.BYOLMAWeightUpdate` to `pl_bolts.callbacks.byol_updates.BYOLMAWeightUpdate` (#288)
- Moved `pl_bolts.callbacks.self_supervised.SSLOnlineEvaluator` to `pl_bolts.callbacks.ssl_online.SSLOnlineEvaluator` (#288)
- Moved `pl_bolts.datamodules.*_dataset` to `pl_bolts.datasets.*_dataset` (#275)
- Ensured sync across val/test step when using DDP (#371)
- Refactored CLI arguments of models (#394)
- Upgraded DQN to use `.log` (#404)
- Decoupled DataModules from models - CPCV2 (#386)
- Refactored datamodules/datasets (#338)
- Refactored Vision DataModules (#400)
- Refactored `pl_bolts.callbacks` (#477)
- Refactored the rest of `pl_bolts.models.self_supervised` (#481, #479

- Update [`torchvision.utils.make_grid`(https://pytorch.org/docs/stable/torchvision/utils.html#torchvision.utils.make_gr
kwargs to `TensorboardGenerativeModelImageSampler` (#494)

31.3.3 [0.3.0] - Fixed

- Fixed duplicate warnings when optional packages are unavailable (#341)
- Fixed `ModuleNotFoundError` when importing datamoules (#303)
- Fixed cyclic imports in `pl_bolts.utils.self_suprvised` (#350)
- Fixed VAE loss to use KL term of ELBO (#330)
- Fixed dataloders of `MNISTDataModule` to use `self.batch_size` (#331)
- Fixed missing `outputs` in SSL hooks for PyTorch Lightning 1.0 (#277)
- Fixed stl10 datamodule (#369)
- Fixes SimCLR transforms (#329)
- Fixed binary MNIST datamodule (#377)
- Fixed the end of batch size mismatch (#389)
- Fixed `batch_size` parameter for DataModules remaining (#344)
- Fixed CIFAR `num_samples` (#432)
- Fixed DQN `run_n_episodes` using the wrong environment variable (#525)

31.4 [0.2.5] - 2020-10-12

- Enabled PyTorch Lightning 1.0 compatibility

31.5 [0.2.4] - 2020-10-12

- Enabled manual returns (#267)

31.6 [0.2.3] - 2020-10-12

31.6.1 [0.2.3] - Added

- Enabled PyTorch Lightning 0.10 compatibility (#264)
- Added dummy datasets (#266)
- Added `KittiDataModule` (#248)
- Added `UNet` (#247)
- Added reinforcement learning models, losses and datamodules (#257)

31.7 [0.2.2] - 2020-09-14

- Fixed confused logit (#222)

31.8 [0.2.1] - 2020-09-13

31.8.1 [0.2.1] - Added

- Added pretrained VAE with resnet encoders and decoders
- Added pretrained AE with resnet encoders and decoders
- Added CPC pretrained on CIFAR10 and STL10
- Verified BYOL implementation

31.8.2 [0.2.1] - Changed

- Dropped all dependencies except PyTorch Lightning and PyTorch
- Decoupled datamodules from GAN (#206)
- Modularize AE & VAE (#196)

31.8.3 [0.2.1] - Fixed

- Fixed gym (#221)
- Fix L1/L2 regularization (#216)
- Fix max_depth recursion crash in AsynchronousLoader (#191)

31.9 [0.2.0] - 2020-09-10

31.9.1 [0.2.0] - Added

- Enabled Apache License, Version 2.0

31.9.2 [0.2.0] - Changed

- Moved unnecessary dependencies to `__main__` section in BYOL (#176)

31.9.3 [0.2.0] - Fixed

- Fixed CPC STL10 finetune (#173)

31.10 [0.1.1] - 2020-08-23

31.10.1 [0.1.1] - Added

- Added Faster RCNN + Pscal VOC DataModule (#157)
- Added a better lars scheduling `LARSWrapper` (#162)
- Added CPC finetuner (#158)
- Added `BinaryMNISTDataModule` (#153)
- Added learning rate scheduler to BYOL (#148)
- Added Cityscapes DataModule (#136)
- Added learning rate scheduler `LinearWarmupCosineAnnealingLR` (#138)
- Added BYOL (#144)
- Added `ConfusedLogitCallback` (#118)
- Added an asynchronous single GPU dataloader. (#1521)

31.10.2 [0.1.1] - Fixed

- Fixed simclr finetuner (#165)
- Fixed STL10 finetuner (#164)
- Fixed Image GPT (#108)
- Fixed unused MNIST transforms in tran/val/test (#109)

31.10.3 [0.1.1] - Changed

- Enhanced train batch function (#107)

31.11 [0.1.0] - 2020-07-02

31.11.1 [0.1.0] - Added

- Added setup and repo structure
- Added requirements
- Added docs
- Added Manifest
- Added coverage
- Added MNIST template

- Added VAE template
- Added GAN + AE + MNIST
- Added Linear Regression
- Added Moco2g
- Added simclr
- Added RL module
- Added Loggers
- Added Transforms
- Added Tiny Datasets
- Added regularization to linear + logistic models
- Added Linear and Logistic Regression tests
- Added Image GPT
- Added Recommenders module

31.11.2 [0.1.0] - Changed

- Device is no longer set in the DQN model init
- Moved RL loss function to the losses module
- Moved rl.common.experience to datamodules
- train_batch function to VPG model to generate batch of data at each step (POC)
- Experience source no longer gets initialized with a device, instead the device is passed at each step()
- Refactored ExperienceSource classes to be handle multiple environments.

31.11.3 [0.1.0] - Removed

- Removed N-Step DQN as the latest version of the DQN supports N-Step by setting the `n_step` arg to n
- Deprecated common.experience

31.11.4 [0.1.0] - Fixed

- Documentation
- Doct tests
- CI pipeline
- Imports and pkg
- CPC fixes

CHAPTER

THIRTYTWO

INDICES AND TABLES

- genindex
- modindex
- search