Open in Colab

BigTransfer (BiT): A step-by-step tutorial for state-of-the-art vision

This colab demonstrates how to:

1. Load BiT models in PyTorch
2. Make predictions using BiT pre-trained on ImageNet
3. Fine-tune BiT on 5-shot CIFAR10 and get amazing results!

It is good to get an understanding or quickly try things. However, to run longer training runs, we recommend using the commandline scripts at http://github.com/google-research/big_transfer

```
from functools import partial
from collections import OrderedDict


%config InlineBackend.figure_format = 'retina'

import numpy as np

import matplotlib.pyplot as plt
from mpl_toolkits.axes_grid1 import ImageGrid


import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.autograd import Variable

import torchvision as tv

torch.cuda.empty_cache()


device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
print(device)
```

```
cuda:0
```

Reading weight data from the Cloud bucket

```
import requests
import io


def get_weights(bit_variant):
  response = requests.get(f'https://storage.googleapis.com/bit_models/{bit_variant}.np
  response.raise_for_status()
  return np.load(io.BytesIO(response.content))


weights = get_weights('BiT-S-R50x3')  # You could use other variants, such as R101x3 c
```

Defining the architecture and loading weights

```
class StdConv2d(nn.Conv2d):
  def forward(self, x):
    w = self.weight
    v, m = torch.var_mean(w, dim=[1, 2, 3], keepdim=True, unbiased=False)
    w = (w - m) / torch.sqrt(v + 1e-10)
    return F.conv2d(x, w, self.bias, self.stride, self.padding, self.dilation, self.gr


def conv3x3(cin, cout, stride=1, groups=1, bias=False):
  return StdConv2d(cin, cout, kernel_size=3, stride=stride, padding=1, bias=bias, grou

def conv1x1(cin, cout, stride=1, bias=False):
  return StdConv2d(cin, cout, kernel_size=1, stride=stride, padding=0, bias=bias)


def tf2th(conv_weights):
  """Possibly convert HWIO to OIHW"""
  if conv_weights.ndim == 4:
    conv_weights = np.transpose(conv_weights, [3, 2, 0, 1])
  return torch.from_numpy(conv_weights)


class PreActBottleneck(nn.Module):
  """
  Follows the implementation of "Identity Mappings in Deep Residual Networks" here:
  https://github.com/KaimingHe/resnet-1k-layers/blob/master/resnet-pre-act.lua

  Except it puts the stride on 3x3 conv when available.
  """
  def __init__(self, cin, cout=None, cmid=None, stride=1):
```

```
    super().__init__()
    cout = cout or cin
    cmid = cmid or cout//4

    self.gn1 = nn.GroupNorm(32, cin)
    self.conv1 = conv1x1(cin, cmid)
    self.gn2 = nn.GroupNorm(32, cmid)
    self.conv2 = conv3x3(cmid, cmid, stride)  # Original ResNetv2 has it on conv1!!
    self.gn3 = nn.GroupNorm(32, cmid)
    self.conv3 = conv1x1(cmid, cout)
    self.relu = nn.ReLU(inplace=True)

    if (stride != 1 or cin != cout):
      # Projection also with pre-activation according to paper.
      self.downsample = conv1x1(cin, cout, stride)

  def forward(self, x):
      # Conv'ed branch
      out = self.relu(self.gn1(x))

      # Residual branch
      residual = x
      if hasattr(self, 'downsample'):
          residual = self.downsample(out)

      # The first block has already applied pre-act before splitting, see Appendix.
      out = self.conv1(out)
      out = self.conv2(self.relu(self.gn2(out)))
      out = self.conv3(self.relu(self.gn3(out)))

      return out + residual

  def load_from(self, weights, prefix=''):
    with torch.no_grad():
      self.conv1.weight.copy_(tf2th(weights[prefix + 'a/standardized_conv2d/kernel']))
      self.conv2.weight.copy_(tf2th(weights[prefix + 'b/standardized_conv2d/kernel']))
      self.conv3.weight.copy_(tf2th(weights[prefix + 'c/standardized_conv2d/kernel']))
      self.gn1.weight.copy_(tf2th(weights[prefix + 'a/group_norm/gamma']))
      self.gn2.weight.copy_(tf2th(weights[prefix + 'b/group_norm/gamma']))
      self.gn3.weight.copy_(tf2th(weights[prefix + 'c/group_norm/gamma']))
      self.gn1.bias.copy_(tf2th(weights[prefix + 'a/group_norm/beta']))
      self.gn2.bias.copy_(tf2th(weights[prefix + 'b/group_norm/beta']))
      self.gn3.bias.copy_(tf2th(weights[prefix + 'c/group_norm/beta']))
      if hasattr(self, 'downsample'):
        self.downsample.weight.copy_(tf2th(weights[prefix + 'a/proj/standardized_conv2
    return self


class ResNetV2(nn.Module):
  BLOCK_UNITS = {
      'r50': [3, 4, 6, 3],
      'r101': [3, 4, 23, 3],
```

```
      'r152': [3, 8, 36, 3],
  }

  def __init__(self, block_units, width_factor, head_size=21843, zero_head=False):
    super().__init__()
    wf = width_factor  # shortcut 'cause we'll use it a lot.

    self.root = nn.Sequential(OrderedDict([
        ('conv', StdConv2d(3, 64*wf, kernel_size=7, stride=2, padding=3, bias=False)),
        ('padp', nn.ConstantPad2d(1, 0)),
        ('pool', nn.MaxPool2d(kernel_size=3, stride=2, padding=0)),
        # The following is subtly not the same!
        #('pool', nn.MaxPool2d(kernel_size=3, stride=2, padding=1)),
    ]))

    self.body = nn.Sequential(OrderedDict([
        ('block1', nn.Sequential(OrderedDict(
            [('unit01', PreActBottleneck(cin= 64*wf, cout=256*wf, cmid=64*wf))] +
            [(f'unit{i:02d}', PreActBottleneck(cin=256*wf, cout=256*wf, cmid=64*wf)) f
        ))),
        ('block2', nn.Sequential(OrderedDict(
            [('unit01', PreActBottleneck(cin=256*wf, cout=512*wf, cmid=128*wf, stride=
            [(f'unit{i:02d}', PreActBottleneck(cin=512*wf, cout=512*wf, cmid=128*wf))
        ))),
        ('block3', nn.Sequential(OrderedDict(
            [('unit01', PreActBottleneck(cin= 512*wf, cout=1024*wf, cmid=256*wf, stric
            [(f'unit{i:02d}', PreActBottleneck(cin=1024*wf, cout=1024*wf, cmid=256*wf)
        ))),
        ('block4', nn.Sequential(OrderedDict(
            [('unit01', PreActBottleneck(cin=1024*wf, cout=2048*wf, cmid=512*wf, stric
            [(f'unit{i:02d}', PreActBottleneck(cin=2048*wf, cout=2048*wf, cmid=512*wf)
        ))),
    ]))

    self.zero_head = zero_head
    self.head = nn.Sequential(OrderedDict([
        ('gn', nn.GroupNorm(32, 2048*wf)),
        ('relu', nn.ReLU(inplace=True)),
        ('avg', nn.AdaptiveAvgPool2d(output_size=1)),
        ('conv', nn.Conv2d(2048*wf, head_size, kernel_size=1, bias=True)),
    ]))

  def forward(self, x):
    x = self.head(self.body(self.root(x)))
    assert x.shape[-2:] == (1, 1)  # We should have no spatial shape left.
    return x[...,0,0]

  def load_from(self, weights, prefix='resnet/'):
    with torch.no_grad():
      self.root.conv.weight.copy_(tf2th(weights[f'{prefix}root_block/standardized_conv
      self.head.gn.weight.copy_(tf2th(weights[f'{prefix}group_norm/gamma']))
      self.head.gn.bias.copy_(tf2th(weights[f'{prefix}group_norm/beta']))
```

```
      self.head.gn.bias.copy_(tf2th(weights[f'{prefix}group_norm/beta']))
      if self.zero_head:
        nn.init.zeros_(self.head.conv.weight)
        nn.init.zeros_(self.head.conv.bias)
      else:
        self.head.conv.weight.copy_(tf2th(weights[f'{prefix}head/conv2d/kernel']))
        self.head.conv.bias.copy_(tf2th(weights[f'{prefix}head/conv2d/bias']))

      for bname, block in self.body.named_children():
        for uname, unit in block.named_children():
          unit.load_from(weights, prefix=f'{prefix}{bname}/{uname}/')
    return self
```

Boilerplate

```
from IPython.display import HTML, display

def progress(value, max=100):
    return HTML("""
        <progress
            value='{value}'
            max='{max}',
            style='width: 100%'
        >
            {value}
        </progress>
    """.format(value=value, max=max))


def stairs(s, v, *svs):
    """ Implements a typical "stairs" schedule for learning-rates.
    Best explained by example:
    stairs(s, 0.1, 10, 0.01, 20, 0.001)
    will return 0.1 if s<10, 0.01 if 10<=s<20, and 0.001 if 20<=s
    """
    for s0, v0 in zip(svs[::2], svs[1::2]):
        if s < s0:
            break
        v = v0
    return v

def rampup(s, peak_s, peak_lr):
  if s < peak_s:  # Warmup
    return s/peak_s * peak_lr
  else:
    return peak_lr

def schedule(s):
  step_lr = stairs(s, 3e-3, 200, 3e-4, 300, 3e-5, 400, 3e-6, 500, None)
  return rampup(s, 100, step_lr)
```

```
  return rampup(s, 100, step_lr)
```

CIFAR-10 Example

```
import PIL

preprocess_train = tv.transforms.Compose([
    tv.transforms.Resize((160, 160), interpolation=PIL.Image.BILINEAR),  # It's the de
    tv.transforms.RandomCrop((128, 128)),
    tv.transforms.RandomHorizontalFlip(),
    tv.transforms.ToTensor(),
    tv.transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))  # Get data into [-1, 1]
])

preprocess_eval = tv.transforms.Compose([
    tv.transforms.Resize((128, 128), interpolation=PIL.Image.BILINEAR),
    tv.transforms.ToTensor(),
    tv.transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
])

trainset = tv.datasets.CIFAR10(root='./data', train=True, download=True, transform=pre
testset = tv.datasets.CIFAR10(root='./data', train=False, download=True, transform=pre
```

```
/usr/local/lib/python3.7/dist-packages/torchvision/transforms/transforms.py:258:
  "Argument interpolation should be of type InterpolationMode instead of int. "
Downloading https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz to ./data/ci
```

170499072/? [00:13<00:00, 12682716.75it/s]

```
Extracting ./data/cifar-10-python.tar.gz to ./data
Files already downloaded and verified
```

```
import random

n = random.randint(0, 10)
```

Find indices to create a N-shot CIFAR10 variant

```
preprocess_tiny = tv.transforms.Compose([tv.transforms.CenterCrop((2, 2)), tv.transfor
trainset_tiny = tv.datasets.CIFAR10(root='./data', train=True, download=True, transfor
loader = torch.utils.data.DataLoader(trainset_tiny, batch_size=50000, shuffle=False, n
images, labels = iter(loader).next()
```

```
Files already downloaded and verified
```

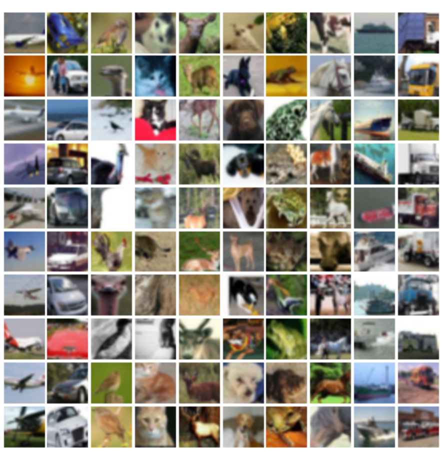
```
indices = {cls: np.random.choice(np.where(labels.numpy() == cls)[0], n, replace=False)
```

```
print(indices)
```

```
{0: array([10148,  4651, 38344, 17965, 13225,  9616, 46343, 42010, 33933,
       16529]), 1: array([10711,  6269, 46693, 36550, 30714,  3062, 26375,  5841
       21003]), 2: array([12675, 42098,  7664, 28238, 21102, 34654, 29730,   803
       15765]), 3: array([18127, 41866, 33955, 27766, 28488,  2982, 45467, 39135
       35245]), 4: array([46319, 37004, 24942,  5919, 44977, 37875,  2106, 25803
       13909]), 5: array([  928, 18280, 26010,  3837, 12371, 43330, 10542, 42862
       11155]), 6: array([47464, 19586, 36304, 15048, 13511, 23683, 20148,  7994
        4026]), 7: array([20738, 17469, 37882,  6939, 45459, 33019, 12838, 47522
       12394]), 8: array([22760, 24629, 18045, 39139, 35171, 38809, 46735,  4502
       21134]), 9: array([26374, 45735, 17704,  2917, 27694,  1590, 35280, 47896
       41348])}
```

```
fig = plt.figure(figsize=(10, 4))
ig = ImageGrid(fig, 111, (n, 10))
for c, cls in enumerate(indices):
  for r, i in enumerate(indices[cls]):
    img, _ = trainset[i]
    ax = ig.axes_column[c][r]
    ax.imshow((img.numpy().transpose([1, 2, 0]) * 127.5 + 127.5).astype(np.uint8))
    ax.set_axis_off()
fig.suptitle('The whole 10-shot CIFAR10 dataset');
```

The whole 10-shot CIFAR10 dataset



```
train_n_shot = torch.utils.data.Subset(trainset, indices=[i for v in indices.values()
len(train_n_shot)
```

```
100
```

Fine-tune BiT-M on this 10-shot CIFAR10 variant

NOTE: In this very low data regime, the performance heavily depends on how "representative" the 5 examples you got are of the class. As shown in the paper, variance is very large, I'm getting anywhere between 78%-85% depending on luck.

Another point is that here I use `batch_size=512` for consistency with the paper. But actually, a much smaller `batch_size=50` works just as well and is about 10x faster!

```
model = ResNetV2(ResNetV2.BLOCK_UNITS['r50'], width_factor=3, head_size=10, zero_head=
model.load_from(weights)
model.to(device);
```

```
# Yes, we still use 512 batch-size! Maybe something else is even better, who knows.
# loader_train = torch.utils.data.DataLoader(train_5shot, batch_size=512, shuffle=True

# NOTE: This is necessary when the batch-size is larger than the dataset.
sampler = torch.utils.data.RandomSampler(train_10shot, replacement=True, num_samples=2
loader_train = torch.utils.data.DataLoader(train_10shot, batch_size=50, num_workers=2,
```

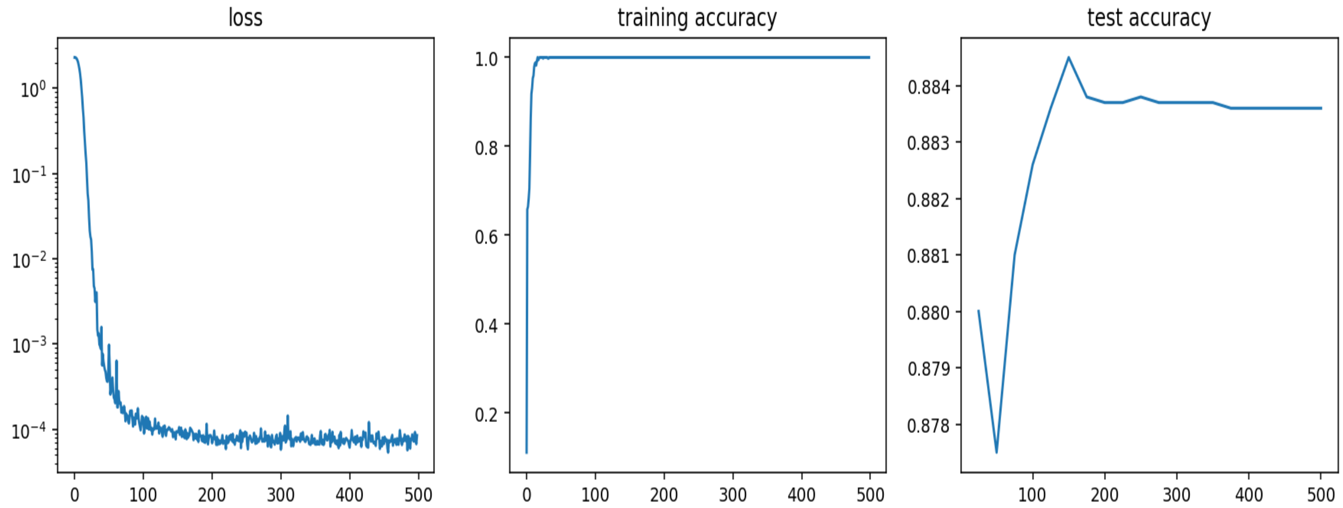
```
crit = nn.CrossEntropyLoss()
opti = torch.optim.SGD(model.parameters(), lr=0.003, momentum=0.9)
model.train();
```

```
S = 500
def schedule(s):
  step_lr = stairs(s, 3e-3, 200, 3e-4, 300, 3e-5, 400, 3e-6, S, None)
  return rampup(s, 100, step_lr)

pb_train = display(progress(0, S), display_id=True)
pb_test = display(progress(0, 100), display_id=True)
losses = [[]]
accus_train = [[]]
accus_test = []

steps_per_iter = 512 // loader_train.batch_size

while len(losses) < S:
  for x, t in loader_train:
    x, t = x.to(device), t.to(device)

    logits = model(x)
    loss = crit(logits, t) / steps_per_iter
    loss.backward()
    losses[-1].append(loss.item())
```

```
    with torch.no_grad():
      accus_train[-1].extend(torch.max(logits, dim=1)[1].cpu().numpy() == t.cpu().nump

    if len(losses[-1]) == steps_per_iter:
      losses[-1] = sum(losses[-1])
      losses.append([])
      accus_train[-1] = np.mean(accus_train[-1])
      accus_train.append([])

      # Update learning-rate according to schedule, and stop if necessary
      lr = schedule(len(losses) - 1)
      for param_group in opti.param_groups:
        param_group['lr'] = lr

      opti.step()
      opti.zero_grad()

      pb_train.update(progress(len(losses) - 1, S))
      print(f'\r[Step {len(losses) - 1}] loss={losses[-2]:.2e} '
            f'train accu={accus_train[-2]:.2%} '
            f'test accu={accus_test[-1] if accus_test else 0:.2%} '
            f'(lr={lr:g})', end='', flush=True)

      if len(losses) % 25 == 0:
        accus_test.append(eval_cifar10(model, progressbar=pb_test))
        model.train()
```

```
[Step 305] loss=6.14e-04 train accu=100.00% test accu=82.22% (lr=3e-05)
```

```
fig, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(15, 4))
ax1.plot(losses[:-1])
ax1.set_yscale('log')
ax1.set_title('loss')
ax2.plot(accus_train[:-1])
ax2.set_title('training accuracy')
ax3.plot(np.arange(25, 501, 25), accus_test)
ax3.set_title('test accuracy');
```


loss
training accuracy
test accuracy
10^0
10^{-1}
10^{-2}
10^{-3}
10^{-4}
0
100
200
300
400
500
1.0
0.8
0.6
0.4
0.2
0.884
0.883
0.882
0.881
0.880
0.879
0.878