TC 5033

Deep Learning

Convolutional Neural Networks

Team Members:

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Activity 2b: Building a CNN for CIFAR10 dataset with PyTorch

- Objective

  The main goal of this activity is to further your understanding of Convolutional Neural Networks (CNNs) by building one using PyTorch. You will apply this architecture to the famous CIFAR10 dataset, taking what you've learned from the guide code that replicated the Fully Connected model in PyTorch (Activity 2a).

- Instructions This activity requires submission in teams of 3 or 4 members. Submissions from smaller or larger teams will not be accepted unless prior approval has been granted (only due to exceptional circumstances). While teamwork is encouraged, each member is expected to contribute individually to the assignment. The final submission should feature the best arguments and solutions from each team member. Only one person per team needs to submit the completed work, but it is imperative that the names of all team members are listed in a Markdown cell at the very beginning of the notebook (either the first or second cell). Failure to include all team member names will result in the grade being awarded solely to the individual who submitted the assignment, with zero points given to other team members (no exceptions will be made to this rule).

Understand the Guide Code: Review the guide code from Activity 2a that implemented a Fully Connected model in PyTorch. Note how PyTorch makes it easier to implement neural networks.

Familiarize Yourself with CNNs: Take some time to understand their architecture and the rationale behind using convolutional layers.

Prepare the Dataset: Use PyTorch's DataLoader to manage the dataset. Make sure the data is appropriately preprocessed for a CNN.

Design the CNN Architecture: Create a new architecture that incorporates convolutional layers. Use PyTorch modules like nn.Conv2d, nn.MaxPool2d, and others to build your network.

Training Loop and Backpropagation: Implement the training loop, leveraging PyTorch’s autograd for backpropagation. Keep track of relevant performance metrics.

Analyze and Document: Use Markdown cells to explain your architectural decisions, performance results, and any challenges you faced. Compare this model with your previous Fully Connected model in terms of performance and efficiency.

- Evaluation Criteria
  - Understanding of CNN architecture and its application to the CIFAR10 dataset
  - Code Readability and Comments
  - Appropriateness and efficiency of the chosen CNN architecture
  - Correct implementation of Traning Loop and Accuracy Function
  - Model's performance metrics on the CIFAR10 dataset (at least 65% accuracy)
  - Quality of Markdown documentation
- Submission

Submit via Canvas your Jupyter Notebook with the CNN implemented in PyTorch. Your submission should include well-commented code and Markdown cells that provide a comprehensive view of your design decisions, performance metrics, and learnings.

In [1]:
```
import numpy as np
import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import DataLoader
from torch.utils.data import sampler
import torchvision.datasets as datasets
import torchvision.transforms as T
import matplotlib.pyplot as plt
#only if you have jupyterthemes
```

```python
#from jupyterthemes import jtplot
#jtplot.style()
```

In [2]:
```python
# Check torch version
torch.__version__
```

Out[2]: '2.1.0'

In [3]:
```python
torch.cuda.is_available()
```

Out[3]: True

In [4]:
```python
if torch.cuda.is_available():
    print(torch.cuda.get_device_name(0))
    print(torch.cuda.get_device_capability(0))
    print(torch.cuda.get_device_properties(0))
else:
    print("No GPU available")
```

```
NVIDIA GeForce GTX 1650
(7, 5)
_CudaDeviceProperties(name='NVIDIA GeForce GTX 1650', major=7, minor=5, total_memory
=4095MB, multi_processor_count=14)
```

Download Cifar10 dataset

In [5]:
```python
DATA_PATH = 'data/cifar10_data'
NUM_TRAIN = 50000
NUM_VAL = 5000
NUM_TEST = 5000
MINIBATCH_SIZE = 64

transform_cifar = T.Compose([
                T.ToTensor(),
                T.Normalize([0.491, 0.482, 0.447], [0.247, 0.243, 0.261])
            ])

# Train dataset
cifar10_train = datasets.CIFAR10(DATA_PATH, train=True, download=True,
                             transform=transform_cifar)
train_loader = DataLoader(cifar10_train, batch_size=MINIBATCH_SIZE,
                          sampler=sampler.SubsetRandomSampler(range(NUM_TRAIN)))
#Validation set
cifar10_val = datasets.CIFAR10(DATA_PATH, train=False, download=True,
                           transform=transform_cifar)
val_loader = DataLoader(cifar10_val, batch_size=MINIBATCH_SIZE,
                        sampler=sampler.SubsetRandomSampler(range(NUM_VAL)))
#Test set
cifar10_test = datasets.CIFAR10(DATA_PATH, train=False, download=True,
                            transform=transform_cifar)
test_loader = DataLoader(cifar10_test, batch_size=MINIBATCH_SIZE,
                        sampler=sampler.SubsetRandomSampler(range(NUM_VAL, len(cifa
```

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

In [6]:
```
cifar10_train
```

Out[6]:
```
Dataset CIFAR10
    Number of datapoints: 50000
    Root location: data/cifar10_data
    Split: Train
    StandardTransform
Transform: Compose(
               ToTensor()
               Normalize(mean=[0.491, 0.482, 0.447], std=[0.247, 0.243, 0.261])
           )
```

In [7]:
```
train_loader.batch_size
```

Out[7]:
```
64
```

In [8]:
```
#for i, (x, y) in enumerate(train_loader):
    #print(x, y)
```

Using GPUs

In [9]:
```
if torch.cuda.is_available():
    device = torch.device('cuda')
else:
    device = torch.device('cpu')
print(device)
```

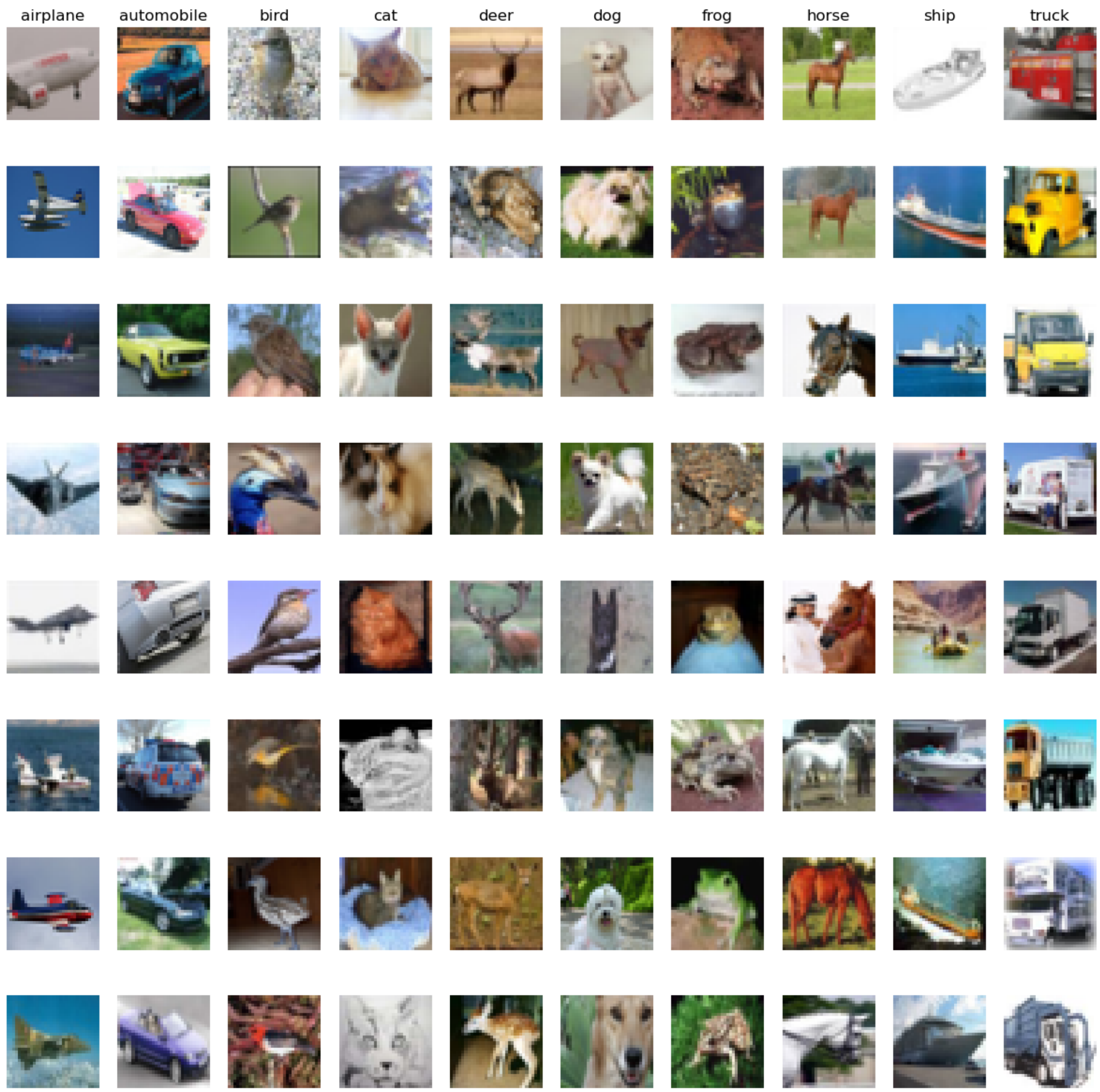
```
cuda
```

Show Images

In [10]:
```
classes = test_loader.dataset.classes
def plot_figure(image):
    plt.imshow(np.transpose(image,(1,2,0)))
    plt.axis('off')
    plt.show()

rnd_sample_idx = np.random.randint(len(test_loader))
print(f'La imagen muestreada representa un: {classes[test_loader.dataset[rnd_sample
image = test_loader.dataset[rnd_sample_idx][0]
image = (image - image.min()) / (image.max() -image.min() )
plot_figure(image)
```

```
La imagen muestreada representa un: automobile
```

In [11]:
```
def plot_cifar10_grid():
    classes = test_loader.dataset.classes
    total_samples = 8
    plt.figure(figsize=(15,15))
    for label, sample in enumerate(classes):
        class_idxs = np.flatnonzero(label == np.array(test_loader.dataset.targets))
        sample_idxs = np.random.choice(class_idxs, total_samples, replace = False)
        for i, idx in enumerate(sample_idxs):
            plt_idx = i*len(classes) + label + 1
            plt.subplot(total_samples, len(classes), plt_idx)
            plt.imshow(test_loader.dataset.data[idx])
            plt.axis('off')

            if i == 0: plt.title(sample)
    plt.show()

plot_cifar10_grid()
```



Calculate Accuracy

In [12]:
```
def accuracy(model, loader):
    num_correct = 0
    num_total = 0

    # Set the model to evaluation mode and move to GPU
    model.eval()
    model.to(device)

    # Disable gradient calculations. Only making predictions and not updating weigh
    # we don't need gradients. This saves memory.
    with torch.no_grad():
        # Iterate over the dataset loader
        for x_i, y_i in loader:
            # Move the input and target data to GPU
            x_i = x_i.to(device=device, dtype=torch.float32)
            y_i = y_i.to(device=device, dtype=torch.long)
```

```python
            # Forward pass. Get output scores
            scores = model(x_i)

            # Get the predictions from the maximum value of the output scores
            _, pred = scores.max(dim=1)

             # Count how many predictions match the true labels
            num_correct += (pred == y_i).sum().item()
            num_total += pred.size(0)

    return num_correct / num_total
```

Training Loop

In [13]:
```python
def train(model, optimiser, epochs=100):
    # move model to GPU
    model = model.to(device)

    # Loop over the epochs
    for epoch in range(epochs):
        # Set model to training mode
        model.train()

        # Loop over training data
        for i, (x_i, y_i) in enumerate(train_loader):
            x_i = x_i.to(device=device, dtype=torch.float32)
            y_i = y_i.to(device=device, dtype=torch.long)

            # Forward pass. Get output scores
            scores = model(x_i)

            # Calculate the cost
            cost = F.cross_entropy(input= scores, target=y_i)

            # Zero the parameter gradients.
            optimiser.zero_grad()

            # Perform a backward pass
            cost.backward()

            # Perform a single optimization step (parameter update)
            optimiser.step()

        # Evaluate model performance after each epoch
        acc = accuracy(model, val_loader)
        print(f'Epoch: {epoch}\t costo: {cost.item():.4f}\t accuracy: {acc:.4f}')
```

Linear model

Model Hyperparameters

In [14]:
```
hidden1 = 256
hidden = 256
lr = 0.001
epochs = 10
```

Neural Network Architecture:

Input -> Flatten -> Linear -> ReLU -> Linear -> ReLU -> Linear -> Output

This architecture is a sequence of layers configured to process input data for classification tasks.

In [15]:
```
# Build neural network with sequential container
nn_model = nn.Sequential(nn.Flatten(),
                         nn.Linear(in_features=32*32*3, out_features=hidden1),
                         nn.ReLU(),
                         nn.Linear(in_features=hidden1, out_features=hidden), nn.Re
                         nn.Linear(in_features=hidden, out_features=10))

optimiser = torch.optim.Adam(nn_model.parameters(), lr=lr)
```

Train model and get accuracy

In [16]:
```
train(nn_model, optimiser, epochs)
```

```
Epoch: 0        costo: 1.3296   accuracy: 0.4536
Epoch: 1        costo: 1.9087   accuracy: 0.4926
Epoch: 2        costo: 1.2613   accuracy: 0.5078
Epoch: 3        costo: 1.9224   accuracy: 0.5274
Epoch: 4        costo: 1.3760   accuracy: 0.5270
Epoch: 5        costo: 1.1816   accuracy: 0.5324
Epoch: 6        costo: 1.1088   accuracy: 0.5256
Epoch: 7        costo: 0.8616   accuracy: 0.5200
Epoch: 8        costo: 0.6553   accuracy: 0.5274
Epoch: 9        costo: 1.0837   accuracy: 0.5416
```

In [17]:
```
#Calculate Test Partition Accuracy
accuracy(nn_model, test_loader)
```

Out[17]:
```
0.5222
```

Sequential CNN

Model Hyperparameters

In [18]:
```
channel1 = 16
channel2 = 32
epochs = 10
lr = 0.0001
```

Input -> Conv2d -> ReLU -> Conv2d -> ReLU -> MaxPool2d -> Flatten -> Linear -> Output

This architecture represents a convolutional neural network (CNN) designed for processing image data.

In [19]:
```
# Build convolutional neural network with sequential container
modelCNN_1 = nn.Sequential(nn.Conv2d(in_channels=3, out_channels=channel1,
                                    kernel_size=3, padding=1),
                          nn.ReLU(),
                          nn.Conv2d(in_channels=channel1, out_channels=channel2,
                                     kernel_size= 3, padding=1),
                          nn.ReLU(),
                          nn.MaxPool2d(2, 2),
                          nn.Flatten(),
                          nn.Linear(in_features=16*16*channel2, out_features=10)
                                    )
optimiser = torch.optim.Adam(modelCNN_1.parameters(), lr)
```

In [20]:
```
train(modelCNN_1, optimiser, epochs)
```

```
Epoch: 0         costo: 1.5983   accuracy: 0.4938
Epoch: 1         costo: 1.7619   accuracy: 0.5366
Epoch: 2         costo: 1.3108   accuracy: 0.5618
Epoch: 3         costo: 1.2336   accuracy: 0.5820
Epoch: 4         costo: 1.2264   accuracy: 0.5846
Epoch: 5         costo: 1.6059   accuracy: 0.5964
Epoch: 6         costo: 1.2219   accuracy: 0.6076
Epoch: 7         costo: 0.7529   accuracy: 0.6144
Epoch: 8         costo: 0.6677   accuracy: 0.6234
Epoch: 9         costo: 1.3023   accuracy: 0.6346
```

In [21]:
```
#Calculate Test Partition Accuracy
accuracy(modelCNN_1, test_loader)
```

Out[21]:
```
0.6216
```

OOP Approach and performance improvement

In [22]:
```
conv_k_3 = lambda channel1, channel2: nn.Conv2d(channel1, channel2, kernel_size=3,
```

In [23]:
```
class CNN_class(nn.Module):
    def __init__(self, in_channel, channel1, channel2):
        super().__init__()
        # # The convolutional layer takes 'in_channel' input channels and produces
        self.conv1 = conv_k_3(in_channel, channel1)
        # batch normalization for 'channel1'
        self.bn1 = nn.BatchNorm2d(channel1)
        # This layer takes 'channel1' input channels from the previous layer and pr
        self.conv2 = conv_k_3(channel1, channel2)
        # batch normalization for 'channel1'
        self.bn2 = nn.BatchNorm2d(channel2)
         # Define a max pooling layer that uses a 2x2 window
        self.max_pool = nn.MaxPool2d(2,2)
    # Forward pass
    def forward(self, x):
```

```python
        x = F.relu(self.bn2(self.conv2(F.relu(self.bn1(self.conv1(x))))))
        return self.max_pool(x)
```

Model Hyperparameters

In [24]:
```python
channel1 = 64
channel2 = 128
channel3 = 256
channel4 = 512
epochs = 20
lr = 0.0001
```

Neural Network Architecture:

Input -> Conv2d -> BatchNorm2d -> ReLU -> Conv2d -> BatchNorm2d -> ReLU -> Flatten -> Linear -> Output

This architecture represents a simple convolutional neural network (CNN) designed for processing image data.

In [25]:
```python
# Build convolutional neural network with sequential container
modelCNN_2 = nn.Sequential(CNN_class(3,channel1, channel2),
                           CNN_class(channel2, channel4, channel4),
                           nn.Flatten(),
                           nn.Linear(in_features=8*8*channel4, out_features=10))

optimiser = torch.optim.Adam(modelCNN_2.parameters(), lr)
```

In [26]:
```python
train(modelCNN_2, optimiser, epochs)
```

```
Epoch: 0         costo: 1.2241   accuracy: 0.6782
Epoch: 1         costo: 0.8293   accuracy: 0.7264
Epoch: 2         costo: 0.2341   accuracy: 0.7516
Epoch: 3         costo: 0.6276   accuracy: 0.7682
Epoch: 4         costo: 0.5623   accuracy: 0.7342
Epoch: 5         costo: 0.0709   accuracy: 0.7702
Epoch: 6         costo: 0.2689   accuracy: 0.7776
Epoch: 7         costo: 0.4365   accuracy: 0.7770
Epoch: 8         costo: 0.0238   accuracy: 0.7662
Epoch: 9         costo: 0.0676   accuracy: 0.7586
Epoch: 10        costo: 0.0808   accuracy: 0.7284
Epoch: 11        costo: 0.0470   accuracy: 0.7476
Epoch: 12        costo: 0.0633   accuracy: 0.7704
Epoch: 13        costo: 0.0117   accuracy: 0.7736
Epoch: 14        costo: 0.0077   accuracy: 0.7724
Epoch: 15        costo: 0.0515   accuracy: 0.7848
Epoch: 16        costo: 0.0040   accuracy: 0.7398
Epoch: 17        costo: 0.0037   accuracy: 0.7714
Epoch: 18        costo: 0.0046   accuracy: 0.7764
Epoch: 19        costo: 0.1167   accuracy: 0.7848
```

In [27]:
```python
#Calculate Test Partition Accuracy
accuracy(modelCNN_2, test_loader)
```

Out[27]: 0.7924

The model's final performance on the ASL dataset achieved an accuracy of 79.24%. The convolutional network architecture, utilizing an OOP approach with batch normalization, outperformed the preceding linear and sequential models.

In [ ]: