Problem 2

(a) Check CIFAR10

In [1]:
```
import torch
import torchvision
import torchvision.transforms as transforms
```

In [2]:
```
transform = transforms.Compose(
    [transforms.ToTensor(),
     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])

batch_size = 4

trainset = torchvision.datasets.CIFAR10(root='./data', train=True,
                                        download=True, transform=transform)
trainloader = torch.utils.data.DataLoader(trainset, batch_size=batch_size,
                                          shuffle=True, num_workers=2)

testset = torchvision.datasets.CIFAR10(root='./data', train=False,
                                       download=True, transform=transform)
testloader = torch.utils.data.DataLoader(testset, batch_size=batch_size,
                                         shuffle=False, num_workers=2)

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

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

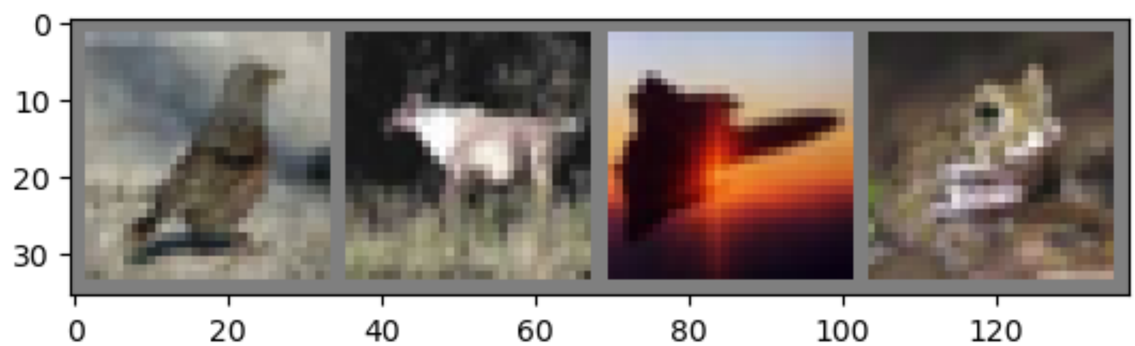
In [3]:
```
trainset
```

Out[3]:
```
Dataset CIFAR10
    Number of datapoints: 50000
    Root location: ./data
    Split: Train
    StandardTransform
Transform: Compose(
               ToTensor()
               Normalize(mean=(0.5, 0.5, 0.5), std=(0.5, 0.5, 0.5))
           )
```

In [4]:
```
testset
```

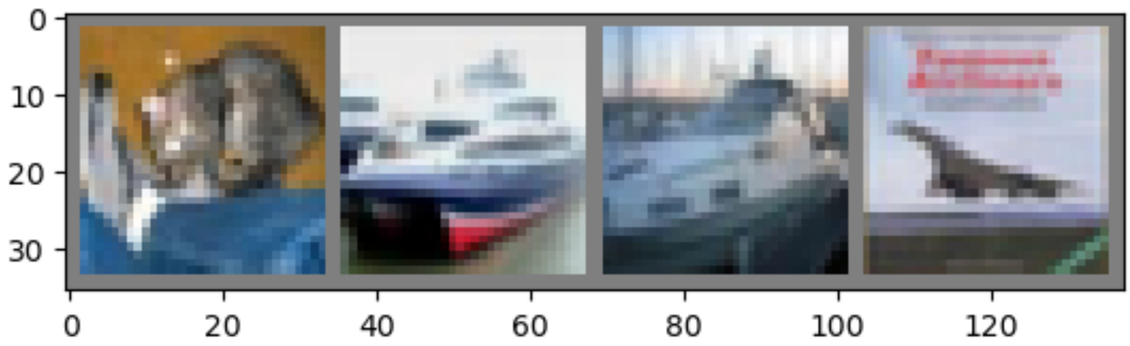
Out[4]:
```
Dataset CIFAR10
    Number of datapoints: 10000
    Root location: ./data
    Split: Test
    StandardTransform
Transform: Compose(
               ToTensor()
               Normalize(mean=(0.5, 0.5, 0.5), std=(0.5, 0.5, 0.5))
           )
```

In [5]:
```
import matplotlib.pyplot as plt
import numpy as np

# functions to show an image


def imshow(img):
    img = img / 2 + 0.5     # unnormalize
    npimg = img.numpy()
    plt.imshow(np.transpose(npimg, (1, 2, 0)))
    plt.show()


# get some random training images
dataiter = iter(trainloader)
images, labels = next(dataiter)

# show images
imshow(torchvision.utils.make_grid(images))
# print labels
print(' '.join(f'{classes[labels[j]]:5s}' for j in range(batch_size)))
```




```
bird  deer  plane frog
```

In [6]:
```
# get some random training images
dataiter = iter(testloader)
images, labels = next(dataiter)

# show images
imshow(torchvision.utils.make_grid(images))
# print labels
print(' '.join(f'{classes[labels[j]]:5s}' for j in range(batch_size)))
```



```
cat   ship  ship  plane
```

In [7]:
```
images, labels = next(dataiter)
images.shape # 4 is batch size
```

Out[7]:
```
torch.Size([4, 3, 32, 32])
```

(b) Train 1 hidden layer ReLU

In [8]:
```
import torch.nn as nn
import torch.nn.functional as F

class Net(nn.Module):
    def __init__(self, k=128):
        super(Net, self).__init__()
        self.k = k
        self.fc1 = nn.Linear(3 * 32 * 32, self.k, bias=False)
        self.fc2 = nn.Linear(self.k, 10, bias=False)

    def forward(self, x):
        x = x.view(-1, 3 * 32 * 32) # [batchsize, 3072]
        x = F.relu(self.fc1(x))
        x = self.fc2(x)
        return x

model = Net(k=128)
```

In [9]:
```
criterion = nn.MSELoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.001)
```

In [11]:
```
# train the model
num_epochs = 20
train_loss_history = []
train_acc_history = []
test_loss_history = []
test_acc_history = []

# Loop through the number of epochs
for epoch in range(num_epochs):
```

```
    train_loss = 0.0
    train_acc = 0.0
    test_loss = 0.0
    test_acc = 0.0

    # set model to train mode
    model.train()
    # iterate over the training data
    for inputs, labels in trainloader:
        optimizer.zero_grad()
        outputs = model(inputs)

        #compute the loss
        one_hot_labels = torch.nn.functional.one_hot(labels, num_classes=10)
        loss = criterion(outputs, one_hot_labels.float())
        loss.backward()
        optimizer.step()
        # increment the running loss and accuracy
        train_loss += loss.item()
        train_acc += (outputs.argmax(1) == labels).sum().item()

    # calculate the average training loss and accuracy
    train_loss /= len(trainloader)
    train_loss_history.append(train_loss)
    train_acc /= len(trainloader.dataset)
    train_acc_history.append(train_acc)

    # set the model to evaluation mode
    model.eval()
    with torch.no_grad():
        for inputs, labels in testloader:
            outputs = model(inputs)

            #compute the loss
            one_hot_labels = torch.nn.functional.one_hot(labels, num_classes
            loss = criterion(outputs, one_hot_labels.float())

            test_loss += loss.item()
            test_acc += (outputs.argmax(1) == labels).sum().item()

    # calculate the average validation loss and accuracy
    test_loss /= len(testloader)
    test_loss_history.append(test_loss)
    test_acc /= len(testloader.dataset)
    test_acc_history.append(test_acc)

    print(f'Epoch {epoch+1}/{num_epochs}, train loss: {train_loss:.4f}, trai
```

```
Epoch 1/20, train loss: 0.0944, train acc: 0.3199, val loss: 0.0879, val acc
: 0.3390
Epoch 2/20, train loss: 0.0952, train acc: 0.3307, val loss: 0.1536, val acc
: 0.2732
Epoch 3/20, train loss: 0.0942, train acc: 0.3431, val loss: 0.0938, val acc
: 0.3313
Epoch 4/20, train loss: 0.0941, train acc: 0.3450, val loss: 0.0846, val acc
: 0.3601
Epoch 5/20, train loss: 0.0935, train acc: 0.3508, val loss: 0.0916, val acc
: 0.3296
Epoch 6/20, train loss: 0.0951, train acc: 0.3520, val loss: 0.0854, val acc
: 0.3571
Epoch 7/20, train loss: 0.0928, train acc: 0.3552, val loss: 0.0904, val acc
: 0.3580
Epoch 8/20, train loss: 0.0945, train acc: 0.3527, val loss: 0.0873, val acc
: 0.3521
Epoch 9/20, train loss: 0.0949, train acc: 0.3622, val loss: 0.0998, val acc
: 0.3059
Epoch 10/20, train loss: 0.0947, train acc: 0.3583, val loss: 0.1001, val ac
c: 0.3121
Epoch 11/20, train loss: 0.0986, train acc: 0.3668, val loss: 0.0846, val ac
c: 0.3774
Epoch 12/20, train loss: 0.0927, train acc: 0.3628, val loss: 0.0929, val ac
c: 0.3458
Epoch 13/20, train loss: 0.0931, train acc: 0.3605, val loss: 0.0930, val ac
c: 0.3446
Epoch 14/20, train loss: 0.0931, train acc: 0.3635, val loss: 0.0958, val ac
c: 0.3356
Epoch 15/20, train loss: 0.0937, train acc: 0.3659, val loss: 0.1190, val ac
c: 0.2893
Epoch 16/20, train loss: 0.0925, train acc: 0.3662, val loss: 0.0881, val ac
c: 0.3417
Epoch 17/20, train loss: 0.0927, train acc: 0.3684, val loss: 0.1048, val ac
c: 0.3247
Epoch 18/20, train loss: 0.0927, train acc: 0.3687, val loss: 0.0908, val ac
c: 0.3416
Epoch 19/20, train loss: 0.0929, train acc: 0.3686, val loss: 0.1023, val ac
c: 0.3099
Epoch 20/20, train loss: 0.0923, train acc: 0.3713, val loss: 0.0980, val ac
c: 0.3216
```

After 20 epochs of training, it achieves 32% of accuracy on test set.