ECE 57000 Assignment 4 Exercise

Your Name:

Exercise 0: Train your model on GPU (0 points)

For some tasks in this assignment, it can take a long time if you run it on CPU. For example, based on our test on Exercise 3 Task 4, it will take roughly 2 hours to train the full model for 1 epoch on CPU. Hence, we highly recommend you try to train your model on GPU.

To do so, first you need to enable GPU on Colab (this will restart the runtime). Click `Runtime -> Change runtime type` and select the `Hardware accelerator` there. You can then run the following code to see if the GPU is correctly initialized and available.

In [1]:
```
import torch
print(f'Can I can use GPU now? -- {torch.cuda.is_available()}')
```

```
Can I can use GPU now? -- True
```

In [2]:
```
print(torch.cuda.get_device_name(0))
```

```
NVIDIA GeForce GTX 1060 with Max-Q Design
```

You must manually move your model and data to the GPU (and sometimes back to the cpu)

After setting the GPU up on colab, then you should put your **model** and **data** to GPU. We give a simple example below. You can use `to` function for this task. See [torch.Tensor.to (https://pytorch.org/docs/stable/generated/torch.Tensor.to.html)](https://pytorch.org/docs/stable/generated/torch.Tensor.to.html) to move a tensor to the GPU (probably your mini-batch of data in each iteration) or [torch.nn.Module.to (https://pytorch.org/docs/stable/generated/torch.nn.Module.html#torch.nn.Module.to)](https://pytorch.org/docs/stable/generated/torch.nn.Module.html#torch.nn.Module.to) to move your NN model to GPU (assuming you create subclass [torch.nn.Module (https://pytorch.org/docs/stable/generated/torch.nn.Module.html)](https://pytorch.org/docs/stable/generated/torch.nn.Module.html)). Note that `to()` of tensor returns a NEW tensor while `to` of a NN model will apply this in-place. To be safe, the best semantics are `obj = obj.to(device)`. For printing, you will need to move a tensor back to the CPU via the `cpu()` function.

Once the model and input data are on the GPU, everything else can be done the same. This is the beauty of PyTorch GPU acceleration. None of the other code needs to be altered.

To summarize, you need to 1) enable GPU acceleration in Colab, 2) put the model on the GPU, and 3) put the input data (i.e., the batch of samples) onto the GPU using `to()` after it is loaded by the data loaders (usually you only put one batch of data on the GPU at a time).

In [3]:
```
import torch.nn as nn
rand_tensor = torch.rand(5,2)
simple_model = nn.Sequential(nn.Linear(2,10), nn.ReLU(), nn.Linear(10,1))
print(f'input is on {rand_tensor.device}')
print(f'model parameters are on {[param.device for param in simple_model.param
eters()]}')
print(f'output is on {simple_model(rand_tensor).device}')

device = torch.device('cuda')
# ----------- <Your code> ---------------
# Move rand_tensor and model onto the GPU device



# transfers tensor & model from CPU to GPU 1
rand_tensor = rand_tensor.to(device)

simple_model = simple_model.to(device)



# --------- <End your code> -------------
print(f'input is on {rand_tensor.device}')
print(f'model parameters are on {[param.device for param in simple_model.param
eters()]}')
print(f'output is on {simple_model(rand_tensor).device}')
```

```
input is on cpu
model parameters are on [device(type='cpu'), device(type='cpu'), device(type
='cpu'), device(type='cpu')]
output is on cpu
input is on cuda:0
model parameters are on [device(type='cuda', index=0), device(type='cuda', in
dex=0), device(type='cuda', index=0), device(type='cuda', index=0)]
output is on cuda:0
```

Exercise 1: Why use a CNN rather than only fully connected layers? (30 points)

In this exercise, you will build two models for the **MNIST** dataset: one uses only fully connected layers and another uses a standard CNN layout (convolution layers everywhere except the last layer is fully connected layer). The two models should be built with roughly the same accuracy performance, your task is to compare the number of network parameters (a huge number of parameters can affect training/testing time, memory requirements, overfitting, etc.).

Task 1: Following the structure used in the instructions, you should create

- One network named **OurFC** which should consist with only fully connected layers
  - You should decide how many layers and how many hidden dimensions you want in your network
  - Your final accuracy on the test dataset should lie roughly around 90% ($\pm$2%)
  - There is no need to make the neural network unnecessarily complex, your total training time should no longer than 3 mins
- Another network named **OurCNN** which applys a standard CNN structure
  - Again, you should decide how many layers and how many channels you want for each layer.
  - Your final accuracy on the test dataset should lie roughly around 90% ($\pm$2%)
  - A standard CNN structure can be composed as **[Conv2d, MaxPooling, ReLU] x num_conv_layers + FC x num_fc_layers**
- Train and test your network on MNIST data as in the instructions
- You are **required** to print out the loss in the training and loss+accuracy in the test as in the instructions.

In [64]:
```
# ----------- <Your code> ---------------

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

In [65]:
```
transform = torchvision.transforms.Compose([torchvision.transforms.ToTensor(),
                      torchvision.transforms.Normalize((0.1307,),(0.3081,))])

train_dataset = torchvision.datasets.MNIST('D:\Jupyter\ECE570\Assignment-4', t
rain=True, download=True, transform=transform)
test_dataset = torchvision.datasets.MNIST('D:\Jupyter\ECE570\Assignment-4', tr
ain=False, download=True, transform=transform)

print(train_dataset)
```

```
Dataset MNIST
    Number of datapoints: 60000
    Root location: D:\Jupyter\ECE570\Assignment-4
    Split: Train
    StandardTransform
Transform: Compose(
               ToTensor()
               Normalize(mean=(0.1307,), std=(0.3081,))
           )
```

In [66]:
```
batch_size_train, batch_size_test = 64, 1000

train_loader = torch.utils.data.DataLoader(train_dataset, batch_size=batch_siz
e_train, shuffle=True)
test_loader = torch.utils.data.DataLoader(test_dataset, batch_size=batch_size_
test, shuffle=False)
```

In [80]:
```
class OurFC(nn.Module): # Any neural generated network should be generate


    def __init__(self):
        super(OurFC, self).__init__()

        self.fc = nn.Linear(784, 10)
        #self.fc1 = nn.Linear(392, 10)


    def forward(self, x):

        x = x.view(-1, 784)      # x now has shape (batchsize x 432)

        x = F.relu(self.fc(x))
        #x = F.relu(self.fc1(x))


        return F.log_softmax(x,-1)
```

In [68]:
```
class OurCNN(nn.Module): # Any neural generated network should be generate

    def __init__(self):
        super(OurCNN, self).__init__()
         #[Conv2d, MaxPooling, ReLU] x num_conv_layers + FC x num_fc_layers
        self.conv = nn.Conv2d(1, 3, kernel_size=5)
        self.fc = nn.Linear(432, 216)
        self.fc1 = nn.Linear(216,10)

    def forward(self, x):
        x = self.conv(x)
        x = F.relu(F.max_pool2d(x,2))
        x = x.view(-1, 432)
        x= self.fc(x)
        x= self.fc1(x)

        return F.log_softmax(x,-1)
```

In [81]:
```
#Initialize the classifiers
classifierFC = OurFC()
classifierCNN = OurCNN()

optimizerFC = optim.SGD(classifierFC.parameters(), lr=0.01, momentum=0.8)
optimizerCNN = optim.SGD(classifierCNN.parameters(), lr=0.01, momentum=0.8)
```

In [90]:
```
def train(classifier, epoch):
    classifier.train() # we need to set the mode for our model

    for batch_idx, (images, targets) in enumerate(train_loader):

        optimizerCNN.zero_grad()
        #optimizerFC.zero_grad()
        output = classifier(images)
        loss = F.nll_loss(output, targets) # Here is a typical loss function
 (negative log likelihood)
        loss.backward()
        optimizerCNN.step()
        #optimizerFC.step()

        if batch_idx % 10 == 0: # We record our output every 10 batches
            train_losses.append(loss.item()) # item() is to get the value of t
he tensor directly
            train_counter.append((batch_idx*64) + ((epoch-1)*len(train_loader.
dataset)))
        if batch_idx % 100 == 0: # We visulize our output every 10 batches
            print(f'Epoch {epoch}: [{batch_idx*len(images)}/{len(train_loader.
dataset)}] Loss: {loss.item()}')


def test(classifier, epoch):
    classifier.eval() # we need to set the mode for our model
    test_loss = 0
    correct = 0

    with torch.no_grad():
        for images, targets in test_loader:
            output = classifier(images)
            test_loss += F.nll_loss(output, targets, reduction='sum').item()
            pred = output.data.max(1, keepdim=True)[1] # we get the estimate o
f our result by look at the largest class value
            correct += pred.eq(targets.data.view_as(pred)).sum() # sum up the
 corrected samples

    test_loss /= len(test_loader.dataset)
    test_losses.append(test_loss)
    test_counter.append(len(train_loader.dataset)*epoch)

    print(f'Test result on epoch {epoch}: Avg loss is {test_loss}, Accuracy:
 {100.*correct/len(test_loader.dataset)}%')
```

Test & Train output of the Fully Connected NN

In [67]:
```
train_losses = []
train_counter = []
test_losses = []
test_counter = []
max_epoch = 3

for epoch in range(1, max_epoch+1):
    train(classifierFC, epoch)
    test(classifierFC, epoch)
```

```
Epoch 1: [0/60000] Loss: 2.344048500061035
Epoch 1: [6400/60000] Loss: 0.4460954964160919
Epoch 1: [12800/60000] Loss: 0.2175951898097992
Epoch 1: [19200/60000] Loss: 0.527032256126403 8
Epoch 1: [25600/60000] Loss: 0.5004987716674805
Epoch 1: [32000/60000] Loss: 0.3437567949295044
Epoch 1: [38400/60000] Loss: 0.13237835466861725
Epoch 1: [44800/60000] Loss: 0.33289915323257446
Epoch 1: [51200/60000] Loss: 0.3084096908569336
Epoch 1: [57600/60000] Loss: 0.23633091151714325
Test result on epoch 1: Avg loss is 0.3022596992492676, Accuracy: 91.23000335
69336%
Epoch 2: [0/60000] Loss: 0.3183317482471466
Epoch 2: [6400/60000] Loss: 0.39392194151878357
Epoch 2: [12800/60000] Loss: 0.4058011472225189
Epoch 2: [19200/60000] Loss: 0.3145514130592346
Epoch 2: [25600/60000] Loss: 0.21817944943904877
Epoch 2: [32000/60000] Loss: 0.42090749740600586
Epoch 2: [38400/60000] Loss: 0.18405500054359436
Epoch 2: [44800/60000] Loss: 0.20996719598770142
Epoch 2: [51200/60000] Loss: 0.6726932525634766
Epoch 2: [57600/60000] Loss: 0.15893703699111938
Test result on epoch 2: Avg loss is 0.2827615692138672, Accuracy: 92.05999755
859375%
Epoch 3: [0/60000] Loss: 0.2107025533914566
Epoch 3: [6400/60000] Loss: 0.18112210929393768
Epoch 3: [12800/60000] Loss: 0.20307490229606628
Epoch 3: [19200/60000] Loss: 0.22188962996006012
Epoch 3: [25600/60000] Loss: 0.3656265437602997
Epoch 3: [32000/60000] Loss: 0.25490766763687134
Epoch 3: [38400/60000] Loss: 0.20031271874904633
Epoch 3: [44800/60000] Loss: 0.19944390654563904
Epoch 3: [51200/60000] Loss: 0.17025333642959595
Epoch 3: [57600/60000] Loss: 0.3198699355125427
Test result on epoch 3: Avg loss is 0.2854252998352051, Accuracy: 91.97000122
070312%
```

Test & Train output of the CNN

In [46]:
```
train_losses = []
train_counter = []
test_losses = []
test_counter = []
max_epoch = 3

for epoch in range(1, max_epoch+1):
    train(classifierCNN, epoch)
    test(classifierCNN, epoch)
```

```
Epoch 1: [0/60000] Loss: 2.3177576065063477
Epoch 1: [6400/60000] Loss: 0.3885684311389923
Epoch 1: [12800/60000] Loss: 0.16379523277282715
Epoch 1: [19200/60000] Loss: 0.4191194474697113
Epoch 1: [25600/60000] Loss: 0.27807432413101196
Epoch 1: [32000/60000] Loss: 0.21233472228050232
Epoch 1: [38400/60000] Loss: 0.08969707787036896
Epoch 1: [44800/60000] Loss: 0.41000786423683167
Epoch 1: [51200/60000] Loss: 0.17236898839473724
Epoch 1: [57600/60000] Loss: 0.19251786172389984
Test result on epoch 1: Avg loss is 0.12640059432983397, Accuracy: 96.0999984
741211%
Epoch 2: [0/60000] Loss: 0.2085951715707779
Epoch 2: [6400/60000] Loss: 0.10022564977407455
Epoch 2: [12800/60000] Loss: 0.1162470206618309
Epoch 2: [19200/60000] Loss: 0.08105329424142838
Epoch 2: [25600/60000] Loss: 0.2331477552652359
Epoch 2: [32000/60000] Loss: 0.1578245759010315
Epoch 2: [38400/60000] Loss: 0.12217027693986893
Epoch 2: [44800/60000] Loss: 0.1632872074842453
Epoch 2: [51200/60000] Loss: 0.15460564196109772
Epoch 2: [57600/60000] Loss: 0.24571436643600464
Test result on epoch 2: Avg loss is 0.10405022735595704, Accuracy: 96.8099975
5859375%
Epoch 3: [0/60000] Loss: 0.17963087558746338
Epoch 3: [6400/60000] Loss: 0.03433581069111824
Epoch 3: [12800/60000] Loss: 0.046823836863040924
Epoch 3: [19200/60000] Loss: 0.07802072912454605
Epoch 3: [25600/60000] Loss: 0.04077259078621864
Epoch 3: [32000/60000] Loss: 0.07629600167274475
Epoch 3: [38400/60000] Loss: 0.23431190848350525
Epoch 3: [44800/60000] Loss: 0.05308881774544716
Epoch 3: [51200/60000] Loss: 0.07985365390777588
Epoch 3: [57600/60000] Loss: 0.2062133550643921
Test result on epoch 3: Avg loss is 0.08462077369689941, Accuracy: 97.3399963
3789062%
```

In [ ]:

Task 2: Compare the number of parameters that are used in both your neural networks by printing out the total number of parameters for both of your networks.

Note: You need to clearly show which number corresponds to which network.

In [82]:
```
# ----------- <Your code> ---------------

total_params_FC = sum(p.numel() for p in classifierFC.parameters())
print(f'The number of parameter for Fully Connected: {total_params_FC}')


total_params_CNN = sum(p.numel() for p in classifierCNN.parameters())
print(f'The number of parameter for CNN: {total_params_CNN}')
```

```
The number of parameter for Fully Connected: 7850
The number of parameter for CNN: 95776
```

In [ ]:

Questions (0 points, just for understanding): Which one has more parameters? Which one is likely to have less computational cost when deployed? Which one took longer to train?

Exercise 2: Train classifier on CIFAR-10 data. (30 points)

Now, lets move our dataset to color images. CIFAR-10 dataset is another widely used dataset. Here all images have colors, i.e each image has 3 color channels instead of only one channel in MNIST. You need to pay more attention to the dimension of the data as it passes through the layers of your network.

Task 1: Create data loaders and plot images

Set up a `train_loader` and `test_loader` for the CIFAR-10 data, and plot a figure:

- 3 x 3 subplot
- each subplot is a randomly chosen image from the test dataset
- label each image with its label

The corresponding names of the classes is given as `classes = ('plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship', 'truck')`

Note: In your transforms, the normalizing constant is given as `transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])`

In [91]:
```
import ssl

ssl._create_default_https_context = ssl._create_unverified_context
```

In [121]:
```
# ----------- <Your code> ---------------
transform = torchvision.transforms.Compose([torchvision.transforms.ToTensor(),
                      torchvision.transforms.Normalize((0.5, 0.5, 0.5), (0.5,
0.5, 0.5))])

train_dataset = torchvision.datasets.CIFAR10('D:\Jupyter\ECE570\Assignment-4',
train=True,
                                             download=True, transform=transfor
m)
test_dataset = torchvision.datasets.CIFAR10('D:\Jupyter\ECE570\Assignment-4',
train=False,
                                            download=True, transform=transform
)

classes = ('plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'shi
p', 'truck')

print(train_dataset)
```

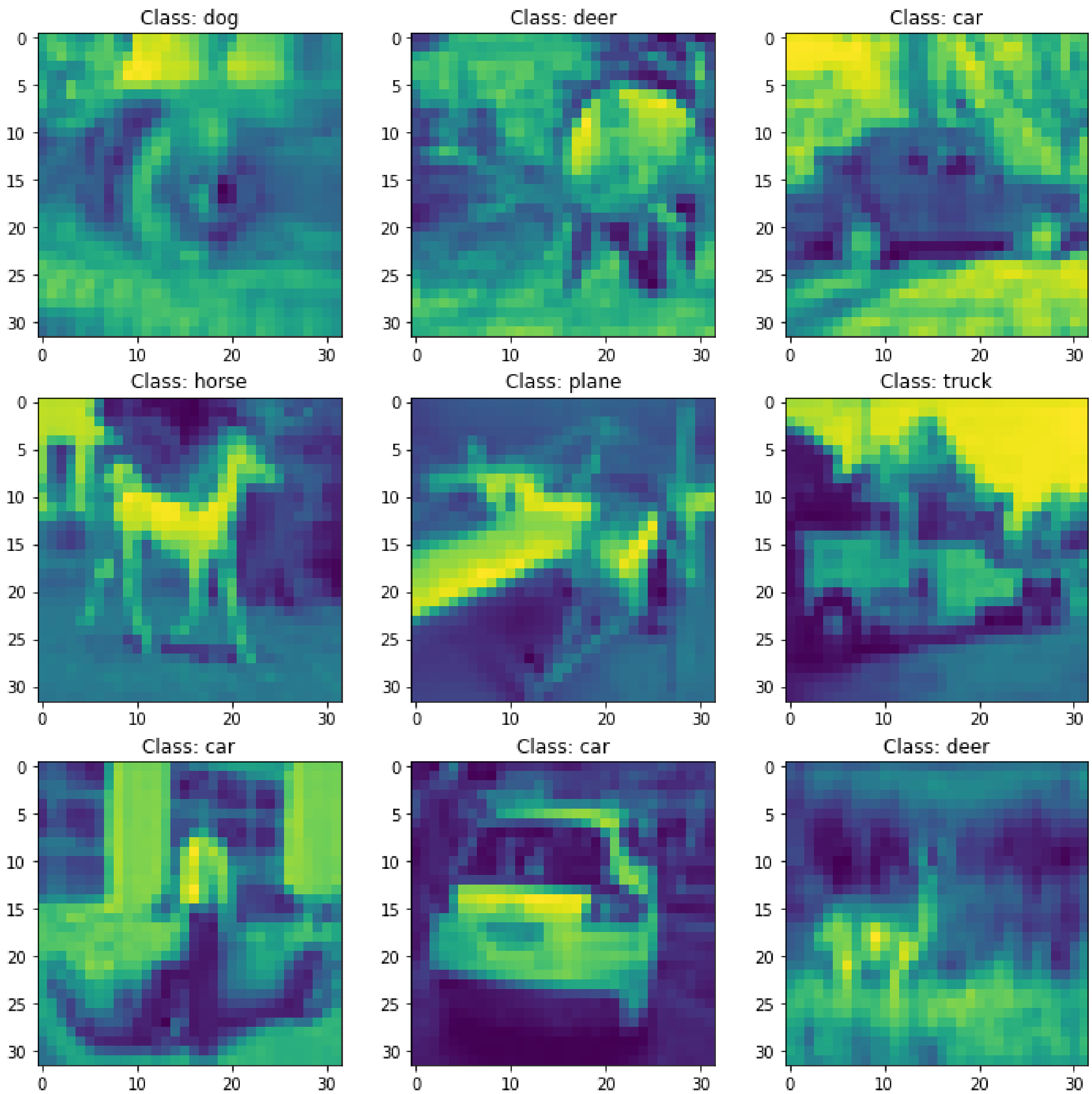
```
Files already downloaded and verified
Files already downloaded and verified
Dataset CIFAR10
    Number of datapoints: 50000
    Root location: D:\Jupyter\ECE570\Assignment-4
    Split: Train
    StandardTransform
Transform: Compose(
               ToTensor()
               Normalize(mean=(0.5, 0.5, 0.5), std=(0.5, 0.5, 0.5))
           )
```

In [122]:
```
batch_size_train, batch_size_test = 64, 1000
train_loader = torch.utils.data.DataLoader(train_dataset, batch_size=batch_siz
e_train, shuffle=True)
test_loader = torch.utils.data.DataLoader(test_dataset, batch_size=batch_size_
test, shuffle=False)

print(train_loader)
print(test_loader)
```

```
<torch.utils.data.dataloader.DataLoader object at 0x0000017A79041948>
<torch.utils.data.dataloader.DataLoader object at 0x0000017A793CD348>
```

In [94]:
```
import matplotlib.pyplot as plt

batch_idx, (images, targets) = next(enumerate(train_loader))
print(f'current batch index is {batch_idx}')
print(f'images has shape {images.size()}')
print(f'targets has shape {targets.size()}')



fig, ax = plt.subplots(3,3)
fig.set_size_inches(12,12)
for i in range(3):
    for j in range(3):
        ax[i,j].imshow(images[i*3+j][0])
        ax[i,j].set_title(f'Class: {classes[targets[i*3+j]]}')
fig.show()
```

```
current batch index is 0
images has shape torch.Size([64, 3, 32, 32])
targets has shape torch.Size([64])

D:\Anaconda3\lib\site-packages\ipykernel_launcher.py:16: UserWarning: Matplot
lib is currently using module://ipykernel.pylab.backend_inline, which is a no
n-GUI backend, so cannot show the figure.
  app.launch_new_instance()
```



Task 2: Create CNN and train it

Set up a convolutional neural network and have your data trained on it. You have to decide all the details in your network, overall your neural network should meet the following standards:

- You should not use more than three convolutional layers and three fully connected layers
- Accuracy on the test dataset should be **above** 50%

In [256]:
```
class OurCNN(nn.Module): # Any neural generated network should be generate

    def __init__(self):
        super(OurCNN, self).__init__()
         #[Conv2d, MaxPooling, ReLU] x num_conv_layers + FC x num_fc_layers
        self.conv = nn.Conv2d(3, 6, kernel_size=5)
        self.conv1 = nn.Conv2d(6, 16, kernel_size=5)
        self.fc = nn.Linear(400, 200)
        self.fc1 = nn.Linear(200, 10)

    def forward(self, x):
        x = self.conv(x)
        x = F.relu(F.max_pool2d(x,2))

        x = self.conv1(x)
        x = F.relu(F.max_pool2d(x,2))

        x = x.view(-1, 400)
        x = F.relu(self.fc(x))
        x = F.relu(self.fc1(x))

        return F.log_softmax(x,-1)
```

In [257]:
```
def train(classifier, epoch):
    classifier.train() # we need to set the mode for our model

    for batch_idx, (images, targets) in enumerate(train_loader):

        optimizerCNN.zero_grad()
        output = classifier(images)
        loss = F.nll_loss(output, targets) # Here is a typical loss function
 (negative log likelihood)
        loss.backward()
        optimizerCNN.step()

        if batch_idx % 10 == 0: # We record our output every 10 batches
            train_losses.append(loss.item()) # item() is to get the value of t
he tensor directly
            train_counter.append((batch_idx*64) + ((epoch-1)*len(train_loader.
dataset)))
        if batch_idx % 100 == 0: # We visulize our output every 10 batches
            print(f'Epoch {epoch}: [{batch_idx*len(images)}/{len(train_loader.
dataset)}] Loss: {loss.item()}')


def test(classifier, epoch):
    classifier.eval() # we need to set the mode for our model
    test_loss = 0
    correct = 0

    with torch.no_grad():
        for images, targets in test_loader:
            output = classifier(images)
            test_loss += F.nll_loss(output, targets, reduction='sum').item()
            pred = output.data.max(1, keepdim=True)[1] # we get the estimate o
f our result by look at the largest class value
            correct += pred.eq(targets.data.view_as(pred)).sum() # sum up the
 corrected samples

            if(pred.eq(targets.data.view_as(pred)).shape[0]/2 > pred.eq(target
s.data.view_as(pred)).sum()):
                _images.append(images)
                _targets.append(targets)
                _output.append(output)

    test_loss /= len(test_loader.dataset)
    test_losses.append(test_loss)
    test_counter.append(len(train_loader.dataset)*epoch)

    print(f'Test result on epoch {epoch}: Avg loss is {test_loss}, Accuracy:
 {100.*correct/len(test_loader.dataset)}%')
```

In [258]:
```
classifierCNN = OurCNN()

optimizerCNN = optim.SGD(classifierCNN.parameters(), lr=0.01, momentum=0.8)

train_losses = []
train_counter = []
test_losses = []
test_counter = []
max_epoch = 10

_images = []
_targets = []
_output = []
```

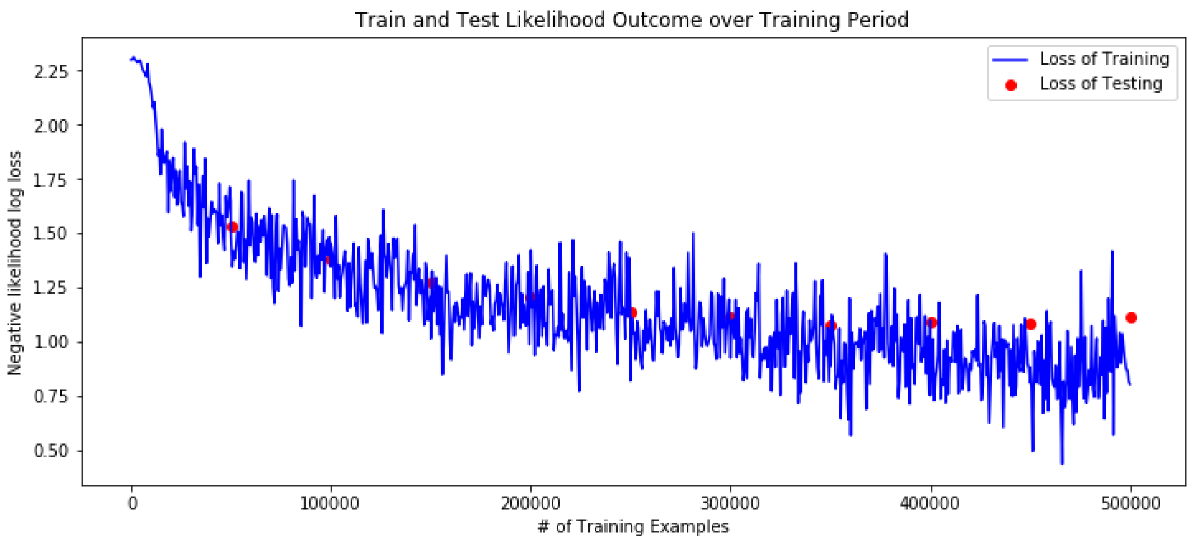
In [259]:
```
# ----------- <Your code> ---------------

for epoch in range(1, max_epoch+1):
    train(classifierCNN, epoch)
    test(classifierCNN, epoch)
```

```
Epoch 1: [0/50000] Loss: 2.304591178894043
Epoch 1: [6400/50000] Loss: 2.299072027206421
Epoch 1: [12800/50000] Loss: 2.202150821685791
Epoch 1: [19200/50000] Loss: 2.004896402359009
Epoch 1: [25600/50000] Loss: 1.9935545921325684
Epoch 1: [32000/50000] Loss: 1.9359965324401855
Epoch 1: [38400/50000] Loss: 1.9499627351760864
Epoch 1: [44800/50000] Loss: 1.948508620262146
Test result on epoch 1: Avg loss is 1.8709885620117188, Accuracy: 35.33000183
105469%
Epoch 2: [0/50000] Loss: 1.9621700048446655
Epoch 2: [6400/50000] Loss: 1.7076371908187866
Epoch 2: [12800/50000] Loss: 1.5381193161010742
Epoch 2: [19200/50000] Loss: 1.8669624328613281
Epoch 2: [25600/50000] Loss: 1.6428872346878052
Epoch 2: [32000/50000] Loss: 1.3562284708023071
Epoch 2: [38400/50000] Loss: 1.3788524866104126
Epoch 2: [44800/50000] Loss: 1.6027708053588867
Test result on epoch 2: Avg loss is 1.429730908203125, Accuracy: 49.119998931
884766%
Epoch 3: [0/50000] Loss: 1.281722068786621
Epoch 3: [6400/50000] Loss: 1.6269010305404663
Epoch 3: [12800/50000] Loss: 1.1605674028396606
Epoch 3: [19200/50000] Loss: 1.5327179431915283
Epoch 3: [25600/50000] Loss: 1.3983114957809448
Epoch 3: [32000/50000] Loss: 1.329913854598999
Epoch 3: [38400/50000] Loss: 1.2708137035369873
Epoch 3: [44800/50000] Loss: 1.3070502281188965
Test result on epoch 3: Avg loss is 1.347917919921875, Accuracy: 50.919998168
94531%
Epoch 4: [0/50000] Loss: 1.2514314651489258
Epoch 4: [6400/50000] Loss: 1.3010333776474
Epoch 4: [12800/50000] Loss: 1.377985954284668
Epoch 4: [19200/50000] Loss: 1.3337912559509277
Epoch 4: [25600/50000] Loss: 1.1956214904785156
Epoch 4: [32000/50000] Loss: 1.1797568798065186
Epoch 4: [38400/50000] Loss: 1.2390949726104736
Epoch 4: [44800/50000] Loss: 1.242339849472046
Test result on epoch 4: Avg loss is 1.2565099365234376, Accuracy: 55.72999954
223633%
Epoch 5: [0/50000] Loss: 1.3509223461151123
Epoch 5: [6400/50000] Loss: 1.235649824142456
Epoch 5: [12800/50000] Loss: 1.0583022832870483
Epoch 5: [19200/50000] Loss: 1.3989678621292114
Epoch 5: [25600/50000] Loss: 1.196450114250183
Epoch 5: [32000/50000] Loss: 1.1626430749893188
Epoch 5: [38400/50000] Loss: 0.9458374977111816
Epoch 5: [44800/50000] Loss: 1.0601166486740112
Test result on epoch 5: Avg loss is 1.1714714477539063, Accuracy: 58.79000091
5527344%
Epoch 6: [0/50000] Loss: 0.9895489811897278
Epoch 6: [6400/50000] Loss: 1.0284019708633423
Epoch 6: [12800/50000] Loss: 1.1749974489212036
Epoch 6: [19200/50000] Loss: 1.339614748954773
Epoch 6: [25600/50000] Loss: 1.1549957990646362
Epoch 6: [32000/50000] Loss: 1.3885409832000732
Epoch 6: [38400/50000] Loss: 1.1818828582763672
```

```
Epoch 6: [44800/50000] Loss: 1.0727722644805908
Test result on epoch 6: Avg loss is 1.1843881713867188, Accuracy: 58.40999984
741211%
Epoch 7: [0/50000] Loss: 1.310736894607544
Epoch 7: [6400/50000] Loss: 0.9779998660087585
Epoch 7: [12800/50000] Loss: 1.4278360605239868
Epoch 7: [19200/50000] Loss: 0.9461607336997986
Epoch 7: [25600/50000] Loss: 0.8788939118385315
Epoch 7: [32000/50000] Loss: 0.9414349794387817
Epoch 7: [38400/50000] Loss: 0.9848574995994568
Epoch 7: [44800/50000] Loss: 1.0959173440933228
Test result on epoch 7: Avg loss is 1.119172216796875, Accuracy: 60.709999084
472656%
Epoch 8: [0/50000] Loss: 0.8963746428489685
Epoch 8: [6400/50000] Loss: 1.0759243965148926
Epoch 8: [12800/50000] Loss: 0.7875061631202698
Epoch 8: [19200/50000] Loss: 1.0813324451446533
Epoch 8: [25600/50000] Loss: 1.1203577518463135
Epoch 8: [32000/50000] Loss: 0.9337418675422668
Epoch 8: [38400/50000] Loss: 1.1338013410568237
Epoch 8: [44800/50000] Loss: 1.0716712474822998
Test result on epoch 8: Avg loss is 1.236481103515625, Accuracy: 57.729999542
23633%
Epoch 9: [0/50000] Loss: 0.8723751902580261
Epoch 9: [6400/50000] Loss: 0.7590051889419556
Epoch 9: [12800/50000] Loss: 0.8572278022766113
Epoch 9: [19200/50000] Loss: 0.8669979572296143
Epoch 9: [25600/50000] Loss: 0.8303475975990295
Epoch 9: [32000/50000] Loss: 0.941517174243927
Epoch 9: [38400/50000] Loss: 0.9257141947746277
Epoch 9: [44800/50000] Loss: 1.04508638381958
Test result on epoch 9: Avg loss is 1.055145867919922, Accuracy: 63.229999542
23633%
Epoch 10: [0/50000] Loss: 0.8791682720184326
Epoch 10: [6400/50000] Loss: 0.5651042461395264
Epoch 10: [12800/50000] Loss: 0.968562126159668
Epoch 10: [19200/50000] Loss: 0.8606730699539185
Epoch 10: [25600/50000] Loss: 0.9273462891578674
Epoch 10: [32000/50000] Loss: 0.6921595931053162
Epoch 10: [38400/50000] Loss: 1.2152265310287476
Epoch 10: [44800/50000] Loss: 0.884882390499115
Test result on epoch 10: Avg loss is 1.0575699340820313, Accuracy: 63.5400009
15527344%
```

In [99]:
```
# ----------- <Your code> ---------------
fig = plt.figure(figsize=(12,5))
plt.plot(train_counter, train_losses, color='blue')
plt.scatter(test_counter, test_losses, color='red')
plt.legend(['Loss of Training', 'Loss of Testing'], loc='upper right')
plt.xlabel('# of Training Examples')
plt.ylabel('Negative likelihood log loss')
plt.title('Train and Test Likelihood Outcome over Training Period')
```

Out[99]: Text(0.5, 1.0, 'Train and Test Likelihood Outcome over Training Period')

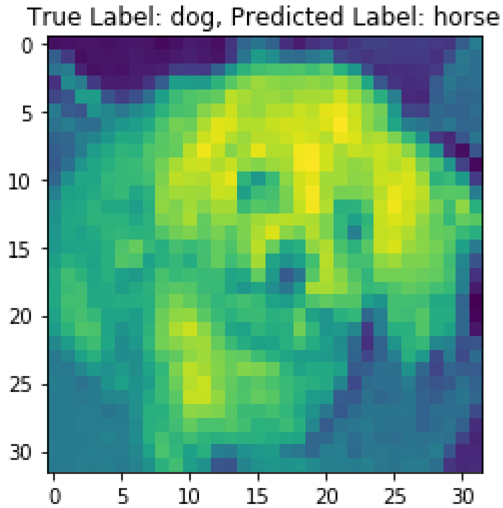


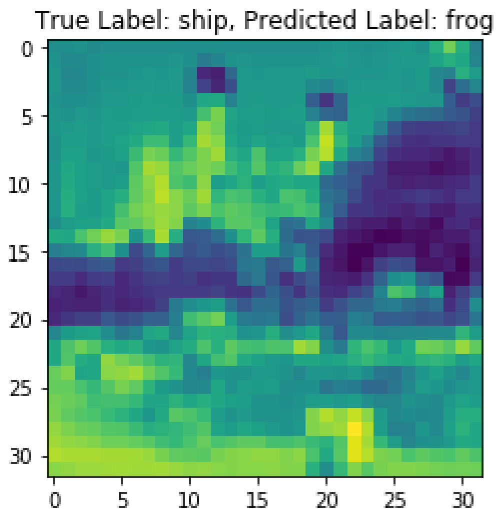
Task 3: Plot misclassified test images

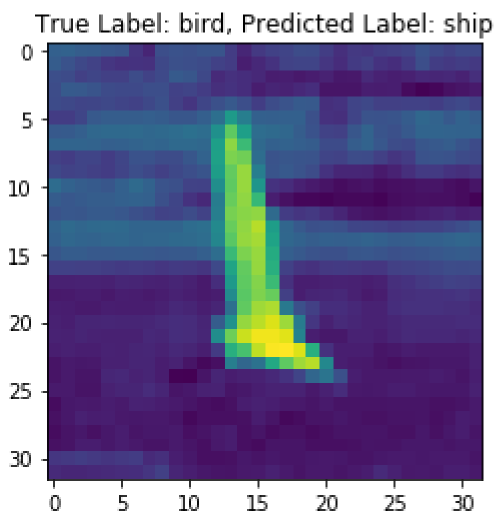
Plot some misclassified images in your test dataset:

- select three images that are **misclassified** by your neural network
- label each images with true label and predicted label

In [292]:
```
import math

for i in range(3):
    plt.imshow(_images[i*3+1][0][0])
    plt.title(f'True Label: {classes[_targets[i*3+1][0]]}, Predicted Label: {classes[math.floor(_output[i*3+1][0][0])]}')
    plt.show()
```







Questions (0 points): Are the mis-classified images also misleading to human eyes?

Exercise 3: Transfer Learning (30 points)

In practice, people won't train an entire CNN from scratch, because it is relatively rare to have a dataset of sufficient size (or sufficient computational power). Instead, it is common to pretrain a CNN on a very large dataset and then use the CNN either as an initialization or a fixed feature extractor for the task of interest.

In this task, you will learn how to use a pretrained CNN for CIFAR-10 classification.

Task1: Load pretrained model

`torchvision.models` (https://pytorch.org/vision/stable/models.html (https://pytorch.org/vision/stable/models.html)) contains definitions of models for addressing different tasks, including: image classification, pixelwise semantic segmentation, object detection, instance segmentation, person keypoint detection and video classification.

First, you should load the **pretrained** ResNet-18 that has already been trained on ImageNet (https://www.image-net.org/) using `torchvision.models` . If you are interested in more details about Resnet-18, read this paper https://arxiv.org/pdf/1512.03385.pdf (https://arxiv.org/pdf/1512.03385.pdf).

In [279]:
```
# ----------- <Your code> ---------------
import torchvision.models as models

resnetClassifier = torchvision.models.resnet18(pretrained=True)
```

Task2: Create data loaders for CIFAR-10

Then you need to create a dataloader of CIFAR-10. Note that the model you load has been trained on **ImageNet** and it expects inputs as mini-batches of 3-channel RGB images of shape (3 x H x W), where H and W are expected to be **at least** 224. So you need to preprocess the CIFAR-10 data to make sure it has a height and width. See `torchvision.transforms.Resize` (https://pytorch.org/vision/stable/transforms.html#torchvision.transforms.Resize). You will probably want to add this transform appropriately to the `transform` you created in a previous task.

In [280]:
```
# ----------- <Your code> ---------------

transform = torchvision.transforms.Compose([torchvision.transforms.ToTensor(),
                    torchvision.transforms.Resize(224),
                      torchvision.transforms.Normalize((0.5, 0.5, 0.5), (0.5,
0.5, 0.5))])


train_dataset = torchvision.datasets.CIFAR10('D:\Jupyter\ECE570\Assignment-4',
train=True,
                                             download=True, transform=transfor
m)
test_dataset = torchvision.datasets.CIFAR10('D:\Jupyter\ECE570\Assignment-4',
train=False,
                                            download=True, transform=transform
)

classes = ('plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'shi
p', 'truck')


batch_size_train, batch_size_test = 64, 1000
train_loader = torch.utils.data.DataLoader(train_dataset, batch_size=batch_siz
e_train, shuffle=True) # 64 images per batch
test_loader = torch.utils.data.DataLoader(test_dataset, batch_size=batch_size_
test, shuffle=False) # 64 images per batch

print(test_loader)
```

```
Files already downloaded and verified
Files already downloaded and verified
<torch.utils.data.dataloader.DataLoader object at 0x0000017A79770988>
```

Task3: Classify test data on pretrained model

Use the model you load to classify the **test** CIFAR-10 data and print out the test accuracy.

Don't be surprised if the accuracy is bad!

In [281]:
```
# ----------- <Your code> ---------------
def train(classifier, epoch):
    classifier.train() # we need to set the mode for our model

    for batch_idx, (images, targets) in enumerate(train_loader):


        #optimizerResnet.Zero_grad()
        output = classifier(images)
        loss = F.nll_loss(output, targets) # Here is a typical loss function
 (negative log likelihood)
        loss.backward()
        optimizerResnet.step()


        if batch_idx % 10 == 0: # We record our output every 10 batches
            train_losses.append(loss.item()) # item() is to get the value of t
he tensor directly
            train_counter.append((batch_idx*64) + ((epoch-1)*len(train_loader.
dataset)))
        if batch_idx % 100 == 0: # We visulize our output every 10 batches
            print(f'Epoch {epoch}: [{batch_idx*len(images)}/{len(train_loader.
dataset)}] Loss: {loss.item()}')

def test(classifier, epoch):
    classifier.eval() # we need to set the mode for our model
    test_loss = 0
    correct = 0

    with torch.no_grad():
        for images, targets in test_loader:
            output = classifier(images)

            test_loss += F.nll_loss(output, targets, reduction='sum').item()
            pred = output.data.max(1, keepdim=True)[1] # we get the estimate o
f our result by look at the largest class value

            correct += pred.eq(targets.data.view_as(pred)).sum() # sum up the
 corrected samples

    test_loss /= len(test_loader.dataset)
    test_losses.append(test_loss)
    test_counter.append(len(train_loader.dataset)*epoch)
    print(pred)
    print(f'Test result on epoch {epoch}: Avg loss is {test_loss}, Accuracy:
 {100.*correct/len(test_loader.dataset)}%')
```

In [62]:
```
optimizerResnet = optim.SGD(resnetClassifier.parameters(), lr=0.01, momentum=
0.8)

train_losses = []
train_counter = []
test_losses = []
test_counter = []
max_epoch = 2


for epoch in range(1, max_epoch+1):
    test(resnetClassifier, epoch)
```

```
Test result on epoch 1: Avg loss is 0.473436279296875, Accuracy: 0.1000000014
9011612%
Test result on epoch 2: Avg loss is 0.473436279296875, Accuracy: 0.1000000014
9011612%
```

Task 4: Update model for CIFAR-10

Now try to improve the test accuracy. We offer several possible solutions:

(1) You can try to directly continue to train the model you load with the CIFAR-10 training data.

(2) For efficiency, you can try to freeze part of the parameters of the loaded models. For example, you can first freeze all parameters by

```
for param in model.parameters():
    param.requires_grad = False
```

and then unfreeze the last few layers by setting `somelayer.requires_grad=True` .

You are also welcome to try any other approach you can think of.

Note: You should print out the test accuracy and to get full credits, the test accuracy should be at least **80%.**

In [60]:
```
# ----------- <Your code> ---------------

for param in resnetClassifier.parameters():
    param.requires_grad = False

train_losses = []
train_counter = []
test_losses = []
test_counter = []
max_epoch = 2
count = 0

for epoch in range(1, max_epoch+1):
    train(resnetClassifier, epoch)

# Unfreaze the last 12 paramaters
for param in resnetClassifier.parameters():
    if count > 49:
        param.requires_grad=True
    count = count + 1


for epoch in range(1, max_epoch+1):
    test(resnetClassifier, epoch)
```

```
Epoch 1: [0/50000] Loss: 0.37766388058662415
Epoch 1: [6400/50000] Loss: 0.005156751722097397
Epoch 1: [12800/50000] Loss: 0.7666345834732056
Epoch 1: [19200/50000] Loss: 0.20051231980323792
Epoch 1: [25600/50000] Loss: 0.4823527932167053
Epoch 1: [32000/50000] Loss: 0.34705430269241333
Epoch 1: [38400/50000] Loss: 0.35396090149879456
Epoch 1: [44800/50000] Loss: 0.3503665030002594
Epoch 2: [0/50000] Loss: 0.9167205095291138
Epoch 2: [6400/50000] Loss: 0.712112307548523
Epoch 2: [12800/50000] Loss: 0.6144130229949951
Epoch 2: [19200/50000] Loss: 0.7184591293334961
Epoch 2: [25600/50000] Loss: 0.652016818523407
Epoch 2: [32000/50000] Loss: 0.532403290271759
Epoch 2: [38400/50000] Loss: 0.4597856104373932
Epoch 2: [44800/50000] Loss: 0.46824154257774353
Test result on epoch 1: Avg loss is 0.473436279296875, Accuracy: 0.1000000014
9011612%
Test result on epoch 2: Avg loss is 0.473436279296875, Accuracy: 0.1000000014
9011612%
```