final_16

March 26, 2023

[1]:
```python
#!pip install torch torchvision
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
import torch
import torchvision
import torchvision.transforms as transforms
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
```

Prepare for Dataset

[2]:
```python
transform = transforms.Compose(
    [transforms.ToTensor(),
     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])

trainset = torchvision.datasets.CIFAR100(root='./data', train=True,
                                        download=True, transform=transform)
trainloader = torch.utils.data.DataLoader(trainset, batch_size=4,
                                          shuffle=True, num_workers=2)

testset = torchvision.datasets.CIFAR100(root='./data', train=False,
                                       download=True, transform=transform)
testloader = torch.utils.data.DataLoader(testset, batch_size=4,
                                         shuffle=False, num_workers=2)

classes = ('apple', 'aquarium_fish', 'baby', 'bear', 'beaver',
           'bed', 'bee', 'beetle', 'bicycle', 'bottle', 'bowl',
           'boy', 'bridge', 'bus', 'butterfly', 'camel', 'can',
           'castle', 'caterpillar', 'cattle', 'chair',
           'chimpanzee', 'clock', 'cloud', 'cockroach', 'couch',
           'crab', 'crocodile', 'cup', 'dinosaur', 'dolphin',
           'elephant', 'flatfish', 'forest', 'fox', 'girl',
           'hamster', 'house', 'kangaroo', 'keyboard', 'lamp',
           'lawn_mower', 'leopard', 'lion', 'lizard', 'lobster',
           'man', 'maple_tree', 'motorcycle', 'mountain', 'mouse',
           'mushroom', 'oak_tree', 'orange', 'orchid', 'otter',
```

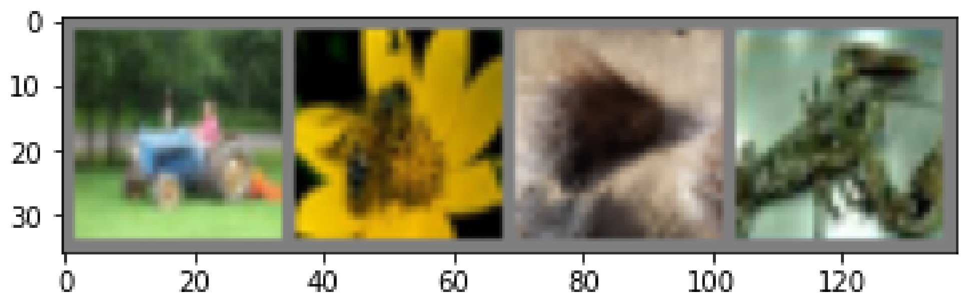
```
            'palm_tree', 'pear', 'pickup_truck', 'pine_tree', 'plain',
            'plate', 'poppy', 'porcupine', 'possum', 'rabbit', 'raccoon',
            'ray', 'road', 'rocket', 'rose', 'sea', 'seal', 'shark',
            'shrew', 'skunk', 'skyscraper', 'snail', 'snake', 'spider',
            'squirrel', 'streetcar', 'sunflower', 'sweet_pepper', 'table',
            'tank', 'telephone', 'television', 'tiger', 'tractor', 'train',
            'trout', 'tulip', 'turtle', 'wardrobe', 'whale', 'willow_tree',
            'wolf', 'woman', 'worm')

#classes = ('plane', 'car', 'bird', 'cat',
#           'deer', 'dog', 'frog', 'horse', 'ship', 'truck')
```

```
Files already downloaded and verified
Files already downloaded and verified
```

[3]:
```
# The function to show an image.
def imshow(img):
    img = img / 2 + 0.5     # Unnormalize.
    npimg = img.numpy()
    plt.imshow(np.transpose(npimg, (1, 2, 0)))
    plt.show()

# Get some random training images.
dataiter = iter(trainloader)
images, labels = next(dataiter)
# Show images.
imshow(torchvision.utils.make_grid(images))
# Print labels.
print(' '.join('%5s' % classes[labels[j]] for j in range(4)))
```



```
tractor   bee porcupine lobster
```

Choose a Device

[4]:
```
# If there are GPUs, choose the first one for computing. Otherwise use CPU.
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
```

```
print(device)
# If 'cuda:0' is printed, it means GPU is available.
```

```
cuda:0
```

Network Definition

[20]:
```
class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(in_channels=3, out_channels=64, kernel_size=3,␣
 ↪padding=1)
        self.bn1 = nn.BatchNorm2d(64)
        self.pool1 = nn.AvgPool2d(kernel_size=2, stride=2)
        self.relu1 = nn.ReLU()
        self.conv2 = nn.Conv2d(64, 128, 3, padding=1)
        self.bn2 = nn.BatchNorm2d(128)
        self.pool2 = nn.AvgPool2d(kernel_size=2, stride=2)
        self.relu2 = nn.ReLU()
        self.conv3 = nn.Conv2d(128, 256, 3, padding=1)
        self.bn3 = nn.BatchNorm2d(256)
        self.pool3 = nn.AvgPool2d(kernel_size=2, stride=2)
        self.relu3 = nn.SELU()

        # Additional Conv layers
        self.conv4 = nn.Conv2d(256, 512, 3, padding=1)
        self.bn4 = nn.BatchNorm2d(512)
        self.pool4 = nn.AvgPool2d(kernel_size=2, stride=2)
        self.relu4 = nn.ReLU()

        self.conv5 = nn.Conv2d(512, 1024, 3, padding=1)
        self.bn5 = nn.BatchNorm2d(1024)
        self.pool5 = nn.AvgPool2d(kernel_size=2, stride=2)
        self.relu5 = nn.ReLU()

        self.fc1 = nn.Linear(1024, 1024)
        self.bn6 = nn.BatchNorm1d(1024)
        self.relu6 = nn.ReLU()
        self.fc2 = nn.Linear(1024, 100)

    def forward(self, x):
        x = self.pool1(self.relu1(self.conv1(x)))
        x = self.pool2(self.relu2(self.conv2(x)))
        x = self.pool3(self.relu3(self.conv3(x)))

        # Forward pass through additional Conv layers
        x = self.pool4(self.relu4(self.bn4(self.conv4(x))))
        x = self.pool5(self.relu5(self.bn5(self.conv5(x))))
```

```
        x = torch.flatten(x, 1)  # Flatten the tensor to 2D
        x = self.relu6(self.bn6(self.fc1(x)))
        x = self.fc2(x)
        return x

net = Net()     # Create the network instance.
net.to(device)  # Move the network parameters to the specified device.
```

[20]:
```
Net(
  (conv1): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
  (pool1): AvgPool2d(kernel_size=2, stride=2, padding=0)
  (relu1): ReLU()
  (conv2): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
  (pool2): AvgPool2d(kernel_size=2, stride=2, padding=0)
  (relu2): ReLU()
  (conv3): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
  (pool3): AvgPool2d(kernel_size=2, stride=2, padding=0)
  (relu3): SELU()
  (conv4): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (bn4): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
  (pool4): AvgPool2d(kernel_size=2, stride=2, padding=0)
  (relu4): ReLU()
  (conv5): Conv2d(512, 1024, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (bn5): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
  (pool5): AvgPool2d(kernel_size=2, stride=2, padding=0)
  (relu5): ReLU()
  (fc1): Linear(in_features=1024, out_features=1024, bias=True)
  (bn6): BatchNorm1d(1024, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
  (relu6): ReLU()
  (fc2): Linear(in_features=1024, out_features=100, bias=True)
)
```

Optimizer and Loss Function

[21]:
```
# We use cross-entropy as loss function.
loss_func = nn.CrossEntropyLoss()
# We use stochastic gradient descent (SGD) as optimizer.
```

```
#opt = optim.SGD(net.parameters(), lr=0.0001, momentum=0.9)
opt = optim.Adam(net.parameters(), lr=0.0001)
```

Training Procedure

[22]:
```
import sys
from tqdm.notebook import tqdm

avg_losses = []   # Avg. losses.
epochs = 8       # Total epochs.
print_freq = 500  # Print frequency.

for epoch in range(epochs):  # Loop over the dataset multiple times.
    running_loss = 0.0       # Initialize running loss.
    for i, data in enumerate(tqdm(trainloader), 0):
        # Get the inputs.
        inputs, labels = data

        # Move the inputs to the specified device.
        inputs, labels = inputs.to(device), labels.to(device)

        # Zero the parameter gradients.
        opt.zero_grad()

        # Forward step.
        outputs = net(inputs)
        loss = loss_func(outputs, labels)

        # Backward step.
        loss.backward()

        # Optimization step (update the parameters).
        opt.step()

        # Print statistics.
        running_loss += loss.item()
        if i % print_freq == print_freq - 1: # Print every several mini-batches.
            avg_loss = running_loss / print_freq
            print('[epoch: {}, i: {:5d}] avg mini-batch loss: {:.3f}'.
↪format(epoch, i, avg_loss),flush=True)
            sys.stdout.flush()
            avg_losses.append(avg_loss)
            running_loss = 0.0

print('Finished Training.')
```

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  0%|          | 0/12500 [00:00<?, ?it/s]
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```
[epoch: 0, i:   499] avg mini-batch loss: 4.525
[epoch: 0, i:   999] avg mini-batch loss: 4.338
[epoch: 0, i:  1499] avg mini-batch loss: 4.243
[epoch: 0, i:  1999] avg mini-batch loss: 4.183
[epoch: 0, i:  2499] avg mini-batch loss: 4.142
[epoch: 0, i:  2999] avg mini-batch loss: 4.045
[epoch: 0, i:  3499] avg mini-batch loss: 4.015
[epoch: 0, i:  3999] avg mini-batch loss: 4.016
[epoch: 0, i:  4499] avg mini-batch loss: 3.990
[epoch: 0, i:  4999] avg mini-batch loss: 3.913
[epoch: 0, i:  5499] avg mini-batch loss: 3.871
[epoch: 0, i:  5999] avg mini-batch loss: 3.827
[epoch: 0, i:  6499] avg mini-batch loss: 3.827
[epoch: 0, i:  6999] avg mini-batch loss: 3.819
[epoch: 0, i:  7499] avg mini-batch loss: 3.823
[epoch: 0, i:  7999] avg mini-batch loss: 3.716
[epoch: 0, i:  8499] avg mini-batch loss: 3.760
[epoch: 0, i:  8999] avg mini-batch loss: 3.664
[epoch: 0, i:  9499] avg mini-batch loss: 3.692
[epoch: 0, i:  9999] avg mini-batch loss: 3.704
[epoch: 0, i: 10499] avg mini-batch loss: 3.613
[epoch: 0, i: 10999] avg mini-batch loss: 3.582
[epoch: 0, i: 11499] avg mini-batch loss: 3.606
[epoch: 0, i: 11999] avg mini-batch loss: 3.565
[epoch: 0, i: 12499] avg mini-batch loss: 3.489
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```
[epoch: 1, i:   499] avg mini-batch loss: 3.440
[epoch: 1, i:   999] avg mini-batch loss: 3.449
[epoch: 1, i:  1499] avg mini-batch loss: 3.444
[epoch: 1, i:  1999] avg mini-batch loss: 3.462
[epoch: 1, i:  2499] avg mini-batch loss: 3.387
[epoch: 1, i:  2999] avg mini-batch loss: 3.372
[epoch: 1, i:  3499] avg mini-batch loss: 3.378
[epoch: 1, i:  3999] avg mini-batch loss: 3.396
[epoch: 1, i:  4499] avg mini-batch loss: 3.343
[epoch: 1, i:  4999] avg mini-batch loss: 3.218
[epoch: 1, i:  5499] avg mini-batch loss: 3.269
[epoch: 1, i:  5999] avg mini-batch loss: 3.284
[epoch: 1, i:  6499] avg mini-batch loss: 3.201
[epoch: 1, i:  6999] avg mini-batch loss: 3.266
[epoch: 1, i:  7499] avg mini-batch loss: 3.150
[epoch: 1, i:  7999] avg mini-batch loss: 3.177
[epoch: 1, i:  8499] avg mini-batch loss: 3.206
[epoch: 1, i:  8999] avg mini-batch loss: 3.177
[epoch: 1, i:  9499] avg mini-batch loss: 3.168
[epoch: 1, i:  9999] avg mini-batch loss: 3.165
[epoch: 1, i: 10499] avg mini-batch loss: 3.122
```

```
[epoch: 1, i: 10999] avg mini-batch loss: 3.070
[epoch: 1, i: 11499] avg mini-batch loss: 3.144
[epoch: 1, i: 11999] avg mini-batch loss: 3.003
[epoch: 1, i: 12499] avg mini-batch loss: 3.088
```

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```
[epoch: 2, i:   499] avg mini-batch loss: 3.018
[epoch: 2, i:   999] avg mini-batch loss: 2.985
[epoch: 2, i:  1499] avg mini-batch loss: 3.024
[epoch: 2, i:  1999] avg mini-batch loss: 3.044
[epoch: 2, i:  2499] avg mini-batch loss: 2.921
[epoch: 2, i:  2999] avg mini-batch loss: 2.993
[epoch: 2, i:  3499] avg mini-batch loss: 2.935
[epoch: 2, i:  3999] avg mini-batch loss: 2.928
[epoch: 2, i:  4499] avg mini-batch loss: 2.950
[epoch: 2, i:  4999] avg mini-batch loss: 2.885
[epoch: 2, i:  5499] avg mini-batch loss: 2.908
[epoch: 2, i:  5999] avg mini-batch loss: 2.888
[epoch: 2, i:  6499] avg mini-batch loss: 2.949
[epoch: 2, i:  6999] avg mini-batch loss: 2.866
[epoch: 2, i:  7499] avg mini-batch loss: 2.863
[epoch: 2, i:  7999] avg mini-batch loss: 2.813
[epoch: 2, i:  8499] avg mini-batch loss: 2.857
[epoch: 2, i:  8999] avg mini-batch loss: 2.905
[epoch: 2, i:  9499] avg mini-batch loss: 2.810
[epoch: 2, i:  9999] avg mini-batch loss: 2.882
[epoch: 2, i: 10499] avg mini-batch loss: 2.901
[epoch: 2, i: 10999] avg mini-batch loss: 2.883
[epoch: 2, i: 11499] avg mini-batch loss: 2.805
[epoch: 2, i: 11999] avg mini-batch loss: 2.877
[epoch: 2, i: 12499] avg mini-batch loss: 2.815
```

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[epoch: 3, i:   499] avg mini-batch loss: 2.699
[epoch: 3, i:   999] avg mini-batch loss: 2.696
[epoch: 3, i:  1499] avg mini-batch loss: 2.669
[epoch: 3, i:  1999] avg mini-batch loss: 2.684
[epoch: 3, i:  2499] avg mini-batch loss: 2.668
[epoch: 3, i:  2999] avg mini-batch loss: 2.722
[epoch: 3, i:  3499] avg mini-batch loss: 2.681
[epoch: 3, i:  3999] avg mini-batch loss: 2.654
[epoch: 3, i:  4499] avg mini-batch loss: 2.693
[epoch: 3, i:  4999] avg mini-batch loss: 2.665
[epoch: 3, i:  5499] avg mini-batch loss: 2.685
[epoch: 3, i:  5999] avg mini-batch loss: 2.597
[epoch: 3, i:  6499] avg mini-batch loss: 2.683
[epoch: 3, i:  6999] avg mini-batch loss: 2.640
[epoch: 3, i:  7499] avg mini-batch loss: 2.681
```

```
[epoch: 3, i:  7999] avg mini-batch loss: 2.581
[epoch: 3, i:  8499] avg mini-batch loss: 2.691
[epoch: 3, i:  8999] avg mini-batch loss: 2.583
[epoch: 3, i:  9499] avg mini-batch loss: 2.623
[epoch: 3, i:  9999] avg mini-batch loss: 2.547
[epoch: 3, i: 10499] avg mini-batch loss: 2.645
[epoch: 3, i: 10999] avg mini-batch loss: 2.678
[epoch: 3, i: 11499] avg mini-batch loss: 2.652
[epoch: 3, i: 11999] avg mini-batch loss: 2.593
[epoch: 3, i: 12499] avg mini-batch loss: 2.628
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[epoch: 4, i:   499] avg mini-batch loss: 2.412
[epoch: 4, i:   999] avg mini-batch loss: 2.540
[epoch: 4, i:  1499] avg mini-batch loss: 2.505
[epoch: 4, i:  1999] avg mini-batch loss: 2.389
[epoch: 4, i:  2499] avg mini-batch loss: 2.420
[epoch: 4, i:  2999] avg mini-batch loss: 2.461
[epoch: 4, i:  3499] avg mini-batch loss: 2.524
[epoch: 4, i:  3999] avg mini-batch loss: 2.490
[epoch: 4, i:  4499] avg mini-batch loss: 2.485
[epoch: 4, i:  4999] avg mini-batch loss: 2.490
[epoch: 4, i:  5499] avg mini-batch loss: 2.466
[epoch: 4, i:  5999] avg mini-batch loss: 2.415
[epoch: 4, i:  6499] avg mini-batch loss: 2.427
[epoch: 4, i:  6999] avg mini-batch loss: 2.427
[epoch: 4, i:  7499] avg mini-batch loss: 2.440
[epoch: 4, i:  7999] avg mini-batch loss: 2.465
[epoch: 4, i:  8499] avg mini-batch loss: 2.501
[epoch: 4, i:  8999] avg mini-batch loss: 2.479
[epoch: 4, i:  9499] avg mini-batch loss: 2.419
[epoch: 4, i:  9999] avg mini-batch loss: 2.433
[epoch: 4, i: 10499] avg mini-batch loss: 2.422
[epoch: 4, i: 10999] avg mini-batch loss: 2.435
[epoch: 4, i: 11499] avg mini-batch loss: 2.468
[epoch: 4, i: 11999] avg mini-batch loss: 2.376
[epoch: 4, i: 12499] avg mini-batch loss: 2.477
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[epoch: 5, i:   499] avg mini-batch loss: 2.362
[epoch: 5, i:   999] avg mini-batch loss: 2.331
[epoch: 5, i:  1499] avg mini-batch loss: 2.197
[epoch: 5, i:  1999] avg mini-batch loss: 2.253
[epoch: 5, i:  2499] avg mini-batch loss: 2.203
[epoch: 5, i:  2999] avg mini-batch loss: 2.243
[epoch: 5, i:  3499] avg mini-batch loss: 2.255
[epoch: 5, i:  3999] avg mini-batch loss: 2.288
[epoch: 5, i:  4499] avg mini-batch loss: 2.343
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```
[epoch: 5, i:  4999] avg mini-batch loss: 2.290
[epoch: 5, i:  5499] avg mini-batch loss: 2.267
[epoch: 5, i:  5999] avg mini-batch loss: 2.272
[epoch: 5, i:  6499] avg mini-batch loss: 2.321
[epoch: 5, i:  6999] avg mini-batch loss: 2.303
[epoch: 5, i:  7499] avg mini-batch loss: 2.307
[epoch: 5, i:  7999] avg mini-batch loss: 2.384
[epoch: 5, i:  8499] avg mini-batch loss: 2.302
[epoch: 5, i:  8999] avg mini-batch loss: 2.353
[epoch: 5, i:  9499] avg mini-batch loss: 2.294
[epoch: 5, i:  9999] avg mini-batch loss: 2.307
[epoch: 5, i: 10499] avg mini-batch loss: 2.271
[epoch: 5, i: 10999] avg mini-batch loss: 2.318
[epoch: 5, i: 11499] avg mini-batch loss: 2.228
[epoch: 5, i: 11999] avg mini-batch loss: 2.290
[epoch: 5, i: 12499] avg mini-batch loss: 2.230
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[epoch: 6, i:   499] avg mini-batch loss: 2.139
[epoch: 6, i:   999] avg mini-batch loss: 2.163
[epoch: 6, i:  1499] avg mini-batch loss: 2.096
[epoch: 6, i:  1999] avg mini-batch loss: 2.154
[epoch: 6, i:  2499] avg mini-batch loss: 2.177
[epoch: 6, i:  2999] avg mini-batch loss: 2.181
[epoch: 6, i:  3499] avg mini-batch loss: 2.129
[epoch: 6, i:  3999] avg mini-batch loss: 2.235
[epoch: 6, i:  4499] avg mini-batch loss: 2.210
[epoch: 6, i:  4999] avg mini-batch loss: 2.087
[epoch: 6, i:  5499] avg mini-batch loss: 2.139
[epoch: 6, i:  5999] avg mini-batch loss: 2.135
[epoch: 6, i:  6499] avg mini-batch loss: 2.171
[epoch: 6, i:  6999] avg mini-batch loss: 2.109
[epoch: 6, i:  7499] avg mini-batch loss: 2.169
[epoch: 6, i:  7999] avg mini-batch loss: 2.122
[epoch: 6, i:  8499] avg mini-batch loss: 2.174
[epoch: 6, i:  8999] avg mini-batch loss: 2.197
[epoch: 6, i:  9499] avg mini-batch loss: 2.172
[epoch: 6, i:  9999] avg mini-batch loss: 2.170
[epoch: 6, i: 10499] avg mini-batch loss: 2.191
[epoch: 6, i: 10999] avg mini-batch loss: 2.113
[epoch: 6, i: 11499] avg mini-batch loss: 2.192
[epoch: 6, i: 11999] avg mini-batch loss: 2.129
[epoch: 6, i: 12499] avg mini-batch loss: 2.168
```

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  0%|          | 0/12500 [00:00<?, ?it/s]
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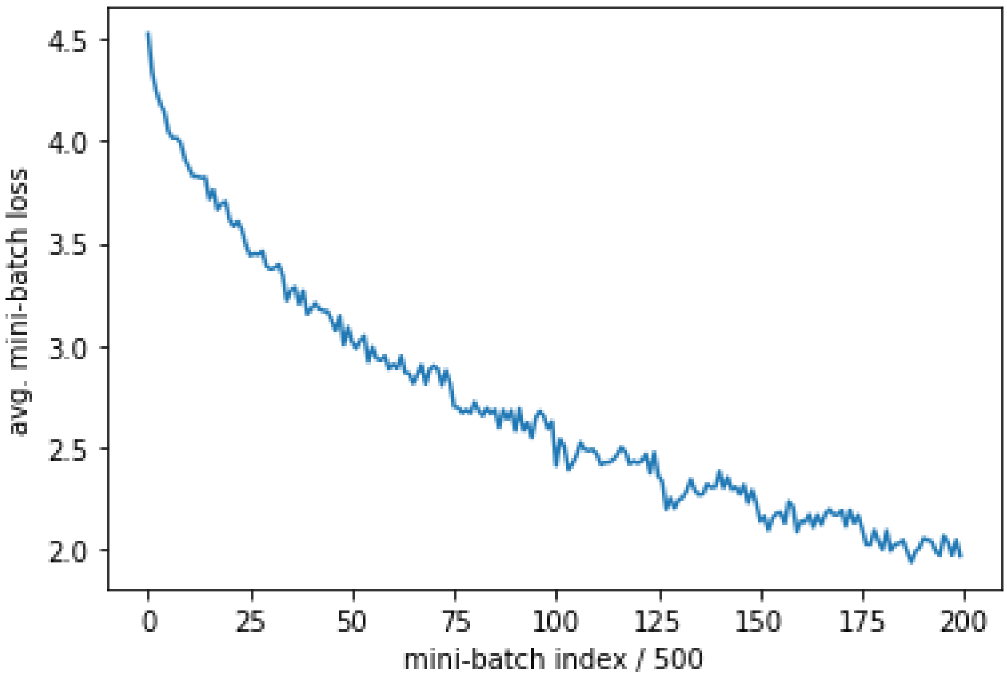
```
[epoch: 7, i:   499] avg mini-batch loss: 2.101
[epoch: 7, i:   999] avg mini-batch loss: 2.025
[epoch: 7, i:  1499] avg mini-batch loss: 2.024
```

```
[epoch: 7, i:  1999] avg mini-batch loss: 2.094
[epoch: 7, i:  2499] avg mini-batch loss: 2.042
[epoch: 7, i:  2999] avg mini-batch loss: 2.001
[epoch: 7, i:  3499] avg mini-batch loss: 2.093
[epoch: 7, i:  3999] avg mini-batch loss: 1.995
[epoch: 7, i:  4499] avg mini-batch loss: 2.025
[epoch: 7, i:  4999] avg mini-batch loss: 2.030
[epoch: 7, i:  5499] avg mini-batch loss: 2.045
[epoch: 7, i:  5999] avg mini-batch loss: 1.990
[epoch: 7, i:  6499] avg mini-batch loss: 1.939
[epoch: 7, i:  6999] avg mini-batch loss: 1.990
[epoch: 7, i:  7499] avg mini-batch loss: 2.009
[epoch: 7, i:  7999] avg mini-batch loss: 2.055
[epoch: 7, i:  8499] avg mini-batch loss: 2.048
[epoch: 7, i:  8999] avg mini-batch loss: 2.039
[epoch: 7, i:  9499] avg mini-batch loss: 1.992
[epoch: 7, i:  9999] avg mini-batch loss: 1.971
[epoch: 7, i: 10499] avg mini-batch loss: 2.066
[epoch: 7, i: 10999] avg mini-batch loss: 2.035
[epoch: 7, i: 11499] avg mini-batch loss: 1.973
[epoch: 7, i: 11999] avg mini-batch loss: 2.046
[epoch: 7, i: 12499] avg mini-batch loss: 1.970
Finished Training.
```

Training Loss Curve

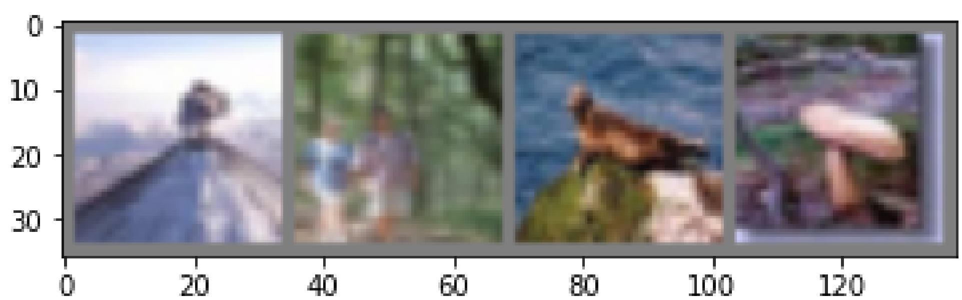
[23]:
```
plt.plot(avg_losses)
plt.xlabel('mini-batch index / {}'.format(print_freq))
plt.ylabel('avg. mini-batch loss')
plt.show()
```



Evaluate on Test Dataset

[24]:
```
# Check several images.
dataiter = iter(testloader)
images, labels = next(dataiter)
imshow(torchvision.utils.make_grid(images))
print('GroundTruth: ', ' '.join('%5s' % classes[labels[j]] for j in range(4)))
outputs = net(images.to(device))
_, predicted = torch.max(outputs, 1)

print('Predicted: ', ' '.join('%5s' % classes[predicted[j]]
                              for j in range(4)))
```



```
GroundTruth:  mountain forest  seal mushroom
Predicted:  mountain rabbit dinosaur  bowl
```

[25]:
```python
# Get test accuracy.
correct = 0
total = 0
with torch.no_grad():
    for data in testloader:
        images, labels = data
        images, labels = images.to(device), labels.to(device)
        outputs = net(images)
        _, predicted = torch.max(outputs.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()

print('Accuracy of the network on the 10000 test images: %d %%' % (
    100 * correct / total))
```

```
Accuracy of the network on the 10000 test images: 43 %
```

[26]:
```python
# Get test accuracy for each class.
class_correct = [0] * len(classes)
class_total = [0] * len(classes)
with torch.no_grad():
    for data in testloader:
        images, labels = data
        images, labels = images.to(device), labels.to(device)
        outputs = net(images)
        _, predicted = torch.max(outputs, 1)
        c = (predicted == labels).squeeze()
        for i in range(len(labels)):
            label = labels[i]
            class_correct[label] += c[i].item()
            class_total[label] += 1

for i in range(len(classes)):
    print('Accuracy of %5s : %2d %%' % (
        classes[i], 100 * class_correct[i] / class_total[i]))
```

```
Accuracy of apple : 76 %
Accuracy of aquarium_fish : 54 %
Accuracy of  baby : 30 %
Accuracy of  bear : 26 %
Accuracy of beaver : 11 %
Accuracy of   bed : 47 %
Accuracy of   bee : 40 %
Accuracy of beetle : 33 %
Accuracy of bicycle : 53 %
```

```
Accuracy of bottle : 54 %
Accuracy of  bowl : 23 %
Accuracy of   boy : 19 %
Accuracy of bridge : 46 %
Accuracy of   bus : 30 %
Accuracy of butterfly : 46 %
Accuracy of camel : 33 %
Accuracy of   can : 46 %
Accuracy of castle : 68 %
Accuracy of caterpillar : 30 %
Accuracy of cattle : 35 %
Accuracy of chair : 73 %
Accuracy of chimpanzee : 54 %
Accuracy of clock : 18 %
Accuracy of cloud : 59 %
Accuracy of cockroach : 61 %
Accuracy of couch : 30 %
Accuracy of  crab : 24 %
Accuracy of crocodile : 29 %
Accuracy of   cup : 62 %
Accuracy of dinosaur : 39 %
Accuracy of dolphin : 48 %
Accuracy of elephant : 43 %
Accuracy of flatfish : 35 %
Accuracy of forest : 46 %
Accuracy of   fox : 38 %
Accuracy of  girl : 39 %
Accuracy of hamster : 31 %
Accuracy of house : 41 %
Accuracy of kangaroo : 41 %
Accuracy of keyboard : 50 %
Accuracy of  lamp : 33 %
Accuracy of lawn_mower : 64 %
Accuracy of leopard : 40 %
Accuracy of  lion : 46 %
Accuracy of lizard : 13 %
Accuracy of lobster : 15 %
Accuracy of   man : 34 %
Accuracy of maple_tree : 53 %
Accuracy of motorcycle : 66 %
Accuracy of mountain : 67 %
Accuracy of mouse :  7 %
Accuracy of mushroom : 47 %
Accuracy of oak_tree : 61 %
Accuracy of orange : 78 %
Accuracy of orchid : 62 %
Accuracy of otter : 11 %
Accuracy of palm_tree : 65 %
```

```
Accuracy of  pear : 49 %
Accuracy of pickup_truck : 52 %
Accuracy of pine_tree : 45 %
Accuracy of plain : 81 %
Accuracy of plate : 74 %
Accuracy of poppy : 59 %
Accuracy of porcupine : 54 %
Accuracy of possum :  8 %
Accuracy of rabbit : 23 %
Accuracy of raccoon : 31 %
Accuracy of   ray : 36 %
Accuracy of  road : 70 %
Accuracy of rocket : 65 %
Accuracy of  rose : 46 %
Accuracy of   sea : 65 %
Accuracy of  seal :  9 %
Accuracy of shark : 31 %
Accuracy of shrew : 16 %
Accuracy of skunk : 68 %
Accuracy of skyscraper : 64 %
Accuracy of snail : 38 %
Accuracy of snake : 25 %
Accuracy of spider : 31 %
Accuracy of squirrel :  4 %
Accuracy of streetcar : 49 %
Accuracy of sunflower : 68 %
Accuracy of sweet_pepper : 17 %
Accuracy of table : 36 %
Accuracy of  tank : 43 %
Accuracy of telephone : 52 %
Accuracy of television : 58 %
Accuracy of tiger : 41 %
Accuracy of tractor : 48 %
Accuracy of train : 44 %
Accuracy of trout : 57 %
Accuracy of tulip : 40 %
Accuracy of turtle : 21 %
Accuracy of wardrobe : 80 %
Accuracy of whale : 53 %
Accuracy of willow_tree : 38 %
Accuracy of  wolf : 32 %
Accuracy of woman : 24 %
Accuracy of  worm : 37 %
```

[ ]:
```
# One of the changes I made was that I added another layer in the network
# that takes the output from the second convolutional layer, applies ReLU␣
↪activation,
```

```
# and passes it through a 2x2 AvgPool layer to capture more relationships.
# I also reduced the learning rate of the optimizer to half (0.0005) which
# which allowed the optimizer to take smaller steps towards the minimum of
# the loss function which might allow for a better chance of finding the global␣
↪min of loss.
```