

```

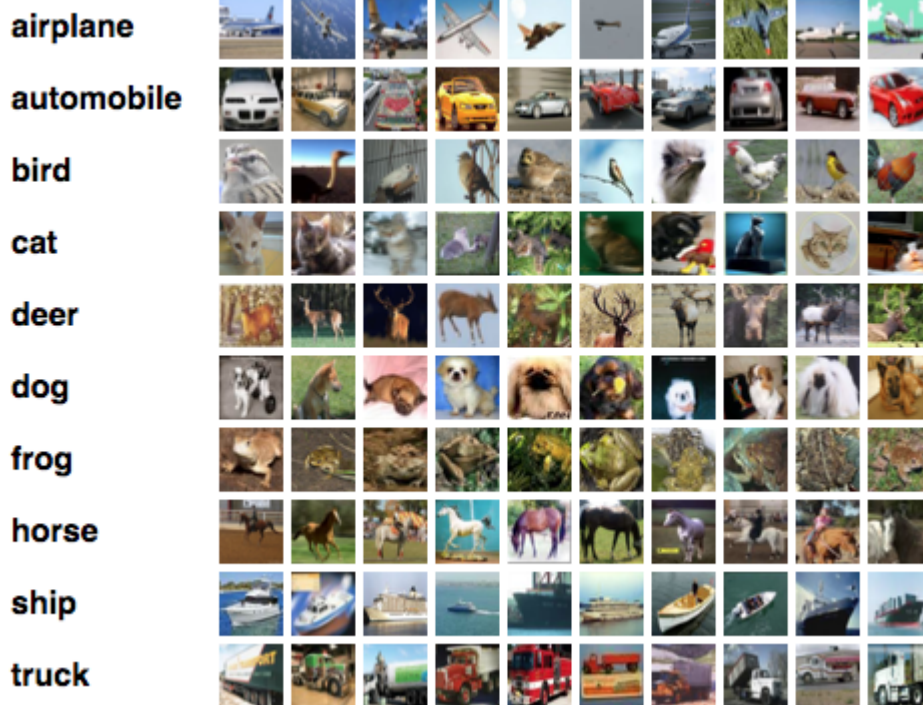
1 import torch
2 import torch.nn as nn
3 import torchvision
4 import torchvision.transforms as transforms
5 import torchvision.datasets as dataset
6 from torchvision.datasets import FashionMNIST
7 import matplotlib.pyplot as plt
8 import numpy as np
9
10
11
12 # Device configuration
13 device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
14 device

device(type='cuda')

```

## ▼ CRFAR10 Dataset

Here are the classes in the dataset, as well as 10 random images from each:



```

1 batch_size = 128
2
3 transform = transforms.Compose([
4     transforms.ToTensor()
5 ])
6
7
8 # CRFAR10 dataset

```

```

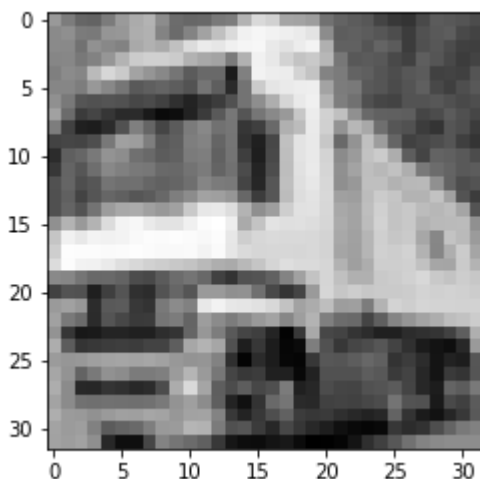
0 # CIFAR-10 dataset
9 train_dataset = dataset.CIFAR10(root='.././data/', train=True, transform=transform, downl
10 test_dataset = dataset.CIFAR10(root='.././data/', train=False, transform=transform, downl
11
12
13 print('Train dataset size = ',len(train_dataset))
14 print('Test dataset size = ',len(test_dataset))
15 img, label = train_dataset[1]
16 print('Image size = ',img.shape, '(', label, ')')
17 plt.imshow(img[0,:,:], cmap='gray')
18
19
20
21 # Data loader
22 train_loader = torch.utils.data.DataLoader(dataset=train_dataset,
23                                             batch_size=batch_size,
24                                             shuffle=True)
25
26 test_loader = torch.utils.data.DataLoader(dataset=test_dataset,
27                                           batch_size=batch_size,
28                                           shuffle=False)
29
30
31 del train_dataset
32 del test_dataset

```

```

Files already downloaded and verified
Files already downloaded and verified
Train dataset size = 50000
Test dataset size = 10000
Image size = torch.Size([3, 32, 32]) ( 9 )

```



## ▼ Neural Network Model

Layer	Operations	Input Size	Output Size
Layer 1	conv3x3 + BatchNorm + Relu	3 x 32 x 32	128 x 32 x 32

Layer	Operations	Input Size	Output Size
Layer 2	conv3x3 + BatchNorm + Relu + maxpool	128 x 32 x 32	256 x 16 x 16
Layer 3	conv3x3 + BatchNorm + Relu	256 x 16 x 16	128 x 16 x 16
Layer 4	conv3x3 + BatchNorm + Relu + maxpool	128 x 16 x 16	64 x 8 x 8
Layer 5	Fully connected	1 x 4096	1 x 512
Layer 6	Fully connected	1 x 512	1 x 10

```

1 class Model(nn.Module):
2     def __init__(self, num_classes):
3         super(Model, self).__init__()
4
5
6
7         self.conv1 = nn.Conv2d(3, 128, kernel_size= 5, padding= 2, stride= 1)
8         self.conv2 = nn.Conv2d(128, 256, kernel_size= 5, padding= 2, stride= 1)
9         self.conv3 = nn.Conv2d(256, 128, kernel_size= 5, padding= 2, stride= 1)
10        self.conv4 = nn.Conv2d(128, 64, kernel_size= 5, padding= 2, stride= 1)
11        self.n= np.int(3*32*32 * 64/3 * 1/4 * 1/4)
12
13        self.linear1  = nn.Linear(self.n , hidden_size)
14        self.linear2  = nn.Linear (hidden_size, num_classes)
15
16        self.bn1 = nn.BatchNorm2d(128)
17        self.bn2 = nn.BatchNorm2d(256)
18        self.bn3 = nn.BatchNorm2d(64)
19        self.bn4 = nn.BatchNorm2d(128)
20
21        self.relu=nn.ReLU()
22        self.max_pool = nn.MaxPool2d(2, stride=2)
23
24
25        self.init()
26
27
28    def init(self):
29        nn.init.xavier_uniform_(self.conv1.weight)
30        nn.init.xavier_uniform_(self.conv2.weight)
31        nn.init.xavier_uniform_(self.conv3.weight)
32        nn.init.xavier_uniform_(self.conv4.weight)
33        nn.init.xavier_uniform_(self.linear1.weight)
34        nn.init.xavier_uniform_(self.linear2.weight)
35
36
37    def forward(self, x):
38
39        out = self.relu(self.bn1(self.conv1(x)))
40        out = self.max_pool(self.relu(self.bn2(self.conv2(out))))
41
42        out = self.relu(self.bn4(self.conv3(out)))
43

```

```
44         out = self.max_pool(self.relu(self.bn3(self.conv4(out))))
45
46
47         out = out.view(out.size(0), -1)
48
49         out = nn.functional.dropout(out, 0.5)
50
51         out = self.linear1(out)
52
53         out = self.linear2(out)
54
55         return out
56
57
```

```
1 num_classes = 10
2 learning_rate = 0.001
3 hidden_size = 512
4
5
6 model1 = Model(num_classes).to(device)
7 model2 = Model(num_classes).to(device)
8
9 # Loss and optimizer
10 criterion = nn.CrossEntropyLoss()
11 optimizer1 = torch.optim.Adam(model1.parameters(), lr=learning_rate)
12 optimizer2 = torch.optim.SGD(model2.parameters(), lr=learning_rate, momentum=0.8, weight_d
13
```

```
1 # Train the model
2 def Train(model, optimizer, num_epochs):
3     total_step = len(train_loader)
4     loss_val = []
5     count = []
6
7     model.train()
8     for epoch in range(num_epochs):
9         for i, (images, labels) in enumerate(train_loader):
10             images = images.to(device)
11             labels = labels.to(device)
12
13             optimizer.zero_grad()
14             outputs = model(images)
15             loss = criterion(outputs, labels)
16             loss.backward()
17             optimizer.step()
18
19
20
21         if (i+1) % 100 == 0:
```

```

22         count.append(i+1 + epoch*total_step)
23         loss_val.append(loss.item())
24         print('Epoch [%d/%d], Step [%d/%d], Loss: %.4f'%(epoch+1, num_epochs, i+1,
25
26         return count, loss_val

```

```

1 # Test the model
2
3
4 def Test(model):
5
6     model.eval()
7
8     correct = 0
9     total = 0
10
11     actual_labels = []
12     predicted_labels = []
13
14     for images, labels in test_loader:
15
16         images = images.to(device)
17         labels = labels.to(device)
18
19         outputs = model(images)
20         _, predicted = torch.max(outputs.data, 1)
21         total += labels.size(0)
22         correct += (predicted == labels).sum()
23
24         labelsCPU = labels.data.cpu().numpy()
25         predictedCPU = predicted.data.cpu().numpy()
26         predicted_labels.append(predictedCPU)
27         actual_labels.append(labelsCPU)
28
29
30
31     print('Accuracy of the model = %f'%(100 * correct / total))
32

```

```

1 num_epochs = 20
2 count, loss1 = Train(model1, optimizer1, num_epochs)
3
4 count, loss2 = Train(model2, optimizer2, num_epochs)

```

epoch [1/20], step [200/391], Loss: 1.7652  
 Epoch [1/20], Step [300/391], Loss: 1.6426  
 Epoch [2/20], Step [100/391], Loss: 1.4393  
  
 Epoch [2/20], Step [200/391], Loss: 1.6557  
 Epoch [2/20], Step [300/391], Loss: 1.3479  
 Epoch [3/20], Step [100/391], Loss: 1.3322  
 Epoch [3/20], Step [200/391], Loss: 1.3158  
 Epoch [3/20], Step [300/391], Loss: 1.2677

```

Epoch [3/20], Step [300/391], Loss: 1.0677
Epoch [4/20], Step [100/391], Loss: 1.2057
Epoch [4/20], Step [200/391], Loss: 1.2035
Epoch [4/20], Step [300/391], Loss: 1.0225
Epoch [5/20], Step [100/391], Loss: 1.1315
Epoch [5/20], Step [200/391], Loss: 0.8841
Epoch [5/20], Step [300/391], Loss: 1.0673
Epoch [6/20], Step [100/391], Loss: 0.7674
Epoch [6/20], Step [200/391], Loss: 0.9342
Epoch [6/20], Step [300/391], Loss: 0.7556
Epoch [7/20], Step [100/391], Loss: 0.9919
Epoch [7/20], Step [200/391], Loss: 0.7885
Epoch [7/20], Step [300/391], Loss: 0.8058
Epoch [8/20], Step [100/391], Loss: 0.9330
Epoch [8/20], Step [200/391], Loss: 0.7137
Epoch [8/20], Step [300/391], Loss: 0.8047
Epoch [9/20], Step [100/391], Loss: 0.7390
Epoch [9/20], Step [200/391], Loss: 0.6854
Epoch [9/20], Step [300/391], Loss: 0.7398
Epoch [10/20], Step [100/391], Loss: 0.5653
Epoch [10/20], Step [200/391], Loss: 0.6788
Epoch [10/20], Step [300/391], Loss: 0.8845
Epoch [11/20], Step [100/391], Loss: 0.7393
Epoch [11/20], Step [200/391], Loss: 0.7727
Epoch [11/20], Step [300/391], Loss: 0.8616
Epoch [12/20], Step [100/391], Loss: 0.6837
Epoch [12/20], Step [200/391], Loss: 0.6214
Epoch [12/20], Step [300/391], Loss: 0.7636
Epoch [13/20], Step [100/391], Loss: 0.7667
Epoch [13/20], Step [200/391], Loss: 0.8357
Epoch [13/20], Step [300/391], Loss: 0.5339
Epoch [14/20], Step [100/391], Loss: 0.5962
Epoch [14/20], Step [200/391], Loss: 0.6393
Epoch [14/20], Step [300/391], Loss: 0.5944
Epoch [15/20], Step [100/391], Loss: 0.5152
Epoch [15/20], Step [200/391], Loss: 0.4546
Epoch [15/20], Step [300/391], Loss: 0.4263
Epoch [16/20], Step [100/391], Loss: 0.5127
Epoch [16/20], Step [200/391], Loss: 0.5115
Epoch [16/20], Step [300/391], Loss: 0.5177
Epoch [17/20], Step [100/391], Loss: 0.5281
Epoch [17/20], Step [200/391], Loss: 0.5542
Epoch [17/20], Step [300/391], Loss: 0.6127
Epoch [18/20], Step [100/391], Loss: 0.6253
Epoch [18/20], Step [200/391], Loss: 0.5253
Epoch [18/20], Step [300/391], Loss: 0.6404
Epoch [19/20], Step [100/391], Loss: 0.4736
Epoch [19/20], Step [200/391], Loss: 0.4581
Epoch [19/20], Step [300/391], Loss: 0.6244
Epoch [20/20], Step [100/391], Loss: 0.4918
Epoch [20/20], Step [200/391], Loss: 0.7330
Epoch [20/20], Step [300/391], Loss: 0.6470

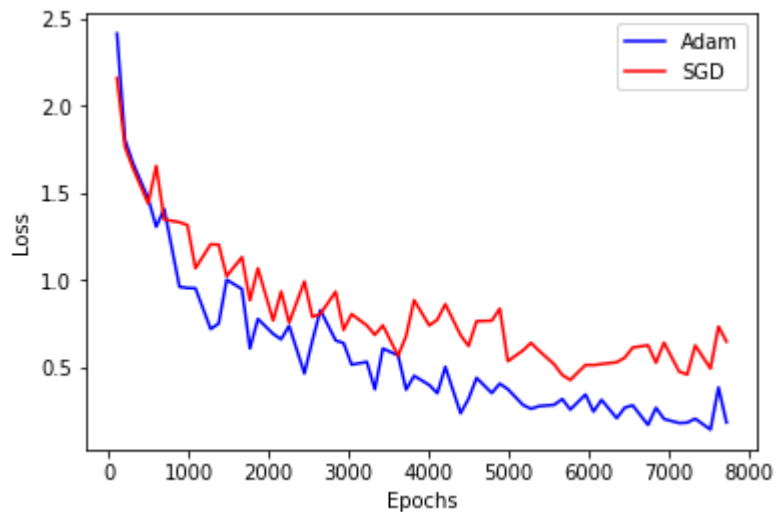
```

```

1 import matplotlib.pyplot as plt
2
3 fig = plt.figure()
4 plt.plot(count, loss1, color='blue', label='Adam')

```

```
5 plt.plot(count, loss2, color='red', label='SGD')
6 plt.xlabel('Epochs')
7 plt.ylabel('Loss')
8 plt.legend()
9 plt.show()
10
11 print('Adam Optimizer')
12 Test(model1)
13
14 print('SGD Optimizer')
15 Test(model2)
```



Adam Optimizer  
Accuracy of the model = 80.459999  
SGD Optimizer  
Accuracy of the model = 73.739998

