Фреймворк PyTorch для разработки искусственных нейронных сетей

Урок 4. CNN Свертки

Практическое задание

- Обучение классификатора картинок на примере CIFAR-100 (датасет можно изменить) сверточной сетью (самописной)
- Обучение классификатора картинок на примере CIFAR-100 (датасет можно изменить) через дообучение ImageNet Resnet-50
- Обучение классификатора картинок на примере CIFAR-100 (датасет можно изменить) через дообучение ImageNet Resnet-50 с аугментацией (самописной, с использованием Pytorch встроенных методов)

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RESNET50 - https://pytorch.org/hub/nvidia_deeplearningexamples_resnet50/

1. Сделаем необходимые импорты

```
# !pip install torch torchvision
```

```
import torch
import numpy as np

from torch import nn
import torchvision

import torch.nn.functional as F
from tqdm import tqdm
```

2. Загрузим датасет CIFAR-100, сразу же создадим dataloader для него

```
from torch import optim
import torchvision.transforms as transforms
import torchvision
from torchvision import models
# from torchvision import transforms, datasets
import matplotlib.pyplot as plt ### воспользуемся для отображения изображения
```

The CIFAR-10 and CIFAR-100 are labeled subsets of the 80 million tiny images dataset. They were collected by Alex Krizhevsky, Vinod Nair, and Geoffrey Hinton.

The CIFAR-10 dataset The CIFAR-10 dataset consists of 60000 32x32 colour images in 10 classes, with 6000 images per class. There are 50000 training images and 10000 test images.

The CIFAR-100 dataset This dataset is just like the CIFAR-10, except it has 100 classes containing 600 images each. There are 500 training images and 100 testing images per class. The 100 classes in the CIFAR-100 are grouped into 20 superclasses. Each image comes with a "fine" label (the class to which it belongs) and a "coarse" label (the superclass to which it belongs).

https://www.cs.toronto.edu/~kriz/cifar.html

```
# Задаем преобразование для применения к CIFAR
# Необходимые трансформации

# Нейронная сеть обучается лучше, когда входные данные нормализованы так,
# что их значения находятся в диапазоне от -1 до 1 или от 0 до 1.
# Для датасета CIFAR с 3 каналами (по одному на каждый цвет из RGB спектра)
# надо указывать среднее и стандартное отклонение для каждого.
normalize = transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                 std=[0.229, 0.224, 0.225])
```

```
# Численные трансформации могут быть соединены вместе в список при использовании функции Compose().
# Устанавливается преобразование, которое конвертирует входной датасет в PyTorch тензор.
transform = transforms.Compose([transforms.Resize(256),
                                transforms.CenterCrop(224),  # Обрезает данное изображение по центру
                                normalize,
                                transforms.ToTensor()])

trans = transforms.Compose([transforms.ToTensor(), normalize])

train_transform = transforms.Compose([# transforms.Resize(256),

                                      transforms.RandomCrop(32, padding=4),  # Обрезает данное изображение по центру
                                      transforms.ToTensor(),
                                      normalize])

test_transform = transforms.Compose([transforms.ToTensor(),
                                          normalize])
```

```
/usr/local/lib/python3.7/dist-packages/torchvision/transforms/transforms.py:317: UserWarning: The use of the transforms.Scale t
  warnings.warn("The use of the transforms.Scale transform is deprecated, " +
```

2.1 Загружаем CIFAR-100

```
# загружаем CIFAR-100
train_dataset = torchvision.datasets.CIFAR10(root='data/',
                                             train=True,
                                             # transform=transforms.ToTensor(),
                                             transform=train_transform,
                                             # transform=trans,
                                             download=True)

test_dataset = torchvision.datasets.CIFAR10(root='./data',
                                             train=False,
                                             # transform=transforms.ToTensor(),
                                             transform=test_transform,
                                             # transform=trans,
                                             download=True)
```

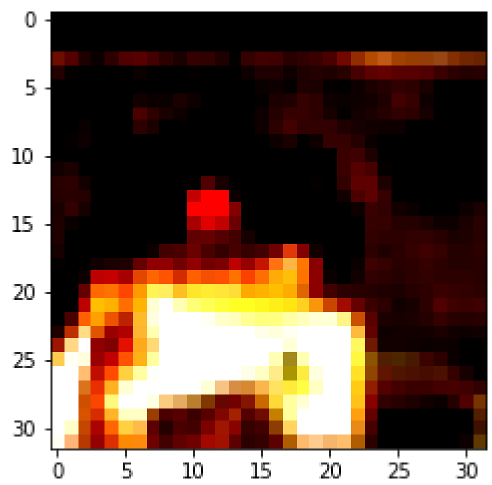
```
image, label = train_dataset[0]  # 0-й рисунок ()
print(image.size())
print(label)

# размерность рисунка 3 * 32 * 32
```

```
Files already downloaded and verified
Files already downloaded and verified
torch.Size([3, 32, 32])
6
```

```
# print('*' * 50)
print(f'label: {label}')
# print('*' * 50)
plt.imshow(image.permute(1, 2, 0).numpy())  # image.permute - Convert image to proper dimension PyTorch
```

```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
label: 6
<matplotlib.image.AxesImage at 0x7f5bf72fd490>
```



2.2 Оборачиваем в Dataloader

```
BATCH_SIZE = 128

train_loader = torch.utils.data.DataLoader(dataset=train_dataset,
                                           batch_size=BATCH_SIZE,
                                           shuffle=True,  # True - чтобы данные перетасовывались в каждую эпоху.
                                           num_workers=3)

test_loader = torch.utils.data.DataLoader(test_dataset,
                                          batch_size=BATCH_SIZE,
                                          shuffle=False,
                                          num_workers=1)
```

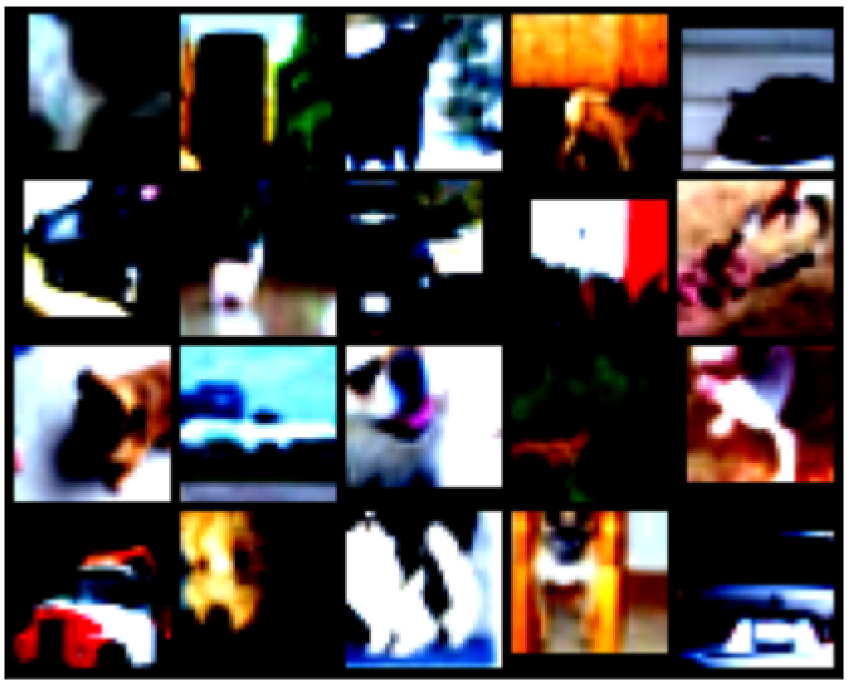
```
/usr/local/lib/python3.7/dist-packages/torch/utils/data/dataloader.py:481: UserWarning: This DataLoader will create 3 worker pr
  cpuset_checked))
```

```
# Let’s look at the images. - https://blog.jovian.ai/image-classification-of-cifar100-dataset-using-pytorch-8b7145242df1

from torchvision.utils import make_grid
def show_batch(dl):
    for batch in dl:
        images,labels = batch
        fig, ax = plt.subplots(figsize=(7.5,7.5))
        ax.set_yticks([])
        ax.set_xticks([])
        ax.imshow(make_grid(images[:20],nrow=5).permute(1,2,0))
        break


show_batch(train_loader)
```

```
/usr/local/lib/python3.7/dist-packages/torch/utils/data/dataloader.py:481: UserWarning: This DataLoader will create 3 worker pr
  cpuset_checked))
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
```



The CIFAR-100 dataset

This dataset is just like the CIFAR-10, except it has 100 classes containing 600 images each. There are 500 training images and 100 testing images per class. The 100 classes in the CIFAR-100 are grouped into 20 superclasses. Each image comes with a "fine" label (the class to which it belongs) and a "coarse" label (the superclass to which it belongs). Here is the list of classes in the CIFAR-100:

https://www.cs.toronto.edu/~kriz/cifar.html

```
# The 100 classes in the CIFAR-100 are grouped into 20 superclasses.
# 20 superclasses
Superclases = ('aquatic mammals', 'fish', 'flowers', 'food containers',
               'fruit and vegetables', 'household electrical devices',
               'household furniture', 'insects', 'large carnivores',
               'large man-made outdoor things', 'large natural outdoor scenes',
               'large omnivores and herbivores', 'medium-sized mammals',
               'non-insect invertebrates', 'people', 'reptiles',
               'small mammals', 'trees', 'vehicles 1', 'vehicles 2')

# 100 classes
classes = ('beaver', 'dolphin', 'otter', 'seal', 'whale',
           'aquarium fish', 'flatfish', 'ray', 'shark', 'trout',
```

```
        'orchids', 'poppies', 'roses', 'sunflowers', 'tulips',
        'bottles', 'bowls', 'cans', 'cups', 'plates',
        'apples', 'mushrooms', 'oranges', 'pears', 'sweet peppers',
        'clock', 'computer keyboard', 'lamp', 'telephone', 'television',
        'bed', 'chair', 'couch', 'table', 'wardrobe',
        'bee', 'beetle', 'butterfly', 'caterpillar', 'cockroach',
        'bear', 'leopard', 'lion', 'tiger', 'wolf',
        'bridge', 'castle', 'house', 'road', 'skyscraper',
        'cloud', 'forest', 'mountain', 'plain', 'sea',
        'camel', 'cattle', 'chimpanzee', 'elephant', 'kangaroo',
        'fox', 'porcupine', 'possum', 'raccoon', 'skunk',
        'crab', 'lobster', 'snail', 'spider', 'worm',
        'baby', 'boy', 'girl', 'man', 'woman',
        'crocodile', 'dinosaur', 'lizard', 'snake', 'turtle',
        'hamster', 'mouse', 'rabbit', 'shrew', 'squirrel',
        'maple', 'oak', 'palm', 'pine', 'willow',
        'bicycle', 'bus', 'motorcycle', 'pickup truck', 'train',
        'lawn-mower', 'rocket', 'streetcar', 'tank', 'tractor')
```

3. Обучение классификатора картинок, на примере CIFAR-100, сверточной сетью (самописной)

3.1 Пишем архитектуру сети

```
class Net(nn.Module):

    def __init__(self):
        super(Net, self).__init__()
        self.dp_three = nn.Dropout(0.2)
        self.dp_four = nn.Dropout(0.2)

        self.bn_one = torch.nn.BatchNorm2d(3)
        self.conv_one = torch.nn.Conv2d(3, 30, 3)
        self.bn_two = torch.nn.BatchNorm2d(30)
        self.conv_two = torch.nn.Conv2d(30, 60, 3)
        self.bn_three = torch.nn.BatchNorm2d(60)
        self.conv_three = torch.nn.Conv2d(60, 120, 3)
        self.bn_four = torch.nn.BatchNorm2d(120)
        self.fc1 = torch.nn.Linear(480, 200)
        ## Для CIFAR100
        self.fc2 = torch.nn.Linear(200, 150)
        self.out = torch.nn.Linear(150, 100)
        ## Для CIFAR10
        # self.fc2 = torch.nn.Linear(200, 60)
        # self.out = torch.nn.Linear(60, 10)


    def forward(self, x):
        x = self.bn_one(x)
        x = self.conv_one(x)
        x = F.relu(x)
        x = F.max_pool2d(x, 2)

        x = self.bn_two(x)
        x = self.conv_two(x)
        x = F.relu(x)
        x = F.max_pool2d(x, 2)

        x = self.bn_three(x)
        x = self.conv_three(x)
        x = F.relu(x)
        x = F.max_pool2d(x, 2)

        x = self.bn_four(x)
        x = x.view(x.size(0), -1)
        x = self.dp_three(x)
        x = self.fc1(x)
        x = F.relu(x)
        x = self.dp_four(x)
        x = self.fc2(x)
        x = F.relu(x)
```

```
        return self.out(x)

# Создаём экземпляр класса Net()
model = Net()
# print(model)


# import torch.nn.functional as F
# from tqdm import tqdm


# Функция потерь
criterion = nn.CrossEntropyLoss()
# Оптимизатор
optimizer = torch.optim.Adam(model.parameters(), lr=0.01)
```

3.2 Обучаем и тестируем

```
for epoch in tqdm(range(10)):
    model.train()
    for i, data in enumerate(train_loader, 0):
        inputs, labels = data[0], data[1]
        optimizer.zero_grad()

        outputs = model(inputs)
        # if i==0:
        #   print('\n'+'*'*100)
        #   print(f'\n\nlabels={labels},\noutputs={outputs[1]}')
        #   print('\n'+'*'*100)

        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()

    model.eval()
    loss_accumed = 0
    for X, y in test_loader:
        output = model(X)
        loss = criterion(output, y)
        loss_accumed += loss
    print("Epoch {} valid_loss {}".format(epoch, loss_accumed))

print('Training is finished!')
```

```
  0%|          | 0/10 [00:00<?, ?it/s]/usr/local/lib/python3.7/dist-packages/torch/utils/data/dataloader.py:481: UserWarning: T
  cpuset_checked))
 10%|█         | 1/10 [01:38<14:50, 98.90s/it]Epoch 0 valid_loss 123.77166748046875
 20%|██        | 2/10 [03:11<12:43, 95.39s/it]Epoch 1 valid_loss 116.73970031738281
 30%|███       | 3/10 [04:43<10:55, 93.60s/it]Epoch 2 valid_loss 106.4568099975586
 40%|████      | 4/10 [06:17<09:22, 93.77s/it]Epoch 3 valid_loss 114.77180480957031
 50%|█████     | 5/10 [07:49<07:46, 93.37s/it]Epoch 4 valid_loss 99.08961486816406
 60%|██████    | 6/10 [09:32<06:26, 96.63s/it]Epoch 5 valid_loss 93.23388671875
 70%|███████   | 7/10 [11:06<04:46, 95.64s/it]Epoch 6 valid_loss 106.19073486328125
 80%|████████  | 8/10 [12:44<03:12, 96.45s/it]Epoch 7 valid_loss 97.37362670898438
 90%|█████████ | 9/10 [14:20<01:36, 96.31s/it]Epoch 8 valid_loss 102.12936401367188
100%|██████████| 10/10 [15:57<00:00, 95.79s/it]Epoch 9 valid_loss 100.9736557006836
Training is finished!
```

4. Обучение классификатора картинок на примере CIFAR-100 (датасет можно изменить) через дообучение ImageNet Resnet-50

```
from torchvision import models

# resnet_50 = models.resnet50()
resnet_50 = models.resnet50(pretrained=True)  # Предобучаем сеть


print(resnet_50)
```

```
        (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
      )
      (4): Bottleneck(
```

```
        (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
      )
      (5): Bottleneck(
        (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
      )
    )
    (layer4): Sequential(
      (0): Bottleneck(
        (conv1): Conv2d(1024, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (downsample): Sequential(
          (0): Conv2d(1024, 2048, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        )
      )
      (1): Bottleneck(
        (conv1): Conv2d(2048, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
      )
      (2): Bottleneck(
        (conv1): Conv2d(2048, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
      )
    )
    (avgpool): AdaptiveAvgPool2d(output_size=(1, 1))
    (fc): Linear(in_features=2048, out_features=1000, bias=True)
  )
```

```
# Необходимые трансформации
normalize = transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                 std=[0.229, 0.224, 0.225])
transform = transforms.Compose([transforms.Resize(256), transforms.CenterCrop(224), normalize, transforms.ToTensor()])


# normalize = transforms.Normalize(mean=[0.485, 0.456, 0.406],
#                                  std=[0.229, 0.224, 0.225])

# trans_actions = transforms.Compose([transforms.Scale(256),
#                                     transforms.RandomCrop(224, padding=4),
#                                     transforms.ToTensor(),
#                                     normalize])


def set_parameter_requires_grad(model, feature_extracting):
    if feature_extracting:
        for param in model.parameters():
            param.requires_grad = False


set_parameter_requires_grad(resnet_50, True)
# resnet_18.fc = nn.Linear(512, 10)
resnet_50.fc = nn.Linear(2048, 100)


params_to_update = []
for name,param in resnet_50.named_parameters():
    if param.requires_grad == True:
```

```
        params_to_update.append(param)

print(params_to_update)
```

```
[Parameter containing:
tensor([[ 0.0034, -0.0115, -0.0017,  ...,  0.0128, -0.0126, -0.0127],
        [ 0.0195,  0.0091, -0.0095,  ..., -0.0178, -0.0136,  0.0062],
        [-0.0038,  0.0063,  0.0158,  ..., -0.0172, -0.0054,  0.0091],
        ...,
        [ 0.0078,  0.0198,  0.0059,  ..., -0.0214, -0.0085,  0.0149],
        [-0.0145, -0.0072, -0.0107,  ..., -0.0150,  0.0086, -0.0154],
        [-0.0056,  0.0146,  0.0162,  ..., -0.0126,  0.0006,  0.0154]],
       requires_grad=True), Parameter containing:
tensor([-0.0085, -0.0221,  0.0159, -0.0178,  0.0084, -0.0080,  0.0091,  0.0203,
         0.0077, -0.0046,  0.0115, -0.0021,  0.0063,  0.0096, -0.0113,  0.0175,
        -0.0025,  0.0060,  0.0112, -0.0131,  0.0006, -0.0019,  0.0162,  0.0037,
         0.0219, -0.0218,  0.0015, -0.0139, -0.0159,  0.0042, -0.0199,  0.0065,
         0.0062,  0.0040, -0.0140, -0.0163, -0.0156, -0.0192,  0.0187, -0.0115,
        -0.0004,  0.0005,  0.0219, -0.0196, -0.0130, -0.0033, -0.0127, -0.0185,
         0.0146,  0.0048, -0.0189,  0.0060,  0.0197, -0.0211,  0.0055, -0.0041,
         0.0146, -0.0138,  0.0147,  0.0012, -0.0204,  0.0035,  0.0051,  0.0218,
         0.0086,  0.0120,  0.0138,  0.0212,  0.0027, -0.0171, -0.0115,  0.0151,
         0.0191,  0.0079, -0.0029, -0.0078, -0.0031, -0.0137, -0.0016,  0.0066,
         0.0082, -0.0093,  0.0024, -0.0139,  0.0109, -0.0103, -0.0138,  0.0196,
         0.0044, -0.0001, -0.0168,  0.0191, -0.0015,  0.0047, -0.0083,  0.0050,
         0.0082, -0.0149, -0.0150,  0.0046], requires_grad=True)]
```

```
# resnet_50.layer3 = Net()
# resnet_50.layer4 = Net()
# resnet_50.fc = Net()
# print(resnet_50.fc)


optimizer = torch.optim.Adam(params_to_update, lr=0.001)
criterion = nn.CrossEntropyLoss()
```

Fine-tuning - заморозка сети

```
for epoch in tqdm(range(10)):
    resnet_50.train()
    for i, data in enumerate(train_loader, 0):
        inputs, labels = data[0], data[1]
        optimizer.zero_grad()

        outputs = resnet_50(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()

    resnet_50.eval()
    loss_accumed = 0
    for X, y in test_loader:
        output = resnet_50(X)
        loss = criterion(output, y)
        loss_accumed += loss
    print("Epoch {} valid_loss {}".format(epoch, loss_accumed))

print('Training is finished!')
```

```
  0%|          | 0/10 [00:00<?, ?it/s]/usr/local/lib/python3.7/dist-packages/torch/utils/data/dataloader.py:481: UserWarning: T
  cpuset_checked))
 10%|█         | 1/10 [07:32<1:07:53, 452.57s/it]Epoch 0 valid_loss 137.86070251464844
 20%|██        | 2/10 [15:19<1:01:28, 461.01s/it]Epoch 1 valid_loss 130.12818908691406
 30%|███       | 3/10 [23:24<55:02, 471.76s/it]  Epoch 2 valid_loss 129.61399841308594
 40%|████      | 4/10 [31:05<46:45, 467.51s/it]Epoch 3 valid_loss 128.58567810058594
 50%|█████     | 5/10 [38:58<39:08, 469.66s/it]Epoch 4 valid_loss 125.10343170166016
 60%|██████    | 6/10 [46:38<31:05, 466.44s/it]Epoch 5 valid_loss 132.31607055664062
 70%|███████   | 7/10 [54:18<23:13, 464.42s/it]Epoch 6 valid_loss 132.4649200439453
 80%|████████  | 8/10 [1:01:55<15:23, 461.77s/it]Epoch 7 valid_loss 130.40292358398438
 90%|█████████ | 9/10 [1:09:30<07:39, 459.69s/it]Epoch 8 valid_loss 133.65895080566406
100%|██████████| 10/10 [1:17:12<00:00, 463.26s/it]Epoch 9 valid_loss 130.14093017578125
Training is finished!
```

5. Обучение классификатора картинок на примере CIFAR-100 (датасет можно изменить) через дообучение ImageNet Resnet-50 с аугментацией (самописной, с

использованием Pytorch встроенных методов)

```
from sklearn.model_selection import train_test_split


dataset = torchvision.datasets.CIFAR10(root='data/', train=True, download=True)

def train_valid_split(Xt):
    X_train, X_test = train_test_split(Xt, test_size=0.05, random_state=13)
    return X_train, X_test

class MyOwnCifar(torch.utils.data.Dataset):

    def __init__(self, init_dataset, transform=None):
        self._base_dataset = init_dataset
        self.transform = transform

    def __len__(self):
        return len(self._base_dataset)

    def __getitem__(self, idx):
        img = self._base_dataset[idx][0]
        if self.transform is not None:
            img = self.transform(img)
        return img, self._base_dataset[idx][1]
```

```
Files already downloaded and verified
```

```
trans_actions = transforms.Compose([transforms.Scale(256),
                                    transforms.RandomCrop(224, padding=4),
                                    transforms.ToTensor(),
                                    transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                                         std=[0.229, 0.224, 0.225])])
valid_transforms = transforms.Compose([transforms.ToTensor(),
                                       transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                                            std=[0.229, 0.224, 0.225])])

train_dataset, valid_dataset = train_valid_split(dataset)

train_dataset = MyOwnCifar(train_dataset, trans_actions)
valid_dataset = MyOwnCifar(valid_dataset, valid_transforms)

train_loader = torch.utils.data.DataLoader(train_dataset,
                          batch_size=128,
                          shuffle=True,
                          num_workers=3)
valid_loader = torch.utils.data.DataLoader(valid_dataset,
                          batch_size=128,
                          shuffle=False,
                          num_workers=1)
```

```
/usr/local/lib/python3.7/dist-packages/torchvision/transforms/transforms.py:317: UserWarning: The use of the transforms.Scale t
  warnings.warn("The use of the transforms.Scale transform is deprecated, " +
/usr/local/lib/python3.7/dist-packages/torch/utils/data/dataloader.py:481: UserWarning: This DataLoader will create 3 worker pr
  cpuset_checked))
```

```
model = models.resnet50(pretrained=True)
set_parameter_requires_grad(model, True)

print(resnet_50.fc)
```

```
Linear(in_features=2048, out_features=100, bias=True)
```

```
# (fc): Linear(in_features=2048, out_features=1000, bias=True)

# model.fc = torch.nn.Linear(2048, 100)
model.fc = nn.Sequential(
    torch.nn.Dropout(0.5),
    torch.nn.Linear(2048, 1024),
    torch.nn.Linear(1024, 512),
    torch.nn.Linear(512, 256),
    torch.nn.Linear(256, 128),
    torch.nn.Linear(128, 100)  # len(train_dataset.classes)
)
```

```
,

params_to_update = []
for name,param in resnet_50.named_parameters():
    if param.requires_grad == True:
        params_to_update.append(param)

# optimizer = torch.optim.Adam(params_to_update, lr=0.001)
optimizer = optim.SGD(model.parameters(), lr=0.01, momentum=0.9)  # https://pytorch.org/docs/stable/optim.html
criterion = nn.CrossEntropyLoss()


for epoch in tqdm(range(10)):
    resnet_50.train()
    for i, data in enumerate(train_loader, 0):
        inputs, labels = data[0], data[1]
        optimizer.zero_grad()

        outputs = resnet_50(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()

    resnet_50.eval()
    loss_accumed = 0
    for X, y in test_loader:
        output = resnet_50(X)
        loss = criterion(output, y)
        loss_accumed += loss
    print("Epoch {} valid_loss {}".format(epoch, loss_accumed))

print('Training is finished!')
```

```
  0%|          | 0/10 [00:00<?, ?it/s]/usr/local/lib/python3.7/dist-packages/torch/utils/data/dataloader.py:481: UserWarning: T
  cpuset_checked))
```

- Сверточная нейронная сеть на PyTorch: пошаговое руководство - https://neurohive.io/ru/tutorial/cnn-na-pytorch/
- How to use an optimizer -https://pytorch.org/docs/stable/optim.html
- Image Classification of CIFAR100 Dataset Using PyTorch - https://blog.jovian.ai/image-classification-of-cifar100-dataset-using-pytorch-8b7145242df1

1 ч. 37 мин. 59 сек. выполнено в 22:24