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CIFAR-10 Classifier Using CNN in PyTorch

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Introduction

In this notebook we will use PyTorch to construct a convolutional neural network. We will then train the CNN on the CIFAR-10 data set to be able to classify images from the CIFAR-10 testing set into the ten categories present in the data set.

CIFAR-10

The CIFAR-10 data set is composed of 60,000 32x32 colour images, 6,000 images per class, so 10 categories in total. The training set is made up of 50,000 images, while the remaining 10,000 make up the testing set.

The categories are: airplane, automobile, bird, cat, deer, dog, frog, horse, ship and truck.

More information regarding the CIFAR-10 and CIFAR-100 data sets can be found here.

Importing Libraries

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```
import torch
import torchvision
import torchvision.transforms as transforms
```

Downloading, Loading and Normalising CIFAR-10

PyTorch provides data loaders for common data sets used in vision applications, such as MNIST, CIFAR-10 and ImageNet through the `torchvision` package. Other handy tools are the `torch.utils.data.DataLoader` that we will use to load the data set for training and testing and the `torchvision.transforms`, which we will use to compose a two-step process to prepare the data for use with the CNN.

```
# First step is to convert Python Image Library (PIL) format
# to PyTorch tensors.

# Second step is used to normalize the data by specifying a
# mean and standard deviation for each of the three channels.
# This will convert the data from [0,1] to [-1,1]

# Normalization of data should help speed up conversion and
# reduce the chance of vanishing gradients with certain
# activation functions.
transform = transforms.Compose(
    [transforms.ToTensor(),
     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])

trainset = torchvision.datasets.CIFAR10(root='/home/CIFAR-10 Classifier Using CNN in
                                        train=True,
                                        download=True,
                                        transform=transform)
trainloader = torch.utils.data.DataLoader(trainset,
                                          batch_size=4,
                                          shuffle=True)

testset = torchvision.datasets.CIFAR10(root='./data',
                                       train=False,
                                       download=True,
                                       transform=transform)
testloader = torch.utils.data.DataLoader(testset,
                                         batch_size=4,
                                         shuffle=False)

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

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

Display Random Batch of 4 Training Images

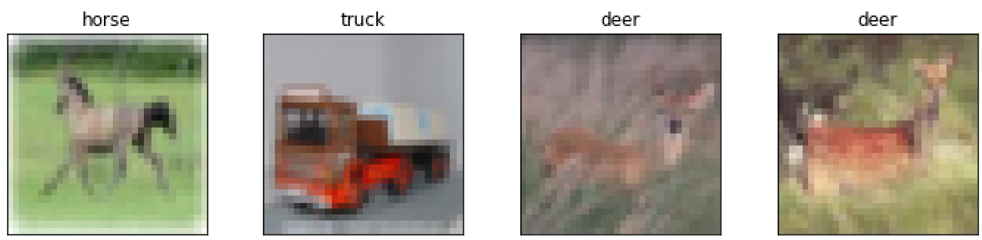
Using the `trainloader` we will now get a random batch of 4 training images and plot them to see what CIFAR-10 images look like.

Hide Code

```
    # first convert back to [0,1] range from [-1,1] range
    image = image / 2 + 0.5
    image = image.numpy()
    # convert from CHW to HWC
    # from 3x32x32 to 32x32x3
    return image.transpose(1,2,0)

dataiter = iter(trainloader)
images, labels = dataiter.next()

fig, axes = plt.subplots(1, len(images), figsize=(12,2.5))
for idx, image in enumerate(images):
    axes[idx].imshow(convert_to_imshow_format(image))
    axes[idx].set_title(classes[labels[idx]])
    axes[idx].set_xticks([])
    axes[idx].set_yticks([])
```



Defining the Convolutional Neural Network

The network has the following layout,

`Input > Conv (ReLU) > MaxPool > Conv (ReLU) > MaxPool > FC (ReLU) > FC (ReLU) > FC (SoftMax) > 10 outputs`

where:

`Conv` is a convolutional layer, `ReLU` is the activation function, `MaxPool` is a pooling layer, `FC` is a fully connected layer and `SoftMax` is the activation function of the output layer.

Layer Dimensions

Input Size

The images are 3x32x32, i.e., 3 channels (red, green, blue) each of size 32x32 pixels.

therefore has $((5 \times 5 \times 3) + 1) \times 6 = 456$ parameters.

First Max-Pooling Layer

The first down-sampling layer uses max pooling with a 2x2 kernel and stride set to 2. This effectively drops the size from 6x28x28 to 6x14x14.

Second Convolutional Layer

The second convolutional layers expects 6 input channels and will convolve 16 filters each of size 6x5x5. Since padding is set to 0 and stride is set to 1, the output size is 16x10x10, because $(14 - 5) + 1 = 10$. This layer therefore has $((5 \times 5 \times 6) + 1) \times 16 = 2416$ parameters.

Second Max-Pooling Layer

The second down-sampling layer uses max pooling with a 2x2 kernel and stride set to 2. This effectively drops the size from 16x10x10 to 16x5x5.

First Fully-Connected Layer

The output from the final max pooling layer needs to be flattened so that we can connect it to a fully connected layer. This is achieved using the `torch.Tensor.view` method. By specifying `-1` the method will automatically infer the number of rows required. This is done to handle the mini-batch size of data.

The fully-connected layer uses ReLU for activation and has 120 nodes, thus in total it needs $((16 \times 5 \times 5) + 1) \times 120 = 48120$ parameters.

Second Fully-Connected Layer

The output from the first fully-connected layer is connected to another fully connected layer with 84 nodes, using ReLU as an activation function. This layer thus needs $(120 + 1) \times 84 = 10164$ parameters.

Output Layer

The last fully-connected layer uses softmax and is made up of ten nodes, one for each category in CIFAR-10. This layer requires $(84 + 1) \times 10 = 850$ parameters.

Total Network Parameters

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

class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(3, 6, 5)
        self.pool = nn.MaxPool2d(2, 2)
        self.conv2 = nn.Conv2d(6, 16, 5)
        self.fc1 = nn.Linear(16 * 5 * 5, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)

    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = x.view(-1, 16 * 5 * 5)
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x

net = Net()
```

Defining the Loss Function and Optimizer

Since we are classifying images into more than two classes we will use cross-entropy as a loss function. To optimize the network we will employ stochastic gradient descent (SGD) with momentum to help get us over local minima and saddle points in the loss function space.

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```
import torch.optim as optim

criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(net.parameters(), lr=0.001, momentum=0.9)
```

Training the Network

We will now train the network using the `trainloader` data, by going over all the training data in batches of 4 images, and repeating the whole process 2 times, i.e., 2 epochs. Every 2000 batches we report on training progress by printing the current epoch and batch number along with the running loss value.

```
import os

model_directory_path = '/home/CIFAR-10 Classifier Using CNN in PyTorch/model/'
model_path = model_directory_path + 'cifar-10-cnn-model.pt'

if not os.path.exists(model_directory_path):
    os.makedirs(model_directory_path)

if os.path.isfile(model_path):
    # load trained model parameters from disk
    net.load_state_dict(torch.load(model_path))
    print('Loaded model parameters from disk.')
else:
    for epoch in range(2):  # loop over the dataset multiple times

        running_loss = 0.0
        for i, data in enumerate(trainloader, 0):
            # get the inputs
            inputs, labels = data

            # 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 % 2000 == 1999:    # print every 2000 mini-batches
                print('[%d, %5d] loss: %.3f' %
                      (epoch + 1, i + 1, running_loss / 2000))
                running_loss = 0.0
    print('Finished Training.')
    torch.save(net.state_dict(), model_path)
    print('Saved model parameters to disk.')
```

```
Loaded model parameters from disk.
```

Testing the Network

Now that the network is trained we can evaluate how it performs on the testing data set. Let us load four random images from the testing data set and their corresponding labels.

```
fig, axes = plt.subplots(1, len(images), figsize=(12,2.5))
for idx, image in enumerate(images):
    axes[idx].imshow(convert_to_imshow_format(image))
    axes[idx].set_title(classes[labels[idx]])
    axes[idx].set_xticks([])
    axes[idx].set_yticks([])
```

Next, we input the four images to the trained network to get class (label/category) predictions.

Hide Code

```
outputs = net(images)
```

The network outputs a 2D tensor (array) of size 4x10, a row for each image and a column for each category. The values are raw outputs from the linear transformation $y = xA^T + b$. The category predicted for each image (row) is thus the column index containing the maximum value in that row.

Hide Code

```
outputs
```

Out[10]:

```
tensor([[ 0.3214, -0.1016,  0.4087,  1.6078, -1.3790,  0.2655, -0.7055, -0.6274,
          0.4320, -0.0205],
        [ 5.4812,  7.9856, -1.7315, -1.3632, -5.0847, -3.8232, -5.6879, -4.3160,
          6.2993,  3.8083],
        [ 3.0471,  3.5417, -0.1734, -0.6367, -1.8952, -2.1822, -2.8114, -1.9013,
          2.7827,  1.6128],
        [ 3.8433,  2.4575,  0.5930, -0.3768, -2.1527, -2.2164, -2.9778, -2.9104,
          3.6113,  1.2065]], grad_fn=<ThAddmmBackward>)
```

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```
sm = nn.Softmax(dim=1)
sm_outputs = sm(outputs)
print(sm_outputs)
```

```
tensor([[9.9337e-02, 6.5070e-02, 1.0840e-01, 3.5955e-01, 1.8140e-02, 9.3933e-02,
         3.5575e-02, 3.8461e-02, 1.1096e-01, 7.0573e-02],
        [6.3723e-02, 7.7977e-01, 4.6974e-05, 6.7891e-05, 1.6428e-06, 5.8002e-06,
         8.9876e-07, 3.5438e-06, 1.4442e-01, 1.1962e-02],
        [2.6785e-01, 4.3926e-01, 1.0697e-02, 6.7305e-03, 1.9120e-03, 1.4349e-03,
         7.6483e-04, 1.9004e-03, 2.0563e-01, 6.3824e-02],
        [4.5973e-01, 1.1499e-01, 1.7821e-02, 6.7572e-03, 1.1441e-03, 1.0736e-03,
         5.0136e-04, 5.3631e-04, 3.6454e-01, 3.2912e-02]],
       grad_fn=<SoftmaxBackward>)
```

Predicted Category for Four Test Images

Hide Code

```
probs, index = torch.max(sm_outputs, dim=1)

for p, i in zip(probs, index):
    print('{0} - {1:.4f}'.format(classes[i], p))
```

```
cat - 0.3596
car - 0.7798
car - 0.4393
plane - 0.4597
```

The model got half of the four testing images correct. It correctly categorised the cat and plane images, but failed on the two ship images, instead categorising them as cars. Let us now evaluate the model on the whole testing set.

Predicting the Category for all Test Images

Hide Code

```
total_correct = 0
total_images = 0
confusion_matrix = np.zeros([10,10], int)
with torch.no_grad():
    for data in testloader:
```

```
        for i, l in enumerate(labels):
            confusion_matrix[l.item(), predicted[i].item()] += 1

model_accuracy = total_correct / total_images * 100
print('Model accuracy on {0} test images: {1:.2f}%'.format(total_images, model_accura
```

```
Model accuracy on 10000 test images: 52.20%
```

The model performed much better than random guessing, which would give us an accuracy of 10% since there are ten categories in CIFAR-10. Let us now use the confusion matrix to compute the accuracy of the model per category.

Hide Code

```
print('{0:10s} - {1}'.format('Category','Accuracy'))
for i, r in enumerate(confusion_matrix):
    print('{0:10s} - {1:.1f}'.format(classes[i], r[i]/np.sum(r)*100))
```

```
Category   - Accuracy
plane      - 53.5
car        - 82.7
bird       - 61.0
cat        - 25.4
deer       - 32.9
dog        - 40.2
frog       - 43.7
horse      - 63.7
ship       - 73.8
truck      - 45.1
```

Finally, let us visualise the confusion matrix to determine common misclassifications.

Hide Code

```
fig, ax = plt.subplots(1,1,figsize=(8,6))
ax.matshow(confusion_matrix, aspect='auto', vmin=0, vmax=1000, cmap=plt.get_cmap('Blu
plt.ylabel('Actual Category')
plt.yticks(range(10), classes)
plt.xlabel('Predicted Category')
plt.xticks(range(10), classes)
plt.show()
```

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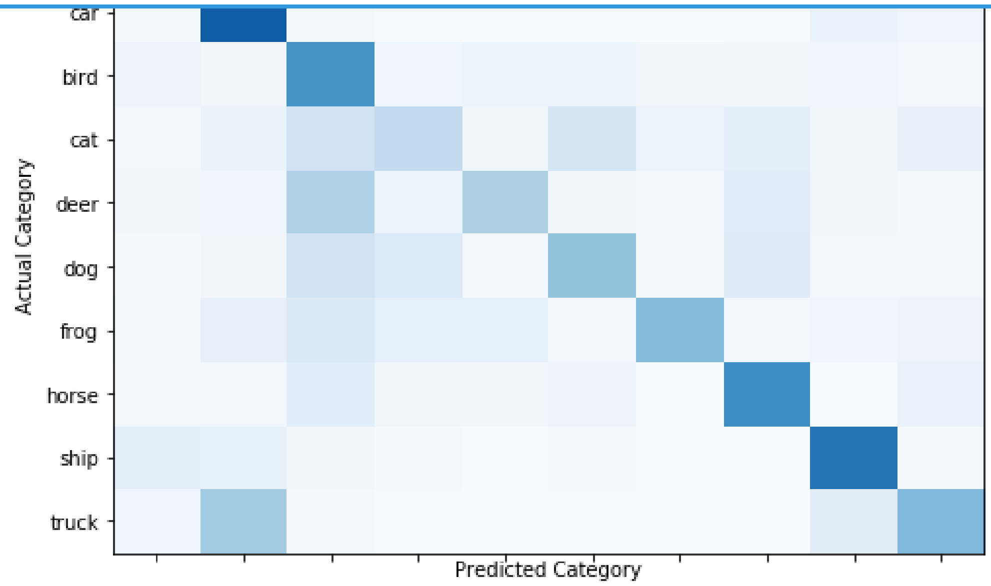

From the above visualisation we can see that the best accuracy was achieved on the `car` and `ship` categories, darkest shades present on the main diagonal. The `truck` category was most frequently confused with the `car` category. This is understandable, since they are both vehicles and have some visual similarities. `Planes` were also commonly confused with `bird` and `ship`. This could have something to do with a common background texture and colour, blue for both sky and sea.

To understand precisely which categories were most commonly confused, we can print the absolute and relative values of the confusion matrix, as follows.

Hide Code

```
print('actual/pred'.ljust(16), end='')
for i,c in enumerate(classes):
    print(c.ljust(10), end='')
print()
for i,r in enumerate(confusion_matrix):
    print(classes[i].ljust(16), end='')
    for idx, p in enumerate(r):
        print(str(p).ljust(10), end='')
    print()

    r = r/np.sum(r)
    print(''.ljust(16), end='')
    for idx, p in enumerate(r):
        print(str(p).ljust(10), end='')
    print()
```

```
actual/pred     plane     car       bird      cat       deer      dog       frog
plane           535       68        195       4         3         2         10
```

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cat	26	64	189	254	38	168	52
	0.026	0.064	0.189	0.254	0.038	0.168	0.052
deer	33	40	319	54	329	33	24
	0.033	0.04	0.319	0.054	0.329	0.033	0.024
dog	14	33	193	136	27	402	22
	0.014	0.033	0.193	0.136	0.027	0.402	0.022
frog	8	81	140	86	93	30	437
	0.008	0.081	0.14	0.086	0.093	0.03	0.437
horse	23	24	108	39	35	56	3
	0.023	0.024	0.108	0.039	0.035	0.056	0.003
ship	98	84	38	9	1	8	1
	0.098	0.084	0.038	0.009	0.001	0.008	0.001
truck	41	361	16	4	1	5	5
	0.041	0.361	0.016	0.004	0.001	0.005	0.005

Conclusion

In this notebook, we trained a simple convolutional neural network using PyTorch on the CIFAR-10 data set. 50,000 images were used for training and 10,000 images were used to evaluate the performance. The model performed well, achieving an accuracy of 52.2% compared to a baseline of 10%, since there are 10 categories in CIFAR-10, if the model guessed randomly.

To improve the performance we can try adding convolution layers, more filters or more fully connected layers. We could also train the model for more than two epochs while introducing some form of regularisation, such as dropout or batch normalization, so as not to overfit the training data.

Keep in mind that complex models with hundreds of thousands of parameters are computationally more expensive to train and thus you should consider training such models on a GPU enabled machine to speed up the process.

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