PyTorch常用代码段汇总

CV开发者都爱看的 极市平台 2023-05-20 22:01:12 发表于广东 手机阅读

作者丨Jack Stark@知乎（已授权）

来源丨https://zhuanlan.zhihu.com/p/104019160

编辑丨极市平台

极市导读

本文是PyTorch常用代码段合集，涵盖基本配置、张量处理、模型定义与操作、数据处理、模型训练与测试等5个方面，还给出了多个值得注意的Tips，内容非常全面。 >>加入极市CV技术交流群，走在计算机视觉的最前沿

PyTorch最好的资料是官方文档。本文是PyTorch常用代码段，在参考资料[1](张皓：PyTorch Cookbook)的基础上做了一些修补，方便使用时查阅。

基本配置

导入包和版本查询

```
import torch
import torch.nn as nn
import torchvision
print(torch.__version__)
print(torch.version.cuda)
print(torch.backends.cudnn.version())
print(torch.cuda.get_device_name(0))
```

可复现性

在硬件设备（CPU、GPU）不同时，完全的可复现性无法保证，即使随机种子相同。但是，在同一个设备上，应该保证可复现性。具体做法是，在程序开始的时候固定torch的随机种子，同时也把numpy的随机种子固定。

```
np.random.seed(0)
torch.manual_seed(0)
torch.cuda.manual_seed_all(0)

torch.backends.cudnn.deterministic = True
torch.backends.cudnn.benchmark = False
```

显卡设置

如果只需要一张显卡

```
# Device configuration
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
```

如果需要指定多张显卡，比如0，1号显卡。

```
import osos.environ['CUDA_VISIBLE_DEVICES'] = '0,1'
```

也可以在命令行运行代码时设置显卡：

```
CUDA_VISIBLE_DEVICES=0,1 python train.py
```

清除显存

```
torch.cuda.empty_cache()
```

也可以使用在命令行重置GPU的指令

```
nvidia-smi --gpu-reset -i [gpu_id]
```

张量(Tensor)处理

张量的数据类型

PyTorch有9种CPU张量类型和9种GPU张量类型。

Data type	dtype	CPU tensor	GPU tensor
32-bit floating point	`torch.float32` or `torch.float`	`torch.FloatTensor`	`torch.cuda.FloatTensor`
64-bit floating point	`torch.float64` or `torch.double`	`torch.DoubleTensor`	`torch.cuda.DoubleTensor`
16-bit floating point	`torch.float16` or `torch.half`	`torch.HalfTensor`	`torch.cuda.HalfTensor`
8-bit integer (unsigned)	`torch.uint8`	`torch.ByteTensor`	`torch.cuda.ByteTensor`
8-bit integer (signed)	`torch.int8`	`torch.CharTensor`	`torch.cuda.CharTensor`
16-bit integer (signed)	`torch.int16` or `torch.short`	`torch.ShortTensor`	`torch.cuda.ShortTensor`
32-bit integer (signed)	`torch.int32` or `torch.int`	`torch.IntTensor`	`torch.cuda.IntTensor`
64-bit integer (signed)	`torch.int64` or `torch.long`	`torch.LongTensor`	`torch.cuda.LongTensor`
Boolean	`torch.bool`	`torch.BoolTensor`	`torch.cuda.BoolTensor`

张量基本信息

```
tensor = torch.randn(3,4,5)print(tensor.type())  # 数据类型print(tensor.size())  # 张量的sha
```

命名张量

张量命名是一个非常有用的方法，这样可以方便地使用维度的名字来做索引或其他操作，大大提高了可读性、易用性，防止出错。

```
# 在PyTorch 1.3之前，需要使用注释
# Tensor[N, C, H, W]
images = torch.randn(32, 3, 56, 56)
```

```
images.sum(dim=1)
images.select(dim=1, index=0)

# PyTorch 1.3之后
NCHW = [‘N’, ‘C’, ‘H’, ‘W’]
images = torch.randn(32, 3, 56, 56, names=NCHW)
images.sum('C')
images.select('C', index=0)
# 也可以这么设置
tensor = torch.rand(3,4,1,2,names=('C', 'N', 'H', 'W'))
# 使用align_to可以对维度方便地排序
tensor = tensor.align_to('N', 'C', 'H', 'W')
```

数据类型转换

```
# 设置默认类型，pytorch中的FloatTensor远远快于DoubleTensor
torch.set_default_tensor_type(torch.FloatTensor)

# 类型转换
tensor = tensor.cuda()
tensor = tensor.cpu()
tensor = tensor.float()
tensor = tensor.long()
```

torch.Tensor与np.ndarray转换

除了CharTensor，其他所有CPU上的张量都支持转换为numpy格式然后再转换回来。

```
ndarray = tensor.cpu().numpy()
tensor = torch.from_numpy(ndarray).float()
tensor = torch.from_numpy(ndarray.copy()).float() # If ndarray has negative stride.
```

Torch.tensor与PIL.Image转换

```
# pytorch中的张量默认采用[N, C, H, W]的顺序，并且数据范围在[0,1]，需要进行转置和规范化
# torch.Tensor -> PIL.Image
image = PIL.Image.fromarray(torch.clamp(tensor*255, min=0, max=255).byte().permute(1,2,0).
image = torchvision.transforms.functional.to_pil_image(tensor)  # Equivalently way

# PIL.Image -> torch.Tensor
```

```
path = r'./figure.jpg'
tensor = torch.from_numpy(np.asarray(PIL.Image.open(path))).permute(2,0,1).float() / 255
tensor = torchvision.transforms.functional.to_tensor(PIL.Image.open(path)) # Equivalently
```

np.ndarray与PIL.Image的转换

```
image = PIL.Image.fromarray(ndarray.astype(np.uint8))
ndarray = np.asarray(PIL.Image.open(path))
```

从只包含一个元素的张量中提取值

```
value = torch.rand(1).item()
```

张量形变

```
# 在将卷积层输入全连接层的情况下通常需要对张量做形变处理,
# 相比torch.view, torch.reshape可以自动处理输入张量不连续的情况

tensor = torch.rand(2,3,4)
shape = (6, 4)
tensor = torch.reshape(tensor, shape)
```

打乱顺序

```
tensor = tensor[torch.randperm(tensor.size(0))]  # 打乱第一个维度
```

水平翻转

```
# pytorch不支持tensor[::-1]这样的负步长操作，水平翻转可以通过张量索引实现
# 假设张量的维度为[N, D, H, W].

tensor = tensor[:,:,:,torch.arange(tensor.size(3) - 1, -1, -1).long()]
```

复制张量

```
# Operation                 |  New/Shared memory | Still in computation graph |tensor.clor
```

张量拼接

```
'''
注意torch.cat和torch.stack的区别在于torch.cat沿着给定的维度拼接，
而torch.stack会新增一维。例如当参数是3个10x5的张量，torch.cat的结果是30x5的张量，
而torch.stack的结果是3x10x5的张量。
'''
tensor = torch.cat(list_of_tensors, dim=0)
tensor = torch.stack(list_of_tensors, dim=0)
```

将整数标签转为one-hot编码

```
# pytorch的标记默认从0开始
tensor = torch.tensor([0, 2, 1, 3])
N = tensor.size(0)
num_classes = 4
one_hot = torch.zeros(N, num_classes).long()
one_hot.scatter_(dim=1, index=torch.unsqueeze(tensor, dim=1), src=torch.ones(N, num_classe
```

得到非零元素

```
torch.nonzero(tensor)               # index of non-zero elements
torch.nonzero(tensor==0)            # index of zero elements
torch.nonzero(tensor).size(0)       # number of non-zero elements
torch.nonzero(tensor == 0).size(0)  # number of zero elements
```

判断两个张量相等

```
torch.allclose(tensor1, tensor2)  # float tensor
torch.equal(tensor1, tensor2)     # int tensor
```

张量扩展

```
# Expand tensor of shape 64*512 to shape 64*512*7*7.
tensor = torch.rand(64,512)
torch.reshape(tensor, (64, 512, 1, 1)).expand(64, 512, 7, 7)
```

矩阵乘法

```
# Matrix multiplcation: (m*n) * (n*p) * -> (m*p).
result = torch.mm(tensor1, tensor2)

# Batch matrix multiplication: (b*m*n) * (b*n*p) -> (b*m*p)
result = torch.bmm(tensor1, tensor2)

# Element-wise multiplication.
result = tensor1 * tensor2
```

计算两组数据之间的两两欧式距离

利用广播机制

```
dist = torch.sqrt(torch.sum((X1[:,None,:] - X2) ** 2, dim=2))
```

模型定义和操作

一个简单两层卷积网络的示例

```python
# convolutional neural network (2 convolutional layers)
class ConvNet(nn.Module):
    def __init__(self, num_classes=10):
        super(ConvNet, self).__init__()
        self.layer1 = nn.Sequential(
            nn.Conv2d(1, 16, kernel_size=5, stride=1, padding=2),
            nn.BatchNorm2d(16),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2))
        self.layer2 = nn.Sequential(
            nn.Conv2d(16, 32, kernel_size=5, stride=1, padding=2),
            nn.BatchNorm2d(32),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2))
        self.fc = nn.Linear(7*7*32, num_classes)

    def forward(self, x):
        out = self.layer1(x)
        out = self.layer2(out)
        out = out.reshape(out.size(0), -1)
        out = self.fc(out)
        return out

model = ConvNet(num_classes).to(device)
```

卷积层的计算和展示可以用这个网站辅助。

双线性汇合（bilinear pooling）

```python
X = torch.reshape(N, D, H * W)                        # Assume X has shape N*D*H*W
X = torch.bmm(X, torch.transpose(X, 1, 2)) / (H * W)  # Bilinear pooling
assert X.size() == (N, D, D)
X = torch.reshape(X, (N, D * D))
X = torch.sign(X) * torch.sqrt(torch.abs(X) + 1e-5)   # Signed-sqrt normalization
X = torch.nn.functional.normalize(X)                  # L2 normalization
```

多卡同步 BN（Batch normalization）

当使用 torch.nn.DataParallel 将代码运行在多张 GPU 卡上时，PyTorch 的 BN 层默认操作是各卡上数据独立地计算均值和标准差，同步 BN 使用所有卡上的数据一起计算 BN 层的均值和标准差，缓解了当批量大小（batch size）比较小时对均值和标准差估计不准的情况，是在目标检测等任务中一个有效的提升性能的技巧。

```
sync_bn = torch.nn.SyncBatchNorm(num_features,
                                 eps=1e-05,
                                 momentum=0.1,
                                 affine=True,
                                 track_running_stats=True)
```

将已有网络的所有BN层改为同步BN层

```
def convertBNtoSyncBN(module, process_group=None):
    '''Recursively replace all BN layers to SyncBN layer.

    Args:
        module[torch.nn.Module]. Network
    '''
    if isinstance(module, torch.nn.modules.batchnorm._BatchNorm):
        sync_bn = torch.nn.SyncBatchNorm(module.num_features, module.eps, module.momentum,
                                         module.affine, module.track_running_stats, proces
        sync_bn.running_mean = module.running_mean
        sync_bn.running_var = module.running_var
        if module.affine:
            sync_bn.weight = module.weight.clone().detach()
            sync_bn.bias = module.bias.clone().detach()
        return sync_bn
    else:
        for name, child_module in module.named_children():
            setattr(module, name) = convert_syncbn_model(child_module, process_group=proce
        return module
```

类似 BN 滑动平均

如果要实现类似 BN 滑动平均的操作，在 forward 函数中要使用原地（inplace）操作给滑动平均赋值。

```
class BN(torch.nn.Module)
    def __init__(self):
        ...
        self.register_buffer('running_mean', torch.zeros(num_features))

    def forward(self, X):
        ...
        self.running_mean += momentum * (current - self.running_mean)
```

计算模型整体参数量

```
num_parameters = sum(torch.numel(parameter) for parameter in model.parameters())
```

查看网络中的参数

可以通过model.state_dict()或者model.named_parameters()函数查看现在的全部可训练参数（包括通过继承得到的父类中的参数）

```
params = list(model.named_parameters())
(name, param) = params[28]
print(name)
print(param.grad)
print('-------------------------------------------------')
(name2, param2) = params[29]
print(name2)
print(param2.grad)
print('----------------------------------------------------')
(name1, param1) = params[30]
print(name1)
print(param1.grad)
```

模型可视化（使用pytorchviz）

```
szagoruyko/pytorchvizgithub.com
```

类似 Keras 的 model.summary() 输出模型信息，使用pytorch-summary

```
sksq96/pytorch-summarygithub.com
```

模型权重初始化

注意 model.modules() 和 model.children() 的区别：model.modules() 会迭代地遍历模型的所有子层，而 model.children() 只会遍历模型下的一层。

```
# Common practise for initialization.
for layer in model.modules():
    if isinstance(layer, torch.nn.Conv2d):
```

```
        torch.nn.init.kaiming_normal_(layer.weight, mode='fan_out',
                                      nonlinearity='relu')
        if layer.bias is not None:
            torch.nn.init.constant_(layer.bias, val=0.0)
    elif isinstance(layer, torch.nn.BatchNorm2d):
        torch.nn.init.constant_(layer.weight, val=1.0)
        torch.nn.init.constant_(layer.bias, val=0.0)
    elif isinstance(layer, torch.nn.Linear):
        torch.nn.init.xavier_normal_(layer.weight)
        if layer.bias is not None:
            torch.nn.init.constant_(layer.bias, val=0.0)

# Initialization with given tensor.
layer.weight = torch.nn.Parameter(tensor)
```

提取模型中的某一层

modules()会返回模型中所有模块的迭代器，它能够访问到最内层，比如self.layer1.conv1这个模块，还有一个与它们相对应的是name_children()属性以及named_modules(),这两个不仅会返回模块的迭代器，还会返回网络层的名字。

```
# 取模型中的前两层
new_model = nn.Sequential(*list(model.children())[:2]
# 如果希望提取出模型中的所有卷积层，可以像下面这样操作：
for layer in model.named_modules():
    if isinstance(layer[1],nn.Conv2d):
         conv_model.add_module(layer[0],layer[1])
```

部分层使用预训练模型

注意如果保存的模型是 torch.nn.DataParallel，则当前的模型也需要是

```
model.load_state_dict(torch.load('model.pth'), strict=False)
```

将在 GPU 保存的模型加载到 CPU

```
model.load_state_dict(torch.load('model.pth', map_location='cpu'))
```

导入另一个模型的相同部分到新的模型

模型导入参数时，如果两个模型结构不一致，则直接导入参数会报错。用下面方法可以把另一个模型的相同的部分导入到新的模型中。

```
# model_new代表新的模型
# model_saved代表其他模型，比如用torch.load导入的已保存的模型
model_new_dict = model_new.state_dict()
model_common_dict = {k:v for k, v in model_saved.items() if k in model_new_dict.keys()}
model_new_dict.update(model_common_dict)
model_new.load_state_dict(model_new_dict)
```

数据处理

计算数据集的均值和标准差

```
import os
import cv2
import numpy as np
from torch.utils.data import Dataset
from PIL import Image


def compute_mean_and_std(dataset):
    # 输入PyTorch的dataset，输出均值和标准差
    mean_r = 0
    mean_g = 0
    mean_b = 0

    for img, _ in dataset:
        img = np.asarray(img) # change PIL Image to numpy array
        mean_b += np.mean(img[:, :, 0])
        mean_g += np.mean(img[:, :, 1])
        mean_r += np.mean(img[:, :, 2])

    mean_b /= len(dataset)
    mean_g /= len(dataset)
    mean_r /= len(dataset)

    diff_r = 0
    diff_g = 0
    diff_b = 0

    N = 0

    for img, _ in dataset:
```

```
        img = np.asarray(img)

        diff_b += np.sum(np.power(img[:, :, 0] - mean_b, 2))
        diff_g += np.sum(np.power(img[:, :, 1] - mean_g, 2))
        diff_r += np.sum(np.power(img[:, :, 2] - mean_r, 2))

        N += np.prod(img[:, :, 0].shape)

    std_b = np.sqrt(diff_b / N)
    std_g = np.sqrt(diff_g / N)
    std_r = np.sqrt(diff_r / N)

    mean = (mean_b.item() / 255.0, mean_g.item() / 255.0, mean_r.item() / 255.0)
    std = (std_b.item() / 255.0, std_g.item() / 255.0, std_r.item() / 255.0)
    return mean, std
```

得到视频数据基本信息

```
import cv2
video = cv2.VideoCapture(mp4_path)
height = int(video.get(cv2.CAP_PROP_FRAME_HEIGHT))
width = int(video.get(cv2.CAP_PROP_FRAME_WIDTH))
num_frames = int(video.get(cv2.CAP_PROP_FRAME_COUNT))
fps = int(video.get(cv2.CAP_PROP_FPS))
video.release()
```

TSN 每段（segment）采样一帧视频

```
K = self._num_segments
if is_train:
    if num_frames > K:
        # Random index for each segment.
        frame_indices = torch.randint(
            high=num_frames // K, size=(K,), dtype=torch.long)
        frame_indices += num_frames // K * torch.arange(K)
    else:
        frame_indices = torch.randint(
            high=num_frames, size=(K - num_frames,), dtype=torch.long)
        frame_indices = torch.sort(torch.cat((
            torch.arange(num_frames), frame_indices)))[0]
else:
    if num_frames > K:
        # Middle index for each segment.
        frame_indices = num_frames / K // 2
        frame_indices += num_frames // K * torch.arange(K)
    else:
```

```
        frame_indices = torch.sort(torch.cat((
            torch.arange(num_frames), torch.arange(K - num_frames))))[0]
assert frame_indices.size() == (K,)
return [frame_indices[i] for i in range(K)]
```

常用训练和验证数据预处理

其中 ToTensor 操作会将 PIL.Image 或形状为 H×W×D，数值范围为 [0, 255] 的 np.ndarray 转换为形状为 D×H×W，数值范围为 [0.0, 1.0] 的 torch.Tensor。

```
train_transform = torchvision.transforms.Compose([
    torchvision.transforms.RandomResizedCrop(size=224,
                                             scale=(0.08, 1.0)),
    torchvision.transforms.RandomHorizontalFlip(),
    torchvision.transforms.ToTensor(),
    torchvision.transforms.Normalize(mean=(0.485, 0.456, 0.406),
                                     std=(0.229, 0.224, 0.225)),
 ])
 val_transform = torchvision.transforms.Compose([
    torchvision.transforms.Resize(256),
    torchvision.transforms.CenterCrop(224),
    torchvision.transforms.ToTensor(),
    torchvision.transforms.Normalize(mean=(0.485, 0.456, 0.406),
                                     std=(0.229, 0.224, 0.225)),
])
```

模型训练和测试

分类模型训练代码

```
# Loss and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model.parameters(), lr=learning_rate)

# Train the model
total_step = len(train_loader)
for epoch in range(num_epochs):
    for i ,(images, labels) in enumerate(train_loader):
        images = images.to(device)
        labels = labels.to(device)

        # Forward pass
        outputs = model(images)
        loss = criterion(outputs, labels)
```

```
        # Backward and optimizer
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        if (i+1) % 100 == 0:
            print('Epoch: [{}/{}], Step: [{}/{}], Loss: {}'
                  .format(epoch+1, num_epochs, i+1, total_step, loss.item()))
```

分类模型测试代码

```
# Test the model
model.eval()  # eval mode(batch norm uses moving mean/variance
              #instead of mini-batch mean/variance)
with torch.no_grad():
    correct = 0
    total = 0
    for images, labels in test_loader:
        images = images.to(device)
        labels = labels.to(device)
        outputs = model(images)
        _, predicted = torch.max(outputs.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()

    print('Test accuracy of the model on the 10000 test images: {} %'
          .format(100 * correct / total))
```

自定义loss

继承torch.nn.Module类写自己的loss。

```
class MyLoss(torch.nn.Moudle):
    def __init__(self):
        super(MyLoss, self).__init__()

    def forward(self, x, y):
        loss = torch.mean((x - y) ** 2)
        return loss
```

标签平滑（label smoothing）

写一个label_smoothing.py的文件，然后在训练代码里引用，用LSR代替交叉熵损失即可。label_smoothing.py内容如下：

```
import torch
import torch.nn as nn


class LSR(nn.Module):

    def __init__(self, e=0.1, reduction='mean'):
        super().__init__()

        self.log_softmax = nn.LogSoftmax(dim=1)
        self.e = e
        self.reduction = reduction

    def _one_hot(self, labels, classes, value=1):
        """

            Convert labels to one hot vectors


        Args:
            labels: torch tensor in format [label1, label2, label3, ...]
            classes: int, number of classes
            value: label value in one hot vector, default to 1


        Returns:
            return one hot format labels in shape [batchsize, classes]
        """

        one_hot = torch.zeros(labels.size(0), classes)

        #labels and value_added  size must match
        labels = labels.view(labels.size(0), -1)
        value_added = torch.Tensor(labels.size(0), 1).fill_(value)

        value_added = value_added.to(labels.device)
        one_hot = one_hot.to(labels.device)

        one_hot.scatter_add_(1, labels, value_added)

        return one_hot

    def _smooth_label(self, target, length, smooth_factor):
        """convert targets to one-hot format, and smooth
        them.
        Args:
```

```
            target: target in form with [label1, label2, label_batchsize]
            length: length of one-hot format(number of classes)
            smooth_factor: smooth factor for label smooth

        Returns:
            smoothed labels in one hot format
        """
        one_hot = self._one_hot(target, length, value=1 - smooth_factor)
        one_hot += smooth_factor / (length - 1)

        return one_hot.to(target.device)

    def forward(self, x, target):

        if x.size(0) != target.size(0):
            raise ValueError('Expected input batchsize ({}) to match target batch_size({})
                    .format(x.size(0), target.size(0)))

        if x.dim() < 2:
            raise ValueError('Expected input tensor to have least 2 dimensions(got {})'
                    .format(x.size(0)))

        if x.dim() != 2:
            raise ValueError('Only 2 dimension tensor are implemented, (got {})'
                    .format(x.size()))


        smoothed_target = self._smooth_label(target, x.size(1), self.e)
        x = self.log_softmax(x)
        loss = torch.sum(- x * smoothed_target, dim=1)

        if self.reduction == 'none':
            return loss

        elif self.reduction == 'sum':
            return torch.sum(loss)

        elif self.reduction == 'mean':
            return torch.mean(loss)

        else:
            raise ValueError('unrecognized option, expect reduction to be one of none, mec
```

或者直接在训练文件里做label smoothing

```
for images, labels in train_loader:
    images, labels = images.cuda(), labels.cuda()
    N = labels.size(0)
    # C is the number of classes.
    smoothed_labels = torch.full(size=(N, C), fill_value=0.1 / (C - 1)).cuda()
    smoothed_labels.scatter_(dim=1, index=torch.unsqueeze(labels, dim=1), value=0.9)

    score = model(images)
    log_prob = torch.nn.functional.log_softmax(score, dim=1)
    loss = -torch.sum(log_prob * smoothed_labels) / N
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
```

Mixup训练

```
beta_distribution = torch.distributions.beta.Beta(alpha, alpha)
for images, labels in train_loader:
    images, labels = images.cuda(), labels.cuda()

    # Mixup images and labels.
    lambda_ = beta_distribution.sample([]).item()
    index = torch.randperm(images.size(0)).cuda()
    mixed_images = lambda_ * images + (1 - lambda_) * images[index, :]
    label_a, label_b = labels, labels[index]

    # Mixup loss.
    scores = model(mixed_images)
    loss = (lambda_ * loss_function(scores, label_a)
            + (1 - lambda_) * loss_function(scores, label_b))
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
```

L1 正则化

```
l1_regularization = torch.nn.L1Loss(reduction='sum')
loss = ...  # Standard cross-entropy loss

for param in model.parameters():
    loss += torch.sum(torch.abs(param))
loss.backward()
```

不对偏置项进行权重衰减（weight decay)

pytorch里的weight decay相当于l2正则

```
bias_list = (param for name, param in model.named_parameters() if name[-4:] == 'bias')
others_list = (param for name, param in model.named_parameters() if name[-4:] != 'bias')
parameters = [{'parameters': bias_list, 'weight_decay': 0},
              {'parameters': others_list}]
optimizer = torch.optim.SGD(parameters, lr=1e-2, momentum=0.9, weight_decay=1e-4)
```

梯度裁剪（gradient clipping）

```
torch.nn.utils.clip_grad_norm_(model.parameters(), max_norm=20)
```

得到当前学习率

```
# If there is one global learning rate (which is the common case).
lr = next(iter(optimizer.param_groups))['lr']

# If there are multiple learning rates for different layers.
all_lr = []
for param_group in optimizer.param_groups:
    all_lr.append(param_group['lr'])
```

另一种方法，在一个batch训练代码里，当前的lr是 `optimizer.param_groups[0]['lr']`

学习率衰减

```
# Reduce learning rate when validation accuarcy plateau.
scheduler = torch.optim.lr_scheduler.ReduceLROnPlateau(optimizer, mode='max', patience=5,
for t in range(0, 80):
    train(...)
    val(...)
    scheduler.step(val_acc)

# Cosine annealing learning rate.
scheduler = torch.optim.lr_scheduler.CosineAnnealingLR(optimizer, T_max=80)
# Reduce learning rate by 10 at given epochs.
scheduler = torch.optim.lr_scheduler.MultiStepLR(optimizer, milestones=[50, 70], gamma=0.1
for t in range(0, 80):
    scheduler.step()
```

```
    train(...)
    val(...)

# Learning rate warmup by 10 epochs.
scheduler = torch.optim.lr_scheduler.LambdaLR(optimizer, lr_lambda=lambda t: t / 10)
for t in range(0, 10):
    scheduler.step()
    train(...)
    val(...)
```

优化器链式更新

从1.4版本开始，torch.optim.lr_scheduler 支持链式更新（chaining），即用户可以定义两个schedulers，并交替在训练中使用。

```
import torch
from torch.optim import SGD
from torch.optim.lr_scheduler import ExponentialLR, StepLR
model = [torch.nn.Parameter(torch.randn(2, 2, requires_grad=True))]
optimizer = SGD(model, 0.1)
scheduler1 = ExponentialLR(optimizer, gamma=0.9)
scheduler2 = StepLR(optimizer, step_size=3, gamma=0.1)
for epoch in range(4):
    print(epoch, scheduler2.get_last_lr()[0])
    optimizer.step()
    scheduler1.step()
    scheduler2.step()
```

模型训练可视化

PyTorch可以使用tensorboard来可视化训练过程。安装和运行TensorBoard。

```
pip install tensorboard
tensorboard --logdir=runs
```

使用SummaryWriter类来收集和可视化相应的数据，放了方便查看，可以使用不同的文件夹，比如'Loss/train'和'Loss/test'。

```
from torch.utils.tensorboard import SummaryWriter
import numpy as np

writer = SummaryWriter()
```

```
for n_iter in range(100):
    writer.add_scalar('Loss/train', np.random.random(), n_iter)
    writer.add_scalar('Loss/test', np.random.random(), n_iter)
    writer.add_scalar('Accuracy/train', np.random.random(), n_iter)
    writer.add_scalar('Accuracy/test', np.random.random(), n_iter)
```

保存与加载断点

注意为了能够恢复训练，我们需要同时保存模型和优化器的状态，以及当前的训练轮数。

```
start_epoch = 0
# Load checkpoint.
if resume: # resume为参数，第一次训练时设为0，中断再训练时设为1
    model_path = os.path.join('model', 'best_checkpoint.pth.tar')
    assert os.path.isfile(model_path)
    checkpoint = torch.load(model_path)
    best_acc = checkpoint['best_acc']
    start_epoch = checkpoint['epoch']
    model.load_state_dict(checkpoint['model'])
    optimizer.load_state_dict(checkpoint['optimizer'])
    print('Load checkpoint at epoch {}.'.format(start_epoch))
    print('Best accuracy so far {}.'.format(best_acc))

# Train the model
for epoch in range(start_epoch, num_epochs):
    ...

    # Test the model
    ...

    # save checkpoint
    is_best = current_acc > best_acc
    best_acc = max(current_acc, best_acc)
    checkpoint = {
        'best_acc': best_acc,
        'epoch': epoch + 1,
        'model': model.state_dict(),
        'optimizer': optimizer.state_dict(),
    }
    model_path = os.path.join('model', 'checkpoint.pth.tar')
    best_model_path = os.path.join('model', 'best_checkpoint.pth.tar')
```

```
    torch.save(checkpoint, model_path)
    if is_best:
        shutil.copy(model_path, best_model_path)
```

提取 ImageNet 预训练模型某层的卷积特征

```
# VGG-16 relu5-3 feature.
model = torchvision.models.vgg16(pretrained=True).features[:-1]
# VGG-16 pool5 feature.
model = torchvision.models.vgg16(pretrained=True).features
# VGG-16 fc7 feature.
model = torchvision.models.vgg16(pretrained=True)
model.classifier = torch.nn.Sequential(*list(model.classifier.children())[:-3])
# ResNet GAP feature.
model = torchvision.models.resnet18(pretrained=True)
model = torch.nn.Sequential(collections.OrderedDict(
    list(model.named_children())[:-1]))

with torch.no_grad():
    model.eval()
    conv_representation = model(image)
```

提取 ImageNet 预训练模型多层的卷积特征

```
class FeatureExtractor(torch.nn.Module):
    """Helper class to extract several convolution features from the given
    pre-trained model.

    Attributes:
        _model, torch.nn.Module.
        _layers_to_extract, list<str> or set<str>

    Example:
        >>> model = torchvision.models.resnet152(pretrained=True)
        >>> model = torch.nn.Sequential(collections.OrderedDict(
                list(model.named_children())[:-1]))
        >>> conv_representation = FeatureExtractor(
                pretrained_model=model,
                layers_to_extract={'layer1', 'layer2', 'layer3', 'layer4'})(image)
    """
    def __init__(self, pretrained_model, layers_to_extract):
        torch.nn.Module.__init__(self)
```

```
        self._model = pretrained_model
        self._model.eval()
        self._layers_to_extract = set(layers_to_extract)

    def forward(self, x):
        with torch.no_grad():
            conv_representation = []
            for name, layer in self._model.named_children():
                x = layer(x)
                if name in self._layers_to_extract:
                    conv_representation.append(x)
            return conv_representation
```

微调全连接层

```
model = torchvision.models.resnet18(pretrained=True)
for param in model.parameters():
    param.requires_grad = False
model.fc = nn.Linear(512, 100)  # Replace the last fc layer
optimizer = torch.optim.SGD(model.fc.parameters(), lr=1e-2, momentum=0.9, weight_decay=1e-
```

以较大学习率微调全连接层，较小学习率微调卷积层

```
model = torchvision.models.resnet18(pretrained=True)
finetuned_parameters = list(map(id, model.fc.parameters()))
conv_parameters = (p for p in model.parameters() if id(p) not in finetuned_parameters)
parameters = [{'params': conv_parameters, 'lr': 1e-3},
              {'params': model.fc.parameters()}]
optimizer = torch.optim.SGD(parameters, lr=1e-2, momentum=0.9, weight_decay=1e-4)
```

其他注意事项

- 不要使用太大的线性层。因为nn.Linear(m,n)使用的是的内存，线性层太大很容易超出现有显存。
- 不要在太长的序列上使用RNN。因为RNN反向传播使用的是BPTT算法，其需要的内存和输入序列的长度呈线性关系。
- model(x) 前用 model.train() 和 model.eval() 切换网络状态。
- 不需要计算梯度的代码块用 with torch.no_grad() 包含起来。

- model.eval() 和 torch.no_grad() 的区别在于，model.eval() 是将网络切换为测试状态，例如 BN 和dropout在训练和测试阶段使用不同的计算方法。torch.no_grad() 是关闭 PyTorch 张量的自动求导机制，以减少存储使用和加速计算，得到的结果无法进行 loss.backward()。
- model.zero_grad()会把整个模型的参数的梯度都归零, 而optimizer.zero_grad()只会把传入其中的参数的梯度归零.
- torch.nn.CrossEntropyLoss 的输入不需要经过 Softmax。torch.nn.CrossEntropyLoss 等价于 torch.nn.functional.log_softmax + torch.nn.NLLLoss。
- loss.backward() 前用 optimizer.zero_grad() 清除累积梯度。
- torch.utils.data.DataLoader 中尽量设置 pin_memory=True，对特别小的数据集如 MNIST 设置 pin_memory=False 反而更快一些。num_workers 的设置需要在实验中找到最快的取值。
- 用 del 及时删除不用的中间变量，节约 GPU 存储。使用 inplace 操作可节约 GPU 存储，如：

```
x = torch.nn.functional.relu(x, inplace=True)
```

减少 CPU 和 GPU 之间的数据传输。例如如果你想知道一个 epoch 中每个 mini-batch 的 loss 和准确率，先将它们累积在 GPU 中等一个 epoch 结束之后一起传输回 CPU 会比每个 mini-batch 都进行一次 GPU 到 CPU 的传输更快。使用半精度浮点数 half() 会有一定的速度提升，具体效率依赖于 GPU 型号。需要小心数值精度过低带来的稳定性问题。时常使用 assert tensor.size() == (N, D, H, W) 作为调试手段，确保张量维度和你设想中一致。除了标记 y 外，尽量少使用一维张量，使用 n*1 的二维张量代替，可以避免一些意想不到的一维张量计算结果。统计代码各部分耗时：

```
with torch.autograd.profiler.profile(enabled=True, use_cuda=False) as profile:
  ...print(profile)# 或者在命令行运行python -m torch.utils.bottleneck main.py
```

使用TorchSnooper来调试PyTorch代码，程序在执行的时候，就会自动 print 出来每一行的执行结果的 tensor 的形状、数据类型、设备、是否需要梯度的信息。

```
# pip install torchsnooper
import torchsnooper# 对于函数，使用修饰器@torchsnooper.snoop()

# 如果不是函数，使用 with 语句来激活 TorchSnooper，把训练的那个循环装进 with 语句中去。
with torchsnooper.snoop():
    原本的代码
```

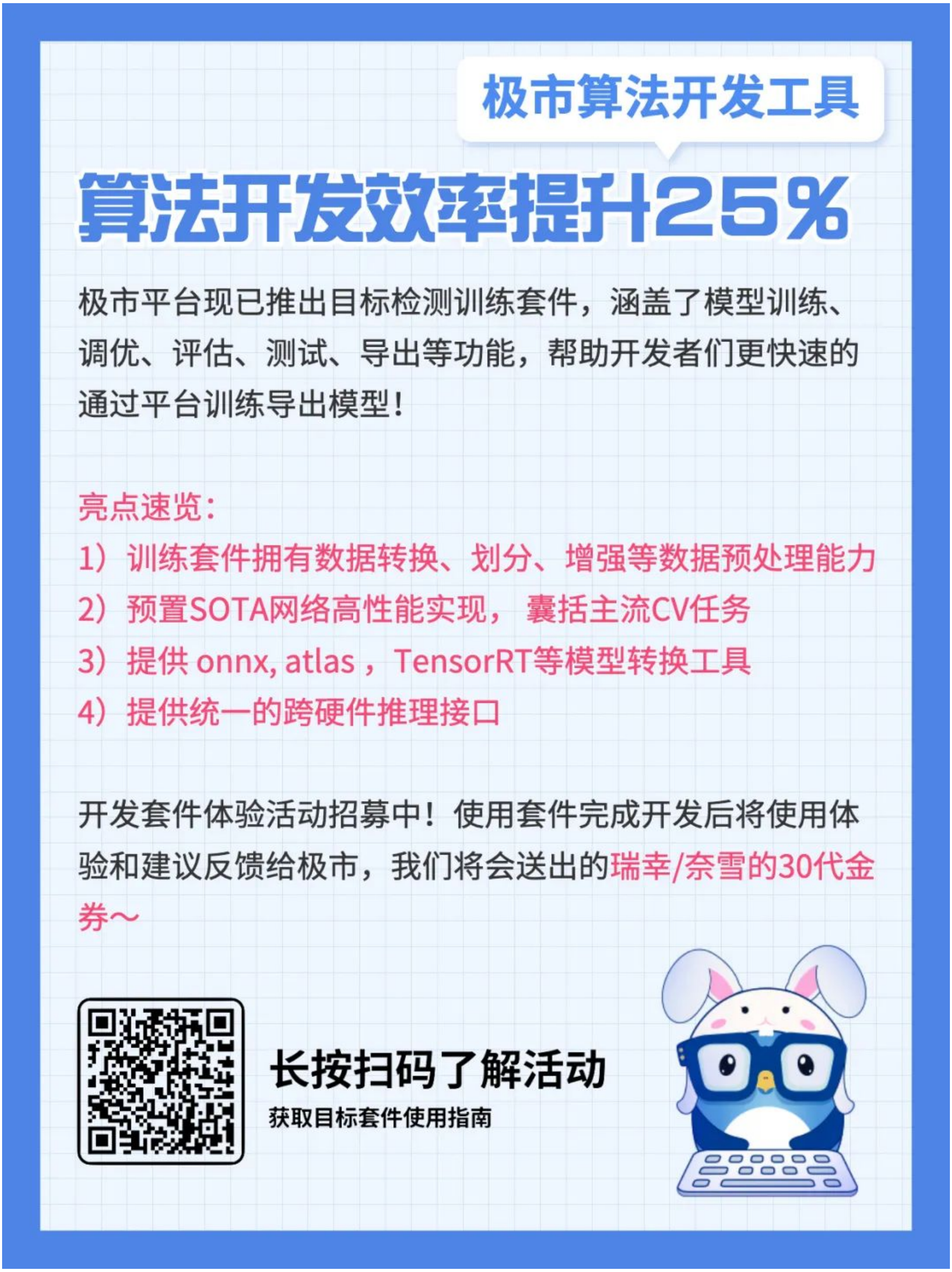
https://github.com/zasdfgbnm/TorchSnoopergithub.com模型可解释性，使用captum库：https://captum.ai/captum.ai

参考资料

- 张皓：PyTorch Cookbook，https://zhuanlan.zhihu.com/p/59205847?
- PyTorch官方文档和示例
- https://pytorch.org/docs/stable/notes/faq.html
- https://github.com/szagoruyko/pytorchviz
- https://github.com/sksq96/pytorch-summary等

> 学术分享，来源丨https://zhuanlan.zhihu.com/p/104019160

多模态学习：CLIP：大规模语言-图像对比预训练实现不俗 Zero-Shot 性能 | ALBEF：图文对齐后再融合，借助动量蒸馏高效学习多模态表征



点击阅读原文进入CV社区

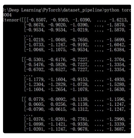
收获更多技术干货

阅读原文

喜欢此内容的人还喜欢

实践教程｜PyTorch数据导入机制与标准化代码模板

极市平台



YOLOv5帮助母猪产仔？南京农业大学研发母猪产仔检测模型并部署到Jetson Nano开发板

极市平台

实践教程｜使用 OpenCV 进行特征提取（颜色、形状和纹理）

极市平台