

Appendix-8: Residual Neural Network (ResNet):

ResNet is a deep neural network architecture that uses residual connections to enable the training of very deep networks. The ResNet18 model consisted of several convolutional layers, each followed by a batch normalization layer and a ReLU activation function, and several residual blocks, each consisting of two convolutional layers and a shortcut connection.

We used PyTorch to implement the model and trained it using the cross-entropy loss function and the SGD optimizer with a learning rate scheduler.

```
In [1]: # import library dependencies
import torch
import torch.nn as nn
import torch.optim as optim
from torchvision.datasets import CIFAR10
from torch.utils.data import DataLoader
import torchvision.transforms as transforms
```

```
In [2]: # check if GPU is available

if torch.cuda.is_available():
    print('Training on GPU!')
    device = torch.device('cuda')
elif torch.has_mps:
    print('Training on Macbook Metal GPU!')
    device = torch.device('mps')
else:
    print('No GPU available. Training on CPU!')
    device = torch.device('cpu')

device
```

Training on Macbook Metal GPU!

```
Out[2]: device(type='mps')
```

Import Data

```
In [3]: ROOT_PATH='../'
```

```
In [4]: BATCH_SIZE=16
```

```
In [5]: transform = transforms.Compose(
    [transforms.ToTensor(),
     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])
```

```
In [6]: train_dataset = CIFAR10(root=ROOT_PATH, download=True, train=True, transform=transform)
eval_dataset = CIFAR10(root=ROOT_PATH, train=False, transform=transform)
```

Files already downloaded and verified

Preprocess Data

```
In [7]: train_data_loader = DataLoader(dataset=train_dataset, num_workers=4, batch_size=batch_size)
eval_data_loader = DataLoader(dataset=eval_dataset, num_workers=4, batch_size=batch_size)
```

Define model and train

```
In [8]: class BasicBlock(nn.Module):
    def __init__(self, in_planes, planes, stride=1):
        super(BasicBlock, self).__init__()
        self.conv1 = nn.Conv2d(in_planes, planes, kernel_size=3, stride=stride, padding=1)
        self.bn1 = nn.BatchNorm2d(planes)
        self.conv2 = nn.Conv2d(planes, planes, kernel_size=3, stride=1, padding=1)
        self.bn2 = nn.BatchNorm2d(planes)

        self.shortcut = nn.Sequential()
        if stride != 1 or in_planes != planes:
            self.shortcut = nn.Sequential(
                nn.Conv2d(in_planes, planes, kernel_size=1, stride=stride, padding=0),
                nn.BatchNorm2d(planes)
            )

    def forward(self, x):
        out = nn.functional.relu(self.bn1(self.conv1(x)))
        out = self.bn2(self.conv2(out))
        out += self.shortcut(x)
        out = nn.functional.relu(out)
        return out
```

```
In [9]: class ResNet(nn.Module):
    def __init__(self, num_classes=10):
        super(ResNet, self).__init__()
        self.in_planes = 64

        self.conv1 = nn.Conv2d(3, 64, kernel_size=3, stride=1, padding=1, bias=False)
        self.bn1 = nn.BatchNorm2d(64)
        self.layer1 = nn.Sequential(
            BasicBlock(64, 64, stride=1),
            BasicBlock(64, 64, stride=1)
        )
        self.layer2 = nn.Sequential(
            BasicBlock(64, 128, stride=2),
            BasicBlock(128, 128, stride=1)
        )
        self.layer3 = nn.Sequential(
            BasicBlock(128, 256, stride=2),
            BasicBlock(256, 256, stride=1)
        )
        self.layer4 = nn.Sequential(
            BasicBlock(256, 512, stride=2),
            BasicBlock(512, 512, stride=1)
        )
        self.avgpool = nn.AdaptiveAvgPool2d((1, 1))
        self.linear = nn.Linear(512, num_classes)

    def forward(self, x):
        out = nn.functional.relu(self.bn1(self.conv1(x)))
        out = self.layer1(out)
        out = self.layer2(out)
        out = self.layer3(out)
        out = self.layer4(out)
        out = self.avgpool(out)
        out = out.view(out.size(0), -1)
        out = self.linear(out)
        return out
```

```
In [10]: # create an instance of the ResNet class
net = ResNet()
net.to(device)
```

```
Out[10]: ResNet(
  (conv1): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1),
    bias=False)
  (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (layer1): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (layer2): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
    (1): BasicBlock(
      (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (layer3): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2), padding=(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)
    )
    (1): BasicBlock(
      (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(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)
    )
  )
  (layer4): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(256, 512, kernel_size=(3, 3), stride=(2, 2), padding=(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)
    )
    (1): BasicBlock(
      (conv1): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(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)
    )
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(1, 1))
  (linear): Linear(512, 10)
```

```

        (shortcut): Sequential()
    )
    (1): BasicBlock(
        (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (shortcut): Sequential()
    )
)
(layer2): Sequential(
    (0): BasicBlock(
        (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (shortcut): Sequential(
            (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
            (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        )
    )
    (1): BasicBlock(
        (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (shortcut): Sequential()
    )
)
(layer3): Sequential(
    (0): BasicBlock(
        (conv1): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2), padding=(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)
        (shortcut): Sequential(
            (0): Conv2d(128, 256, kernel_size=(1, 1), stride=(2, 2), bias=False)
            (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        )
    )

```

```

    )
    (l1): BasicBlock(
      (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(
1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_ru
nning_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_ru
nning_stats=True)
      (shortcut): Sequential()
    )
  )
  (layer4): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(256, 512, kernel_size=(3, 3), stride=(2, 2), padding=(
1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_ru
nning_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_ru
nning_stats=True)
      (shortcut): Sequential(
        (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_ru
nning_stats=True)
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(
1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_ru
nning_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_ru
nning_stats=True)
      (shortcut): Sequential()
    )
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(1, 1))
  (linear): Linear(in_features=512, out_features=10, bias=True)
)

```

```

In [11]: # define the loss function and optimizer
criterion = nn.CrossEntropyLoss().to(device)
optimizer = optim.SGD(net.parameters(), lr=0.001, momentum=0.9)

```

```

In [12]: num_epochs = 50

```

```
In [13]: # train the ResNet
for epoch in range(num_epochs): # loop over the dataset multiple times

    running_loss = 0.0
    for i, data in enumerate(train_data_loader, 0):
        # get the inputs; data is a list of [inputs, labels]
        inputs, labels = data[0].to(device), data[1].to(device)

        # zero the parameter gradients
        optimizer.zero_grad()

        # forward + backward + optimize
        outputs = net(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()

        # print statistics
        running_loss += loss.item()
        if i % 1000 == 999: # print every 2000 mini-batches
            print('[%d, %5d] loss: %.3f' %
                  (epoch + 1, i + 1, running_loss / 1000))
            running_loss = 0.0

print('Finished Training')
```

```
[1, 1000] loss: 2.102
[1, 2000] loss: 1.806
[1, 3000] loss: 1.663
[1, 4000] loss: 1.542
[1, 5000] loss: 1.433
[1, 6000] loss: 1.340
[1, 7000] loss: 1.289
[1, 8000] loss: 1.189
[1, 9000] loss: 1.137
[1, 10000] loss: 1.072
[1, 11000] loss: 1.065
[1, 12000] loss: 1.008
[2, 1000] loss: 0.918
[2, 2000] loss: 0.893
[2, 3000] loss: 0.869
[2, 4000] loss: 0.860
[2, 5000] loss: 0.834
[2, 6000] loss: 0.827
[2, 7000] loss: 0.785
[2, 8000] loss: 0.763
[2, 9000] loss: 0.785
[2, 10000] loss: 0.775
[2, 11000] loss: 0.770
[2, 12000] loss: 0.733
[3, 1000] loss: 0.586
[3, 2000] loss: 0.598
[3, 3000] loss: 0.623
[3, 4000] loss: 0.611
[3, 5000] loss: 0.594
[3, 6000] loss: 0.616
```

[3, 7000] loss: 0.607
[3, 8000] loss: 0.589
[3, 9000] loss: 0.642
[3, 10000] loss: 0.566
[3, 11000] loss: 0.562
[3, 12000] loss: 0.576
[4, 1000] loss: 0.444
[4, 2000] loss: 0.444
[4, 3000] loss: 0.439
[4, 4000] loss: 0.461
[4, 5000] loss: 0.449
[4, 6000] loss: 0.462
[4, 7000] loss: 0.477
[4, 8000] loss: 0.473
[4, 9000] loss: 0.460
[4, 10000] loss: 0.471
[4, 11000] loss: 0.454
[4, 12000] loss: 0.475
[5, 1000] loss: 0.312
[5, 2000] loss: 0.337
[5, 3000] loss: 0.322
[5, 4000] loss: 0.351
[5, 5000] loss: 0.362
[5, 6000] loss: 0.326
[5, 7000] loss: 0.339
[5, 8000] loss: 0.353
[5, 9000] loss: 0.330
[5, 10000] loss: 0.361
[5, 11000] loss: 0.363
[5, 12000] loss: 0.382
[6, 1000] loss: 0.226
[6, 2000] loss: 0.230
[6, 3000] loss: 0.230
[6, 4000] loss: 0.247
[6, 5000] loss: 0.256
[6, 6000] loss: 0.258
[6, 7000] loss: 0.265
[6, 8000] loss: 0.284
[6, 9000] loss: 0.268
[6, 10000] loss: 0.275
[6, 11000] loss: 0.273
[6, 12000] loss: 0.259
[7, 1000] loss: 0.157
[7, 2000] loss: 0.150
[7, 3000] loss: 0.161
[7, 4000] loss: 0.164
[7, 5000] loss: 0.160
[7, 6000] loss: 0.173
[7, 7000] loss: 0.187
[7, 8000] loss: 0.194
[7, 9000] loss: 0.195
[7, 10000] loss: 0.190
[7, 11000] loss: 0.195
[7, 12000] loss: 0.210
[8, 1000] loss: 0.109
[8, 2000] loss: 0.097
[8, 3000] loss: 0.099

```
[8, 4000] loss: 0.111
[8, 5000] loss: 0.112
[8, 6000] loss: 0.122
[8, 7000] loss: 0.132
[8, 8000] loss: 0.129
[8, 9000] loss: 0.121
[8, 10000] loss: 0.131
[8, 11000] loss: 0.134
[8, 12000] loss: 0.146
[9, 1000] loss: 0.071
[9, 2000] loss: 0.072
[9, 3000] loss: 0.064
[9, 4000] loss: 0.079
[9, 5000] loss: 0.081
[9, 6000] loss: 0.102
[9, 7000] loss: 0.097
[9, 8000] loss: 0.090
[9, 9000] loss: 0.079
[9, 10000] loss: 0.105
[9, 11000] loss: 0.081
[9, 12000] loss: 0.089
[10, 1000] loss: 0.057
[10, 2000] loss: 0.060
[10, 3000] loss: 0.051
[10, 4000] loss: 0.049
[10, 5000] loss: 0.063
[10, 6000] loss: 0.055
[10, 7000] loss: 0.056
[10, 8000] loss: 0.072
[10, 9000] loss: 0.070
[10, 10000] loss: 0.070
[10, 11000] loss: 0.058
[10, 12000] loss: 0.055
[11, 1000] loss: 0.047
[11, 2000] loss: 0.032
[11, 3000] loss: 0.035
[11, 4000] loss: 0.037
[11, 5000] loss: 0.043
[11, 6000] loss: 0.049
[11, 7000] loss: 0.056
[11, 8000] loss: 0.055
[11, 9000] loss: 0.052
[11, 10000] loss: 0.060
[11, 11000] loss: 0.059
[11, 12000] loss: 0.053
[12, 1000] loss: 0.038
[12, 2000] loss: 0.035
[12, 3000] loss: 0.032
[12, 4000] loss: 0.039
[12, 5000] loss: 0.034
[12, 6000] loss: 0.030
[12, 7000] loss: 0.034
[12, 8000] loss: 0.037
[12, 9000] loss: 0.038
[12, 10000] loss: 0.049
[12, 11000] loss: 0.045
[12, 12000] loss: 0.043
```


[13, 1000] loss: 0.023
[13, 2000] loss: 0.019
[13, 3000] loss: 0.020
[13, 4000] loss: 0.026
[13, 5000] loss: 0.026
[13, 6000] loss: 0.032
[13, 7000] loss: 0.025
[13, 8000] loss: 0.018
[13, 9000] loss: 0.022
[13, 10000] loss: 0.023
[13, 11000] loss: 0.028
[13, 12000] loss: 0.026
[14, 1000] loss: 0.016
[14, 2000] loss: 0.015
[14, 3000] loss: 0.017
[14, 4000] loss: 0.014
[14, 5000] loss: 0.019
[14, 6000] loss: 0.018
[14, 7000] loss: 0.013
[14, 8000] loss: 0.013
[14, 9000] loss: 0.018
[14, 10000] loss: 0.018
[14, 11000] loss: 0.024
[14, 12000] loss: 0.023
[15, 1000] loss: 0.016
[15, 2000] loss: 0.013
[15, 3000] loss: 0.011
[15, 4000] loss: 0.011
[15, 5000] loss: 0.011
[15, 6000] loss: 0.015
[15, 7000] loss: 0.010
[15, 8000] loss: 0.010
[15, 9000] loss: 0.013
[15, 10000] loss: 0.013
[15, 11000] loss: 0.011
[15, 12000] loss: 0.013
[16, 1000] loss: 0.012
[16, 2000] loss: 0.011
[16, 3000] loss: 0.010
[16, 4000] loss: 0.013
[16, 5000] loss: 0.007
[16, 6000] loss: 0.010
[16, 7000] loss: 0.007
[16, 8000] loss: 0.013
[16, 9000] loss: 0.013
[16, 10000] loss: 0.015
[16, 11000] loss: 0.020
[16, 12000] loss: 0.013
[17, 1000] loss: 0.005
[17, 2000] loss: 0.004
[17, 3000] loss: 0.008
[17, 4000] loss: 0.006
[17, 5000] loss: 0.009
[17, 6000] loss: 0.009
[17, 7000] loss: 0.009
[17, 8000] loss: 0.005
[17, 9000] loss: 0.004

[17, 10000] loss: 0.005
[17, 11000] loss: 0.009
[17, 12000] loss: 0.006
[18, 1000] loss: 0.006
[18, 2000] loss: 0.004
[18, 3000] loss: 0.005
[18, 4000] loss: 0.006
[18, 5000] loss: 0.006
[18, 6000] loss: 0.007
[18, 7000] loss: 0.007
[18, 8000] loss: 0.005
[18, 9000] loss: 0.007
[18, 10000] loss: 0.007
[18, 11000] loss: 0.008
[18, 12000] loss: 0.005
[19, 1000] loss: 0.005
[19, 2000] loss: 0.004
[19, 3000] loss: 0.005
[19, 4000] loss: 0.006
[19, 5000] loss: 0.004
[19, 6000] loss: 0.006
[19, 7000] loss: 0.004
[19, 8000] loss: 0.002
[19, 9000] loss: 0.003
[19, 10000] loss: 0.002
[19, 11000] loss: 0.005
[19, 12000] loss: 0.004
[20, 1000] loss: 0.003
[20, 2000] loss: 0.004
[20, 3000] loss: 0.003
[20, 4000] loss: 0.003
[20, 5000] loss: 0.003
[20, 6000] loss: 0.007
[20, 7000] loss: 0.005
[20, 8000] loss: 0.004
[20, 9000] loss: 0.002
[20, 10000] loss: 0.004
[20, 11000] loss: 0.003
[20, 12000] loss: 0.005
[21, 1000] loss: 0.003
[21, 2000] loss: 0.003
[21, 3000] loss: 0.002
[21, 4000] loss: 0.002
[21, 5000] loss: 0.002
[21, 6000] loss: 0.002
[21, 7000] loss: 0.001
[21, 8000] loss: 0.001
[21, 9000] loss: 0.002
[21, 10000] loss: 0.002
[21, 11000] loss: 0.002
[21, 12000] loss: 0.002
[22, 1000] loss: 0.002
[22, 2000] loss: 0.002
[22, 3000] loss: 0.001
[22, 4000] loss: 0.002
[22, 5000] loss: 0.004
[22, 6000] loss: 0.006

[22, 7000] loss: 0.003
[22, 8000] loss: 0.002
[22, 9000] loss: 0.004
[22, 10000] loss: 0.005
[22, 11000] loss: 0.003
[22, 12000] loss: 0.004
[23, 1000] loss: 0.003
[23, 2000] loss: 0.002
[23, 3000] loss: 0.003
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Finished Training

Save and load model

```
In [ ]: # save the trained model
torch.save(net, 'resnet.pt')
```

```
In [ ]: # load the saved model
net = torch.load('resnet.pt')
```

Evaluate the model

```
In [14]: correct = 0
total = 0
with torch.no_grad():
    for data in eval_data_loader:
        images, labels = data
        images = images.to(device)
        labels = 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 %d test images: %d %%' % (len(eval_data_loader),
    Accuracy of the network on the 10000 test images: 85 %
```

```
In [15]: classes = ['plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship', 'truck']
```

```
In [16]: class_correct = [0] * 10
class_total = [0] * 10
with torch.no_grad():
    for data in eval_data_loader:
        images, labels = data
        images = images.to(device)
        labels = 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(10):
    print('Accuracy of %5s : %2d %%' % (classes[i], 100 * class_correct[i] / class_total[i]))
```

```
Accuracy of plane : 89 %
Accuracy of car : 93 %
Accuracy of bird : 78 %
Accuracy of cat : 71 %
Accuracy of deer : 81 %
Accuracy of dog : 76 %
Accuracy of frog : 88 %
Accuracy of horse : 88 %
Accuracy of ship : 91 %
Accuracy of truck : 91 %
```

```
In [17]: TP = 0
FP = 0
TN = 0
FN = 0

with torch.no_grad():
    for data in eval_data_loader:
        images, labels = data
        images = images.to(device)
        labels = labels.to(device)
        outputs = net(images)
        _, predicted = torch.max(outputs.data, 1)
        for i in range(len(labels)):
            if predicted[i] == labels[i]:
                if predicted[i] == 1:
                    TP += 1
                else:
                    TN += 1
            else:
                if predicted[i] == 1:
                    FP += 1
                else:
                    FN += 1

accuracy = 100 * (TP + TN) / (TP + TN + FP + FN)
precision = 100 * TP / (TP + FP)
recall = 100 * TP / (TP + FN)
f1_score = 2 * precision * recall / (precision + recall)

print('Accuracy: %.2f %%' % (accuracy))
print('Precision: %.2f %%' % (precision))
print('Recall: %.2f %%' % (recall))
print('F1 Score: %.2f %%' % (f1_score))

Accuracy: 85.11 %
Precision: 93.62 %
Recall: 39.72 %
F1 Score: 55.78 %
```