Mutliple Classification Cifar10

October 16, 2025

[1]:
```
from torchvision import datasets
from torchvision.transforms import ToTensor,transforms
import matplotlib.pyplot as plt
import matplotlib
from torch.utils.data import DataLoader
import torch
import random
from torch import nn
```

[2]:
```
train_data = datasets.CIFAR10(
    root = "image",
    train = True,
    download = True,
    transform = transforms.Compose([
        transforms.ToTensor()
    ])
)

test_data = datasets.CIFAR10(
    root = "image",
    train = False,
    download = True,
    transform = transforms.Compose([
        transforms.ToTensor()
    ])
)
```

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

[3]:
```
train_data,test_data
```

[3]:
```
(Dataset CIFAR10
     Number of datapoints: 50000
     Root location: image
     Split: Train
     StandardTransform
 Transform: Compose(
```

```
                ToTensor()
            ),
 Dataset CIFAR10
     Number of datapoints: 10000
     Root location: image
     Split: Test
     StandardTransform
 Transform: Compose(
                ToTensor()
            ))
```

[4]:
```
train_data[0]
```

[4]:
```
(tensor([[[0.2314, 0.1686, 0.1961,  …, 0.6196, 0.5961, 0.5804],
          [0.0627, 0.0000, 0.0706,  …, 0.4824, 0.4667, 0.4784],
          [0.0980, 0.0627, 0.1922,  …, 0.4627, 0.4706, 0.4275],
          …,
          [0.8157, 0.7882, 0.7765,  …, 0.6275, 0.2196, 0.2078],
          [0.7059, 0.6784, 0.7294,  …, 0.7216, 0.3804, 0.3255],
          [0.6941, 0.6588, 0.7020,  …, 0.8471, 0.5922, 0.4824]],

         [[0.2431, 0.1804, 0.1882,  …, 0.5176, 0.4902, 0.4863],
          [0.0784, 0.0000, 0.0314,  …, 0.3451, 0.3255, 0.3412],
          [0.0941, 0.0275, 0.1059,  …, 0.3294, 0.3294, 0.2863],
          …,
          [0.6667, 0.6000, 0.6314,  …, 0.5216, 0.1216, 0.1333],
          [0.5451, 0.4824, 0.5647,  …, 0.5804, 0.2431, 0.2078],
          [0.5647, 0.5059, 0.5569,  …, 0.7216, 0.4627, 0.3608]],

         [[0.2471, 0.1765, 0.1686,  …, 0.4235, 0.4000, 0.4039],
          [0.0784, 0.0000, 0.0000,  …, 0.2157, 0.1961, 0.2235],
          [0.0824, 0.0000, 0.0314,  …, 0.1961, 0.1961, 0.1647],
          …,
          [0.3765, 0.1333, 0.1020,  …, 0.2745, 0.0275, 0.0784],
          [0.3765, 0.1647, 0.1176,  …, 0.3686, 0.1333, 0.1333],
          [0.4549, 0.3686, 0.3412,  …, 0.5490, 0.3294, 0.2824]]]),
 6)
```

[5]:
```
img, label = train_data[0]
train_data.classes
```

[5]:
```
['airplane',
 'automobile',
 'bird',
 'cat',
 'deer',
 'dog',
```

```
 'frog',
 'horse',
 'ship',
 'truck']
```

[6]:
```python
class_names = train_data.classes
class_names[label]
```

[6]: 'frog'

[7]:
```python
img.shape
```

[7]: torch.Size([3, 32, 32])

[8]:
```python
#When working with large datasets (like CIFAR-10), always wrap them in a␣
↪DataLoader

BATCH_SIZE = 32

train_dataloader = DataLoader(train_data,batch_size = BATCH_SIZE,shuffle = True)
test_dataloader = DataLoader(test_data,batch_size = BATCH_SIZE,shuffle = False)
```

[9]:
```python
x_first_batch, y_first_batch = next(iter(train_dataloader))
x_first_batch.shape,y_first_batch.shape
```

[9]: (torch.Size([32, 3, 32, 32]), torch.Size([32]))

[10]:
```python
x_first_batch[0].shape
```

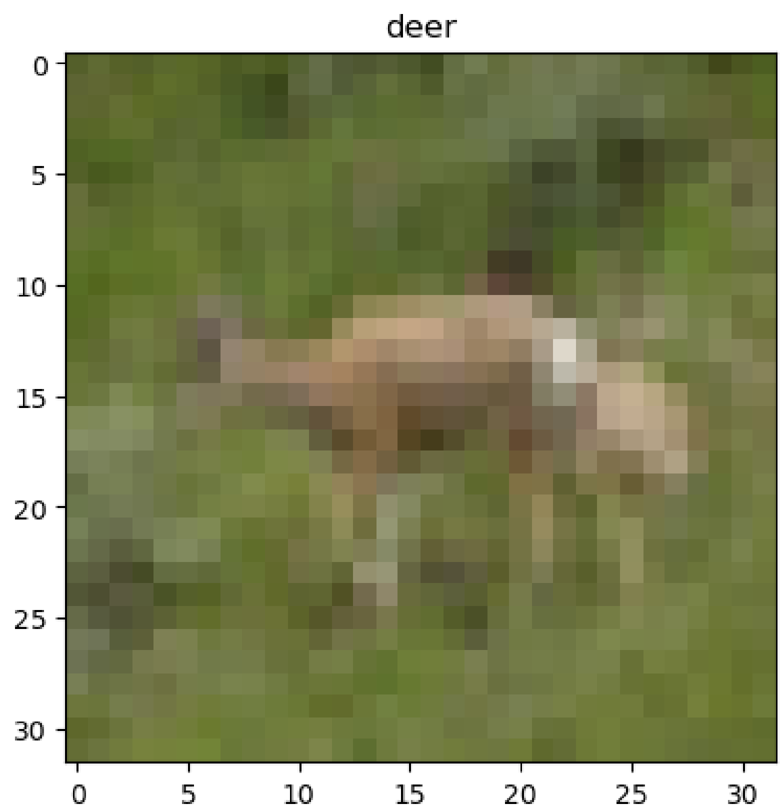
[10]: torch.Size([3, 32, 32])

[11]:
```python
img = x_first_batch[0]
img = img.permute(1,2,0)
img.shape
```

[11]: torch.Size([32, 32, 3])

[12]:
```python
plt.imshow(img) #reshape to torch.Size([32, 32, 3])
plt.title(class_names[y_first_batch[0]])
```

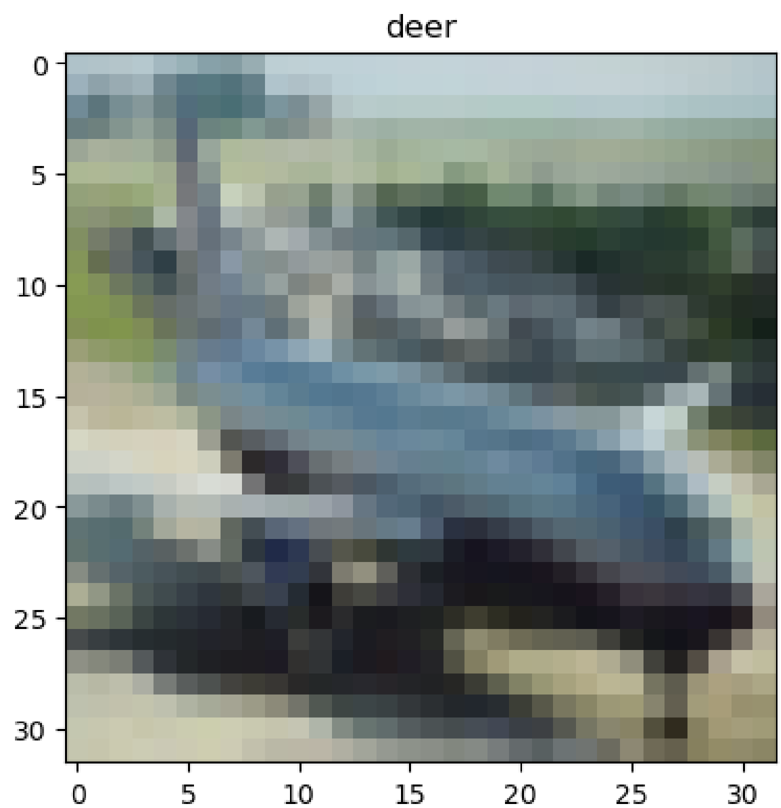
[12]: Text(0.5, 1.0, 'deer')



0.1 Random Pick

[13]:
```
random_img = random.randint(0, len(x_first_batch))
rand_img, rand_label = x_first_batch[random_img], y_first_batch[random_img]
# rand_img = rand_img / 2 + 0.5

plt.imshow(rand_img.permute(1,2,0))
plt.title(class_names[y_first_batch[rand_label]])
```

[13]:
```
Text(0.5, 1.0, 'deer')
```



0.2 Flatten

[14]:
```
#reference: https://docs.pytorch.org/docs/stable/generated/torch.nn.Flatten.
↪html#torch.nn.Flatten
```

[15]:
```
x_first_batch.shape
```

[15]: torch.Size([32, 3, 32, 32])

[16]:
```
x_first_batch[0].shape
```

[16]: torch.Size([3, 32, 32])

[17]:
```
f = nn.Flatten(start_dim=0, end_dim=-1) # Default is nn.Flatten(start_dim=1,␣
↪end_dim=-1)
f(x_first_batch[0]).shape
```

[17]: torch.Size([3072])

[18]:
```
# link to check kernel size, stride, padding
# https://poloclub.github.io/cnn-explainer/
```

0.3 Model

[19]:
```
# reference: https://docs.pytorch.org/docs/stable/generated/torch.nn.Conv2d.
↪html#torch.nn.Conv2d
conv_layer = nn.Conv2d(in_channels = 3 , out_channels = 16, kernel_size = (3,3)␣
↪, stride=1, padding=1)
conv_layer(x_first_batch[0]).shape
```

[19]:
```
torch.Size([16, 32, 32])
```

[20]:
```
# reference: https://docs.pytorch.org/docs/stable/generated/torch.nn.MaxPool2d.
↪html#torch.nn.MaxPool2d
maxpool = nn.MaxPool2d(kernel_size = (2,2) , stride=2, padding=0)
conv_output = conv_layer(x_first_batch[0])
maxpool(conv_output).shape
```

[20]:
```
torch.Size([16, 16, 16])
```

[21]:
```
# class ImageClassificationModel(nn.Module):
#     def __init__(self,input_shape,output_shape):
#         super().__init__()
#         self.layer_stack = nn.Sequential(
#             nn.Flatten(start_dim = 1, end_dim = -1),  # x_first_batch.shape =␣
↪torch.Size([32, 3, 32, 32]) should pick(3,32,32). Thus, change start_dim to 1
#             nn.Linear(in_features = input_shape, out_features = 16),
            # nn.ReLU(),
            # nn.Linear(in_features = 16, out_features = 16),
            # nn.ReLU(),
            # nn.Linear(in_features = 16, out_features = output_shape)
#         )

#     def forward(self, x):
#         return self.layer_stack(x)
```

[22]:
```
# Simplified VGG
class ImageClassificationModel(nn.Module):
    def __init__(self,input_shape,output_shape):
        super().__init__()
        self.conv_block_1 = nn.Sequential(
            nn.Conv2d(in_channels = input_shape,
                      out_channels = 16,
                      kernel_size = (3,3),
                      stride=1,
                      padding=1),
            nn.ReLU(),
            nn.Conv2d(in_channels = 16,
                      out_channels = 16,
                      kernel_size = (3,3),
```

```
                    stride=1,
                    padding=1),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size = (2,2),
                    stride=2,
                    padding=0),
            nn.Dropout(0.25)

        )

        self.conv_block_2 = nn.Sequential(
            nn.Conv2d(in_channels = 16,
                    out_channels = 32,
                    kernel_size = (3,3),
                    stride=1,
                    padding=1),
            nn.ReLU(),
            nn.Conv2d(in_channels = 32,
                    out_channels = 32,
                    kernel_size = (3,3),
                    stride=1,
                    padding=1),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size = (2,2),
                    stride=2,
                    padding=0),
            nn.Dropout(0.25)
        )

        self.classifier = nn.Sequential(
            nn.Flatten(start_dim=1,end_dim=-1),
            nn.Dropout(0.25),
            nn.Linear(in_features = 32*8*8, out_features = output_shape)
        )

    # def forward(self, x):
    #     return self.conv_block_2(self.conv_block_1(x))

    def forward(self, x):
        x = self.conv_block_1(x)
        x = self.conv_block_2(x)
        x = self.classifier(x)
        return x
```

[23]:
```
torch.manual_seed(87)
model = ImageClassificationModel(3,10)
# model(x_first_batch[0]).shape
```

[24]:
```
# softmax
# reference: https://docs.pytorch.org/docs/stable/generated/torch.nn.Softmax.
↪html#torch.nn.Softmax
# softmax has included in loss function CrossEntropyLoss. So, no need to include
```

[25]:
```
device = "cuda" if torch.cuda.is_available() else "cpu"
model.to(device)
```

[25]:
```
ImageClassificationModel(
  (conv_block_1): Sequential(
    (0): Conv2d(3, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU()
    (2): Conv2d(16, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (3): ReLU()
    (4): MaxPool2d(kernel_size=(2, 2), stride=2, padding=0, dilation=1,
ceil_mode=False)
    (5): Dropout(p=0.25, inplace=False)
  )
  (conv_block_2): Sequential(
    (0): Conv2d(16, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU()
    (2): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (3): ReLU()
    (4): MaxPool2d(kernel_size=(2, 2), stride=2, padding=0, dilation=1,
ceil_mode=False)
    (5): Dropout(p=0.25, inplace=False)
  )
  (classifier): Sequential(
    (0): Flatten(start_dim=1, end_dim=-1)
    (1): Dropout(p=0.25, inplace=False)
    (2): Linear(in_features=2048, out_features=10, bias=True)
  )
)
```

[26]:
```
from torch.optim.lr_scheduler import StepLR

cost_fn = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(params = model.parameters(), lr = 0.01, momentum=0.
↪9, weight_decay=1e-4)
scheduler = StepLR(optimizer, step_size=5, gamma=0.5)
```

[27]:
```
def accuracy_fn(y_pred, y_true):
    correct_num = (y_pred == y_true).sum()
    acc = correct_num / len(y_true) * 100
    return acc
```

[28]:
```
def train_step(dataloader, model, cost_fn, optimizer, accuracy_fn, device):
    train_cost = 0
    train_acc = 0
    for batch, (x, y) in enumerate(dataloader):

        x = x.to(device)
        y = y.to(device)

        model.train()
        y_pred =  model(x)
        cost = cost_fn(y_pred,y)
        train_acc += accuracy_fn(y_pred.argmax(dim=1), y)

        train_cost += cost

        optimizer.zero_grad()
        cost.backward()
        optimizer.step()

    train_cost /= len(train_dataloader)
    train_acc /= len(train_dataloader)

    return train_cost, train_acc

def test_step(dataloader, model, cost_fn, accuracy_fn, device):
    test_cost = 0
    test_acc = 0
    model.eval()
    with torch.inference_mode():
        for x, y in dataloader:
            x = x.to(device)
            y = y.to(device)
            test_pred =  model(x)

            test_cost += cost_fn(test_pred,y)
            test_acc += accuracy_fn(test_pred.argmax(dim=1), y)

        test_cost /= len(test_dataloader)
        test_acc /= len(test_dataloader)

        return test_cost, test_acc
```

[29]:
```
train_losses, test_losses = [], []
train_accuracies, test_accuracies = [], []

epochs = 10
for epoch in range(epochs):
```

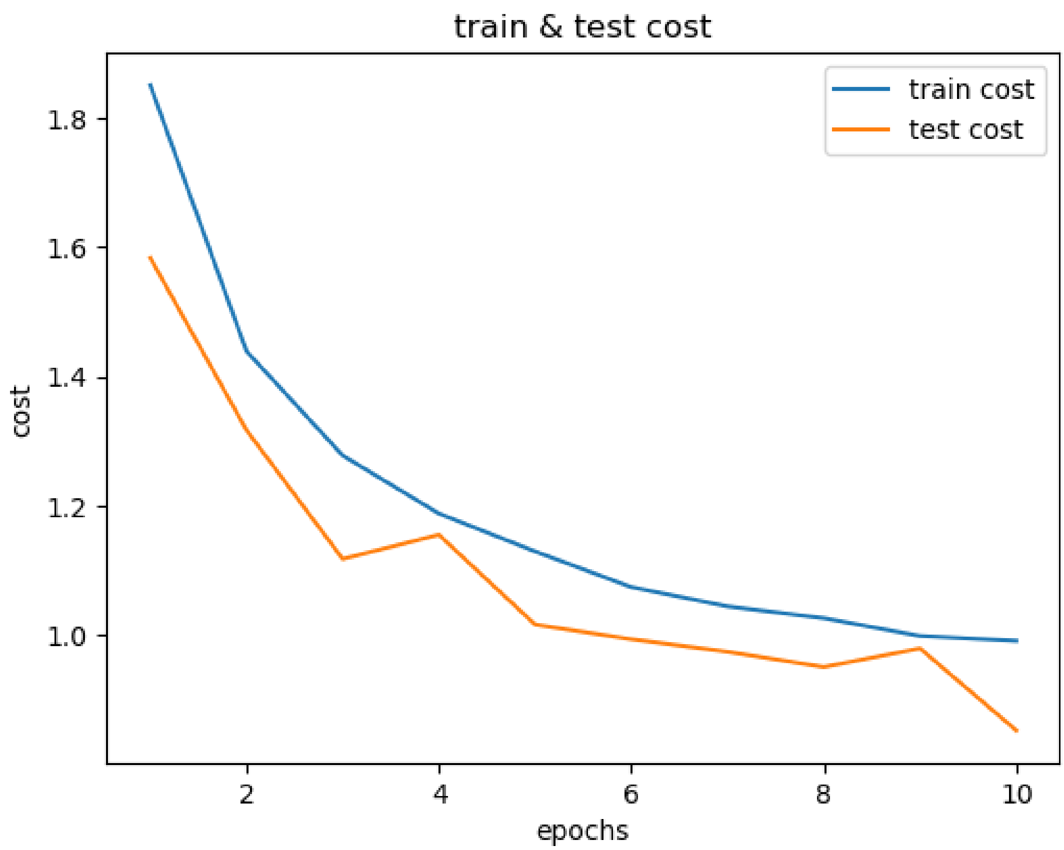
```
    print(f"Epoch: {epoch} \n -----")

    train_cost, train_acc = train_step(train_dataloader, model, cost_fn,␣
↪optimizer, accuracy_fn, device)

    test_cost, test_acc = test_step(test_dataloader, model, cost_fn,␣
↪accuracy_fn, device)

    train_losses.append(train_cost.item())
    test_losses.append(test_cost.item())
    train_accuracies.append(train_acc.item())
    test_accuracies.append(test_acc.item())

    print(f"\nTrain Cost: {train_cost:.4f}, {train_acc:.2f}")

    print(f"Test Cost: {test_cost:.4f}, {test_acc:.2f} \n")
```

```
Epoch: 0
 -----

Train Cost: 1.8507, 31.91
Test Cost: 1.5836, 42.61

Epoch: 1
 -----

Train Cost: 1.4394, 48.03
Test Cost: 1.3173, 53.21

Epoch: 2
 -----

Train Cost: 1.2780, 54.28
Test Cost: 1.1181, 59.72

Epoch: 3
 -----

Train Cost: 1.1882, 57.90
Test Cost: 1.1554, 59.40

Epoch: 4
 -----

Train Cost: 1.1297, 60.18
Test Cost: 1.0165, 64.41
```

```
Epoch: 5
 -----

Train Cost: 1.0745, 62.21
Test Cost: 0.9938, 64.70

Epoch: 6
 -----

Train Cost: 1.0447, 63.45
Test Cost: 0.9745, 65.37

Epoch: 7
 -----

Train Cost: 1.0264, 64.04
Test Cost: 0.9509, 66.41

Epoch: 8
 -----

Train Cost: 0.9989, 65.17
Test Cost: 0.9797, 65.54

Epoch: 9
 -----

Train Cost: 0.9913, 65.28
Test Cost: 0.8529, 70.18
```

[30]:

```
plt.plot(range(1,len(train_losses) + 1), train_losses, label = "train cost")
plt.plot(range(1,len(test_losses) + 1), test_losses, label = "test cost")
plt.title("train & test cost")
plt.xlabel("epochs")
plt.ylabel("cost")
plt.legend()
plt.show()
```



train & test cost
train cost
test cost
cost
epochs
1.8
1.6
1.4
1.2
1.0
2
4
6
8
10


```
[ ]:
```