## ZHENGYUNLONG

# 学习Pytorch中hook函数并分享

### 1.hook简介

Pytorch中自带hook函数用于提取非叶子节点的梯度,进一步,可利用hook函数提取特征图。

Pytorch中有四类hook函数:

- 1. torch.Tensor.register\_hook
- 2. torch.nn.Module.register\_forward\_pre\_hook
- 3. torch.nn.Module.register\_forward\_hook
- 4. torch.nn.Module.register\_backward\_hook

## 2.torch.Tensor.register\_hook()

Tensor类下的hook函数,当注册hook函数后,再次计算某个tensor的梯度会执行注册的hook函数。

## 3.torch.nn.Module.register\_forward\_pre\_hook()

Module类下的hook函数, 当注册hook函数后, 模型执行forward前自动调用注册的hook函数。

## 4.torch.nn.Module.register\_forward\_hook()

Module类下的hook函数, 当注册hook函数后, 模型执行forward时自动调用注册的hook函数。

具体执行过程: 网络模型被调用执行时,先执行Moule.call函数,该函数内会首先判定当前是否注册了hook函数,若注册,则调用hook函数。基于此,我们可以编写特定hook函数来可视化非叶子节点的梯度。

## 5.torch.nn.Module.register\_backward\_hook()

Module类下的hook函数,反向传播时调用,可依此提取特征图梯度。

#### 6.代码示例

MNIST数据集上数字识别,模型结构: 俩个卷积层+三个全连接层。

```
from pathlib import Path import pickle import gzip import torch import struct import numpy as np import matplotlib.pyplot as plt import torch.nn as nn import torch.nn.functional as F from torch.utils.data import TensorDataset, DataLoader

# 加载MNIST数据集
```

```
train_img_path = Path("D:\\Daily\\training\\code\\Dataset\\MNIST\\train-
images.idx3-ubyte")
train_label_path = Path("D:\\Daily\\training\\code\\Dataset\\MNIST\\train-
labels.idx1-ubyte")
test_img_img = Path("D:\\Daily\\training\\code\\Dataset\\MNIST\\t10k-
images.idx3-ubyte")
test_label_path = Path("D:\\Daily\\training\\code\\Dataset\\MNIST\\t10k-
labels.idx1-ubyte")
with open(train_img_path, "rb") as f1:
    images_magic, images_num, rows, cols = struct.unpack('>IIII', f1.read(16))
    x_train = np.fromfile(f1, dtype=np.uint8).reshape(images_num, rows * cols)
with open(train_label_path, "rb") as f2:
    labels_magic, labels_num = struct.unpack('>II', f2.read(8))
    y_train = np.fromfile(f2, dtype=np.uint8)
with open(test_img_img, "rb") as f3:
    test_images_magic, test_images_num, test_rows, test_cols =
struct.unpack('>IIII', f3.read(16))
    x_test = np.fromfile(f3, dtype=np.uint8).reshape(test_images_num, test_rows
* test_cols)
with open(test_label_path, "rb") as f4:
    test_labels_magic, test_labels_num = struct.unpack('>II', f4.read(8))
    y_test = np.fromfile(f4, dtype=np.uint8)
\# img = x_{train}[1].reshape(28, 28)
# plt.imshow(img)
# plt.title("the label is : {}".format(y_train[1]))
# plt.show()
# print(x_train[0])
print(torch.cuda.is_available())
dev = torch.device("cuda:0")
# 转换成tensor
x_train = torch.tensor(x_train).float().to(dev)
y_train = torch.tensor(y_train).float().to(dev)
x_test = torch.tensor(x_test).float().to(dev)
y_test = torch.tensor(y_test).float().to(dev)
bs = 64
train_ds = TensorDataset(x_train, y_train)
train_dl = DataLoader(dataset=train_ds, batch_size=bs, shuffle=True)
test_ds = TensorDataset(x_test, y_test)
test_dl = DataLoader(dataset=test_ds, batch_size=bs * 2)
# 定义模型
class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(in_channels=1, out_channels=6, kernel_size=3)
```

```
self.conv2 = nn.Conv2d(in_channels=6, out_channels=16, kernel_size=4)
        self.fc1 = nn.Linear(16 * 5 * 5, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)
    def forward(self, x):
        x = x.view(-1, 1, 28, 28)
        x = F.max_pool2d(F.relu(self.conv1(x)), (2, 2))
        x = F.max_pool2d(F.relu(self.conv2(x)), 2)
        x = x.view(-1, self.num_flat_features(x))
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x
    def num_flat_features(self, x):
        size = x.size()[1:]
        num_features = 1
        for s in size:
            num_features *= s
        return num_features
cnn_model = Net()
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(cnn_model.parameters(), 1r=0.05)
cnn_model.to(dev)
# 训练模型
\# epochs = 10
# for epoch in range(epochs):
     for xb, yb in train_dl:
         pred = cnn_model(xb)
         loss = criterion(pred, yb.long())
         optimizer.zero_grad()
          loss.backward()
         optimizer.step()
def loss_mean(model, valid_dl):
    valid_loss = 0
    for xb, yb in valid_dl:
        valid_loss += criterion(model(xb), yb.long())
    return valid_loss / len(valid_dl)
def accuracy(out, yb):
    preds = torch.argmax(out, dim=1)
    return (preds == yb).float().mean()
def accuracy_rate(model, valid_dl):
    acc = 0
    for xb, yb in valid_dl:
        acc += accuracy(model(xb), yb.long())
```

```
return (acc / len(valid_dl))
def hook(module, grad_input, grad_output):
    print("grad_input: ", grad_input)
    # plt.imshow(grad_input.reshape(28, 28))
    # plt.title("the label is : {}".format("grad_input"))
    # plt.show()
    print("grad_output: ", grad_output)
    # plt.imshow(grad_output.reshape(-1, 28, 28))
    # plt.title("the label is : {}".format("grad_output"))
    # plt.show()
    # return grad_input[0]
# with torch.no_grad():
     print('验证集loss: %.4f' % loss_mean(cnn_model, train_dl).item())
      print('准确率acc: %.2f%%' % (accuracy_rate(cnn_model, test_dl).item() *
100))
for para in cnn_model.named_parameters():
    print(para[0])
x = x_test[0]
handle = cnn_model.conv1.register_forward_hook(hook)
y = cnn_model(x)
handle.remove()
```

该代码目前能可视化模型在前向传播时非叶子节点的梯度,但由于尺寸问题,暂时未将其显示成图片,以及Grad cam热力图未绘制,这将是下一阶段工作的主要内容。

## **XIEMENGYING**

• 在图片分类网络任务上验证深度可分卷积效果

#### 数据集

- tfds horses\_or\_humans
- 大小300\*300, training set 1027张图片两二元分类, validation set 256张

#### 网络结构

5层卷积+1全连接

Layer (type)	Output	Shape	Param #
conv2d_15 (Conv2D)	(None,	298, 298, 16)	448
max_pooling2d_66 (MaxPooling	(None,	149, 149, 16)	0
conv2d_16 (Conv2D)	(None,	147, 147, 64)	9280
max_pooling2d_67 (MaxPooling	(None,	73, 73, 64)	0
conv2d_17 (Conv2D)	(None,	71, 71, 64)	36928
max_pooling2d_68 (MaxPooling	(None,	35, 35, 64)	0
conv2d_18 (Conv2D)	(None,	33, 33, 128)	73856
max_pooling2d_69 (MaxPooling	(None,	16, 16, 128)	0
conv2d_19 (Conv2D)	(None,	14, 14, 128)	147584
max_pooling2d_70 (MaxPooling	(None,	7, 7, 128)	0
flatten_12 (Flatten)	(None,	6272)	0
dense_24 (Dense)	(None,	32)	200736
dropout_11 (Dropout)	(None,	32)	0
dense_25 (Dense)	(None,	1)	33

Total params: 468,865

### 结果

Epoch 1/10 - 5s 578ms/step - loss: 0.6816 - accuracy: 0.5787 - val\_loss: 0.6797 - val\_accuracy: 0.5000 Epoch 2/10 - 4s 501ms/step - loss: 0.6585 - accuracy: 0.6208 - val\_loss: 0.6452 - val\_accuracy: 0.5742 Epoch 3/10 - 4s 552ms/step - loss: 0.6117 - accuracy: 0.7574 - val\_loss: 0.6545 - val\_accuracy: 0.5352 Epoch 4/10 - 4s 547ms/step - loss: 0.5149 - accuracy: 0.8047 - val\_loss: 0.6068 - val\_accuracy: 0.7031 Epoch 5/10 - 4s 507ms/step - loss: 0.4141 - accuracy: 0.8431 - val\_loss: 0.4577 - val\_accuracy: 0.8320