#### 1. Import Libraries

```
In [142]:
```

```
import torch
import torch.nn as nn
import torch.optim as optim
from torchvision import datasets, transforms
from matplotlib import pyplot as plt
```

# 1. Basic Settings

```
In [143]:
```

```
batch_size = 20
learning_rate = .01
epochs = 50
```

#### 1. Prepare the Data

```
In [144]:
```

Files already downloaded and verified

# 1. Define the Module

```
In [145]:
```

```
class MLP(nn.Module):
    def init (self):
        super(MLP, self).__init_ ()
        self.model = nn.Sequential(
            nn.Linear(3072,6000),
            nn.ReLU(inplace=True),
            nn.Linear(6000,6000),
            nn.ReLU(inplace=True),
            nn.Linear(6000,6000),
            nn.ReLU(inplace=True),
            nn.Linear(6000,6000),
            nn.ReLU(inplace=True),
            nn.Linear(6000,6000),
            nn.ReLU(inplace=True),
            nn.Linear(6000,6000),
            nn.ReLU(inplace=True),
            nn.Linear(6000, 10),
    def forward(self, x):
        x = self.model(x)
        return x
```

### 1. Cuda, Optimizer, Loss Function

#### In [148]:

```
device = torch.device('cuda:0')
net = MLP().to(device)
optimizer = optim.SGD(net.parameters(), lr=learning_rate)
criteon = nn.CrossEntropyLoss().to(device)
```

# 1. Start Training

```
In [149]:
for epoch in range(epochs):
  train_loss = 0
  train acc = 0
  for data, target in train loader:
    data = data.view(-1, 32*32*3)
    data, target = data.to(device), target.to(device)
    logits = net(data)
    loss = criteon(logits, target)
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
    ,pred = logits.max(1)
    num_correct = (pred==target).sum().item()
    acc = num correct/data.shape[0]
    train acc += acc
    train loss += loss.data
  print('Train Epoch: {} Loss: {:.6f} Training Accuracy: {:.6f}'.format(epoch+1, train_los
s/len(train loader), train acc/len(train loader)))
Train Epoch: 1 Loss: 2.246491 Training Accuracy: 0.168020
Train Epoch: 2 Loss: 1.861921 Training Accuracy: 0.303680
Train Epoch: 3 Loss: 1.607362 Training Accuracy: 0.413580
Train Epoch: 4 Loss: 1.447467 Training Accuracy: 0.477280
Train Epoch: 5 Loss: 1.326011 Training Accuracy: 0.521420
Train Epoch: 6 Loss: 1.221435 Training Accuracy: 0.559900
Train Epoch: 7 Loss: 1.126308 Training Accuracy: 0.593960
Train Epoch: 8 Loss: 1.028003 Training Accuracy: 0.633300
Train Epoch: 9 Loss: 0.934547 Training Accuracy: 0.663760
Train Epoch: 10 Loss: 0.835291 Training Accuracy: 0.699140
Train Epoch: 11 Loss: 0.738954 Training Accuracy: 0.733500
Train Epoch: 12 Loss: 0.650593 Training Accuracy: 0.768420
Train Epoch: 13 Loss: 0.563912 Training Accuracy: 0.797780
Train Epoch: 14 Loss: 0.487000 Training Accuracy: 0.825580
Train Epoch: 15 Loss: 0.418204 Training Accuracy: 0.850980
Train Epoch: 16 Loss: 0.356919 Training Accuracy: 0.873760
Train Epoch: 17 Loss: 0.300846 Training Accuracy: 0.893800
Train Epoch: 18 Loss: 0.265264 Training Accuracy: 0.906880
Train Epoch: 19 Loss: 0.226921 Training Accuracy: 0.918920
Train Epoch: 20 Loss: 0.193748 Training Accuracy: 0.932980
Train Epoch: 21 Loss: 0.186749 Training Accuracy: 0.935320
Train Epoch: 22 Loss: 0.146558 Training Accuracy: 0.949020
Train Epoch: 23 Loss: 0.132519 Training Accuracy: 0.955240
Train Epoch: 24 Loss: 0.119683 Training Accuracy: 0.958940
Train Epoch: 25 Loss: 0.107644 Training Accuracy: 0.962640
Train Epoch: 26 Loss: 0.088223 Training Accuracy: 0.970040
Train Epoch: 27 Loss: 0.085317 Training Accuracy: 0.970820
Train Epoch: 28 Loss: 0.083620 Training Accuracy: 0.971540
Train Epoch: 29 Loss: 0.072746 Training Accuracy: 0.975580
Train Epoch: 30 Loss: 0.067181 Training Accuracy: 0.977040
Train Epoch: 31 Loss: 0.057029 Training Accuracy: 0.981000
Train Epoch: 32 Loss: 0.059055 Training Accuracy: 0.980640
Train Epoch: 33 Loss: 0.049335 Training Accuracy: 0.983560
Train Epoch: 34 Loss: 0.050138 Training Accuracy: 0.983720
Train Epoch: 35 Loss: 0.035821 Training Accuracy: 0.988560
Train Epoch: 36 Loss: 0.040724 Training Accuracy: 0.986380
```

Train Epoch: 37 Loss: 0.036546 Training Accuracy: 0.988260

```
Train Epoch: 38 Loss: 0.039892 Training Accuracy: 0.986860
Train Epoch: 39 Loss: 0.040126 Training Accuracy: 0.986740
Train Epoch: 40 Loss: 0.020161 Training Accuracy: 0.993620
Train Epoch: 41 Loss: 0.025165 Training Accuracy: 0.992280
Train Epoch: 42 Loss: 0.014221 Training Accuracy: 0.995540
Train Epoch: 43 Loss: 0.005151 Training Accuracy: 0.998480
Train Epoch: 44 Loss: 0.004949 Training Accuracy: 0.998660
Train Epoch: 45 Loss: 0.001692 Training Accuracy: 0.999580
Train Epoch: 46 Loss: 0.001409 Training Accuracy: 0.999540
Train Epoch: 47 Loss: 0.001348 Training Accuracy: 0.999520
Train Epoch: 48 Loss: 0.000501 Training Accuracy: 0.999840
Train Epoch: 49 Loss: 0.002131 Training Accuracy: 0.999840
Train Epoch: 50 Loss: 0.000647 Training Accuracy: 0.999860
```

#### 1. Evaluate the Model

```
In [150]:
```

```
correct = 0
for data, target in test_loader:
    data = data.view(-1, 32*32*3)
    data, target = data.to(device), target.cuda()
    logits = net(data)

    pred = logits.argmax(dim=1)
    correct += pred.eq(target).float().sum().item()

total_num = len(test_loader.dataset)
acc = correct / total_num
print('test_accuracy:', acc)
```

test accuracy: 0.5878

#### 1. Make Predictions

```
In [151]:
```

```
def plot_image(img, prediction, label):
    fig = plt.figure()
    for i in range(6):
        plt.imshow(img[i])
        plt.title("Prediction = {} Label = {}".format(prediction[i].item(),label[i].item()))
        plt.show()
```

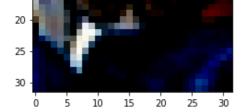
# In [153]:

```
import numpy as np
x, y = next(iter(test_loader))

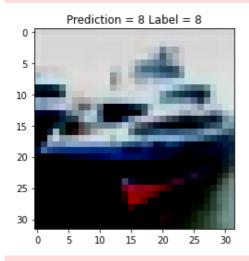
x = x.view(-1, 32*32*3)
x, y = x.to(device), y.cuda()
out = net(x)
pred = out.argmax(dim = 1)
x = x.detach().cpu().reshape((20,3,32,32)).permute(0,2,3,1).numpy()
plot_image(x, pred, y)

Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..2 55] for integers).
```

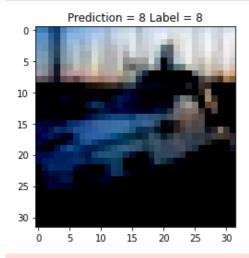
# 



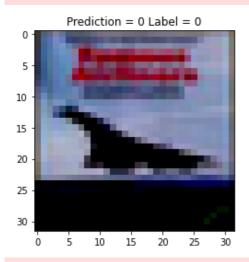
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..25] for integers).



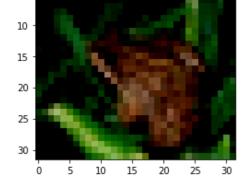
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..2 55] for integers).



Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).



Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..2 55] for integers).



Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..2 55] for integers).

