Homework 10 - CIFAR10 Image Classification with PyTorch

About

The goal of the homework is to train a convolutional neural network on the standard CIFAR10 image classfication dataset.

When solving machine learning tasks using neural networks, one typically starts with a simple network architecture and then improves the network by adding new layers, retraining, adjusting parameters, retraining, etc. We attempt to illustrate this process below with several architecture improvements.

Dev Environment

Working on Google Colab

You may choose to work locally or on Google Colaboratory. You have access to free compute through this service. Colab is recommended since it will be setup correctly and will have access to GPU resources.

1. Visit [https://colab.research.google.com/drive (https://colab.research.google.com/drive)](https://colab.research.google.com/drive)
2. Navigate to the **`Upload`** tab, and upload your `HW10.ipynb`
3. Now on the top right corner, under the `Comment` and `Share` options, you should see a `Connect` option. Once you are connected, you will have access to a VM with 12GB RAM, 50 GB disk space and a single GPU. The dropdown menu will allow you to connect to a local runtime as well.

Notes:

- **If you do not have a working setup for Python 3, this is your best bet. It will also save you from heavy installations like `tensorflow` if you don't want to deal with those.**
- ***There is a downside*. You can only use this instance for a single 12-hour stretch, after which your data will be deleted, and you would have redownload all your datasets, any libraries not already on the VM, and regenerate your logs**.

Installing PyTorch and Dependencies

The instructions for installing and setting up PyTorch can be found at [https://pytorch.org/get-started/locally/ (https://pytorch.org/get-started/locally/)](https://pytorch.org/get-started/locally/). Make sure you follow the instructions for your machine. For any of the remaining libraries used in this assignment:

- We have provided a `hw8_requirements.txt` file on the homework web page.
- Download this file, and in the same directory you can run `pip3 install -r hw8_requirements.txt` Check that PyTorch installed correctly by running the following:

In [1]:
```
import torch
torch.rand(5, 3)
```

Out[1]:
```
tensor([[0.9958, 0.9572, 0.7579],
        [0.6061, 0.3698, 0.0266],
        [0.3498, 0.0755, 0.3379],
        [0.7357, 0.7874, 0.4365],
        [0.8793, 0.5149, 0.4847]])
```

Part 0 Imports and Basic Setup (5 Points)

First, import the required libraries as follows. The libraries we will use will be the same as those in HW8.

In [0]:
```
import numpy as np
import torch
from torch import nn
from torch import optim

import matplotlib.pyplot as plt
```

GPU Support

Training of large network can take a long time. PyTorch supports GPU with just a small amount of effort.

When creating our networks, we will call `net.to(device)` to tell the network to train on the GPU, if one is available. Note, if the network utilizes the GPU, it is important that any tensors we use with it (such as the data) also reside on the CPU. Thus, a call like `images = images.to(device)` is necessary with any data we want to use with the GPU.

Note: If you can't get access to a GPU, don't worry to much. Since we use very small networks, the difference between CPU and GPU isn't large and in some cases GPU will actually be slower.

In [3]:
```
import torch.cuda as cuda

# Use a GPU, i.e. cuda:0 device if it available.
device = torch.device("cuda:0" if cuda.is_available() else "cpu")
print(device)
```

```
cuda:0
```

Training Code

In [0]:
```
import time

class Flatten(nn.Module):
  """NN Module that flattens the incoming tensor."""
  def forward(self, input):
    return input.view(input.size(0), -1)

best_acc = 0
def train(model, train_loader, test_loader, loss_func, opt, num_epochs=100,
  all_training_loss = np.zeros((0,2))
  all_training_acc = np.zeros((0,2))
  all_test_loss = np.zeros((0,2))
  all_test_acc = np.zeros((0,2))
  best_acc = 0
  training_step = 0
  training_loss, training_acc = 2.0, 0.0
  print_every = 1000

  start = time.clock()

  for i in range(start_epoch, start_epoch + num_epochs):
    epoch_start = time.clock()

    model.train()
    for images, labels in train_loader:
      images, labels = images.to(device), labels.to(device)
      opt.zero_grad()

      preds = model(images)
      loss = loss_func(preds, labels)
      loss.backward()
      opt.step()

      training_loss += loss.item()
      training_acc += (torch.argmax(preds, dim=1)==labels).float().mean()

      if training_step % print_every == 0:
        training_loss /= print_every
        training_acc /= print_every

        all_training_loss = np.concatenate((all_training_loss, [[training_s
        all_training_acc = np.concatenate((all_training_acc, [[training_ste

        print('  Epoch %d @ step %d: Train Loss: %3f, Train Accuracy: %3f'
            i, training_step, training_loss, training_acc))
        training_loss, training_acc = 0.0, 0.0

      training_step+=1

    model.eval()
    with torch.no_grad():
      validation_loss, validation_acc = 0.0, 0.0
      count = 0
      for images, labels in test_loader:
        images, labels = images.to(device), labels.to(device)
        output = model(images)
```

```
            validation_loss+=loss_func(output,labels)
            validation_acc+=(torch.argmax(output, dim=1) == labels).float().mea
            count += 1
          validation_loss/=count
          validation_acc/=count

          all_test_loss = np.concatenate((all_test_loss, [[training_step, valid
          all_test_acc = np.concatenate((all_test_acc, [[training_step, validat

          epoch_time = time.clock() - epoch_start

          print('Epoch %d Test Loss: %3f, Test Accuracy: %3f, time: %.1fs' % (
              i, validation_loss, validation_acc, epoch_time))

         # Save checkpoint.
        acc = validation_acc
        if acc > best_acc:
          print('Prev accuracy: %3f ; Current accuracy: %3f' %(best_acc, acc))
        if enable_saving and acc > best_acc:
            print('Saving..')
            state = {
                'model': model.state_dict(),
                'acc': acc,
                'epoch': i,
            }
            torch.save(state, './ckpt.t7')
            best_acc = acc

    total_time = time.clock() - start
    print('Final Test Loss: %3f, Test Accuracy: %3f, Total time: %.1fs' % (
        validation_loss, validation_acc, total_time))

    return {'loss': { 'train': all_training_loss, 'test': all_test_loss },
            'accuracy': { 'train': all_training_acc, 'test': all_test_acc }}

def plot_graphs(model_name, metrics):
  for metric, values in metrics.items():
    for name, v in values.items():
      plt.plot(v[:,0], v[:,1], label=name)
    plt.title(f'{metric} for {model_name}')
    plt.legend()
    plt.xlabel("Training Steps")
    plt.ylabel(metric)
    plt.show()
```

Load the** CIFA-10** dataset and define the transformations. You may also want to print its structure, size, as well as sample a few images to get a sense of how to design the network.

In [0]:
```
!mkdir hw10_data
```

In [6]:
```
# Download the data.
from torchvision import datasets, transforms

transformations = transforms.Compose(
    [transforms.ToTensor(),
     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])
train_set = datasets.CIFAR10(root='hw10_data/', download=True, transform=tr
test_set = datasets.CIFAR10(root='hw10_data', download=True, train=False, t
```

```
  0%|          | 0/170498071 [00:00<?, ?it/s]

Downloading https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz (http
s://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz) to hw10_data/cifar-1
0-python.tar.gz

100%|█████████▉| 170090496/170498071 [00:15<00:00, 8391534.97it/s]

Files already downloaded and verified
```

Use `DataLoader` to create a loader for the training set and a loader for the testing set. You can use a `batch_size` of 8 to start, and change it if you wish.

In [7]:
```
from torch.utils.data import DataLoader

batch_size = 8
train_loader = torch.utils.data.DataLoader(train_set, batch_size, shuffle=T
test_loader = torch.utils.data.DataLoader(test_set, batch_size, shuffle=Tru

input_shape = np.array(train_set[0][0]).shape
print(input_shape)
input_dim = input_shape[1]*input_shape[2]*input_shape[0]
```

```
(3, 32, 32)
```

In [0]:
```
training_epochs = 5
```

Part 1 CIFAR10 with Fully Connected Neural Netowrk (25 Points)

As a warm-up, let's begin by training a two-layer fully connected neural network model on ** CIFAR-10** dataset. You may go back to check HW8 for some basics.

We will give you this code to use as a baseline to compare against your CNN models.

In [9]:
```
class TwoLayerModel(nn.Module):
  def __init__(self):
    super(TwoLayerModel, self).__init__()
    self.net = nn.Sequential(
      Flatten(),
      nn.Linear(input_dim, 64),
      nn.ReLU(),
      nn.Linear(64, 10))

  def forward(self, x):
    return self.net(x)

model = TwoLayerModel().to(device)

loss = nn.CrossEntropyLoss()
optimizer = optim.RMSprop(model.parameters(), lr=0.001, weight_decay=0.01)

# Training epoch should be about 15-20 sec each on GPU.
metrics = train(model, train_loader, test_loader, loss, optimizer, training
```

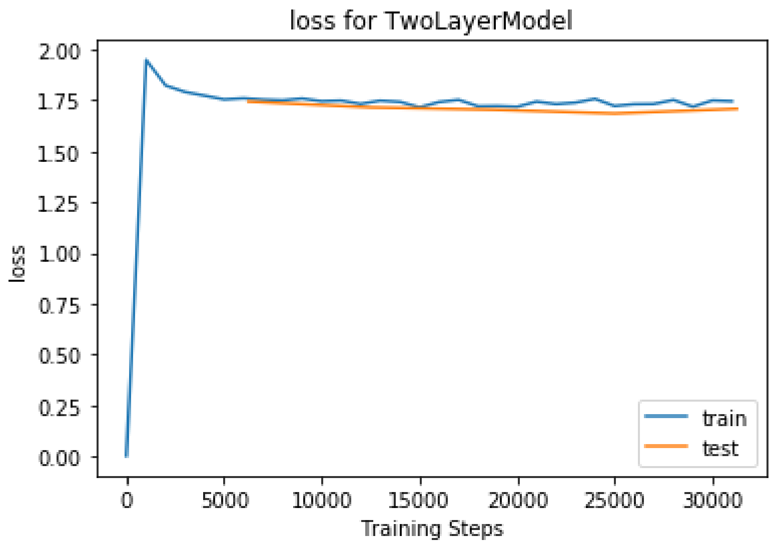
```
  Epoch 0 @ step 0: Train Loss: 0.004340, Train Accuracy: 0.000000
  Epoch 0 @ step 1000: Train Loss: 1.946467, Train Accuracy: 0.329000

170500096it [00:30, 8391534.97it/s]

  Epoch 0 @ step 2000: Train Loss: 1.820833, Train Accuracy: 0.349625
  Epoch 0 @ step 3000: Train Loss: 1.788873, Train Accuracy: 0.362125
  Epoch 0 @ step 4000: Train Loss: 1.770899, Train Accuracy: 0.372125
  Epoch 0 @ step 5000: Train Loss: 1.752406, Train Accuracy: 0.370500
  Epoch 0 @ step 6000: Train Loss: 1.758057, Train Accuracy: 0.375125
Epoch 0 Test Loss: 1.741880, Test Accuracy: 0.376500, time: 17.3s
  Epoch 1 @ step 7000: Train Loss: 1.751309, Train Accuracy: 0.377000
  Epoch 1 @ step 8000: Train Loss: 1.748058, Train Accuracy: 0.370875
  Epoch 1 @ step 9000: Train Loss: 1.756846, Train Accuracy: 0.371500
  Epoch 1 @ step 10000: Train Loss: 1.743470, Train Accuracy: 0.379750
  Epoch 1 @ step 11000: Train Loss: 1.746668, Train Accuracy: 0.376000
  Epoch 1 @ step 12000: Train Loss: 1.730267, Train Accuracy: 0.387000
Epoch 1 Test Loss: 1.713121, Test Accuracy: 0.386700, time: 16.4s
  Epoch 2 @ step 13000: Train Loss: 1.746124, Train Accuracy: 0.378250
  Epoch 2 @ step 14000: Train Loss: 1.740328, Train Accuracy: 0.391875
  Epoch 2 @ step 15000: Train Loss: 1.713558, Train Accuracy: 0.387125
  Epoch 2 @ step 16000: Train Loss: 1.739471, Train Accuracy: 0.381250
  Epoch 2 @ step 17000: Train Loss: 1.750356, Train Accuracy: 0.373000
  Epoch 2 @ step 18000: Train Loss: 1.718776, Train Accuracy: 0.395625
Epoch 2 Test Loss: 1.701751, Test Accuracy: 0.393400, time: 16.4s
  Epoch 3 @ step 19000: Train Loss: 1.719814, Train Accuracy: 0.383750
  Epoch 3 @ step 20000: Train Loss: 1.716075, Train Accuracy: 0.394250
  Epoch 3 @ step 21000: Train Loss: 1.741589, Train Accuracy: 0.388000
  Epoch 3 @ step 22000: Train Loss: 1.729419, Train Accuracy: 0.377625
  Epoch 3 @ step 23000: Train Loss: 1.736583, Train Accuracy: 0.377500
  Epoch 3 @ step 24000: Train Loss: 1.755096, Train Accuracy: 0.380250
Epoch 3 Test Loss: 1.683128, Test Accuracy: 0.398900, time: 17.4s
  Epoch 4 @ step 25000: Train Loss: 1.720132, Train Accuracy: 0.382750
  Epoch 4 @ step 26000: Train Loss: 1.729002, Train Accuracy: 0.382875
  Epoch 4 @ step 27000: Train Loss: 1.729874, Train Accuracy: 0.384875
  Epoch 4 @ step 28000: Train Loss: 1.749811, Train Accuracy: 0.383750
  Epoch 4 @ step 29000: Train Loss: 1.716631, Train Accuracy: 0.392750
```

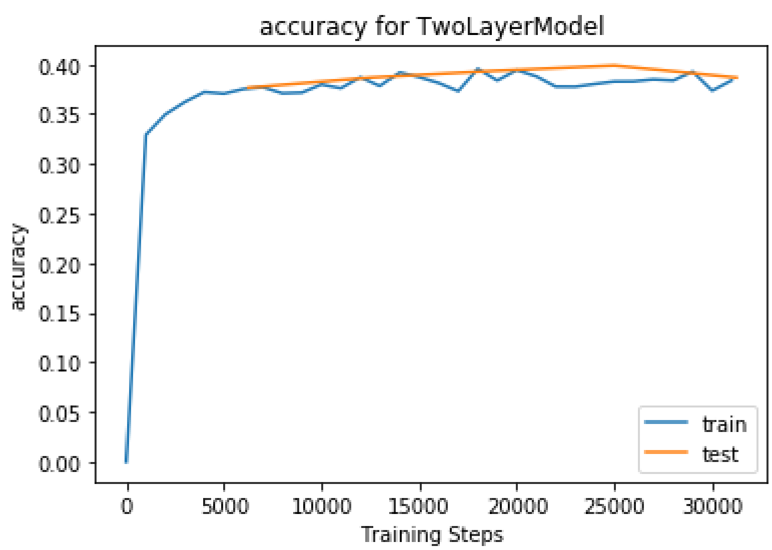
```
  Epoch 4 @ step 30000: Train Loss: 1.747359, Train Accuracy: 0.373500
  Epoch 4 @ step 31000: Train Loss: 1.743549, Train Accuracy: 0.383875
Epoch 4 Test Loss: 1.706095, Test Accuracy: 0.386700, time: 17.0s
Final Test Loss: 1.706095, Test Accuracy: 0.386700, Total time: 84.5s
```

Plot the model results

Normally we would want to use Tensorboard for looking at metrics. However, if colab reset while we are working, we might lose our logs and therefore our metrics. Let's just plot some graphs that will survive across colab instances.

In [10]:
```
plot_graphs("TwoLayerModel", metrics)
```





Part 2 Convolutional Neural Network (CNN) (35 Points)

Now, let's design a convolution neural netwrok!

Build a simple CNN model, inserting 2 CNN layers in from of our 2 layer fully connect model from above:

1. A convolution with 3x3 filter, 16 output channels, stride = 1, padding=1
2. A ReLU activation
3. A Max-Pooling layer with 2x2 window
4. A convolution, 3x3 filter, 16 output channels, stride = 1, padding=1
5. A ReLU activation
6. Flatten layer
7. Fully connected linear layer with output size 64
8. ReLU
9. Fully connected linear layer, with output size 10

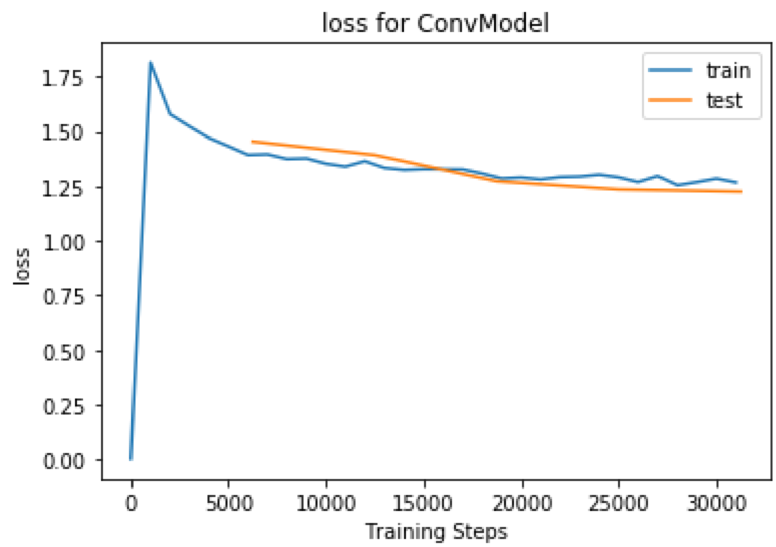
You will have to figure out the input sizes of the first fully connnected layer based on the previous layer sizes. Note that you also need to fill those in the report section (see report section in the notebook for details)

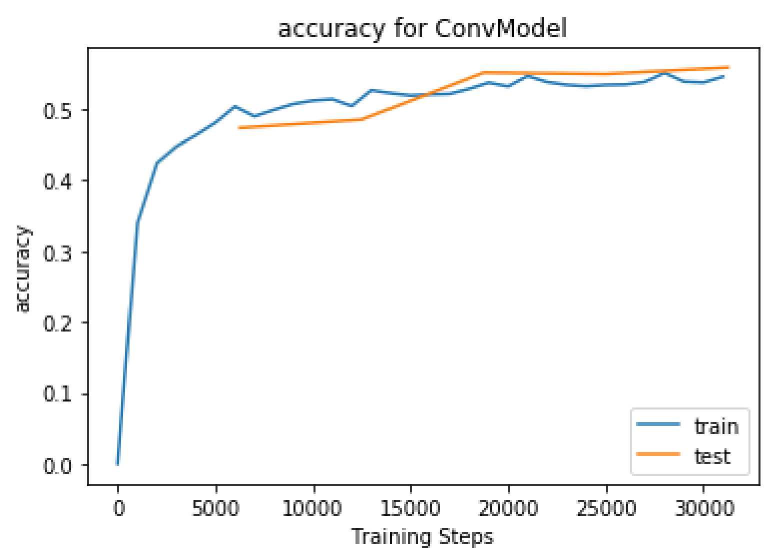
In [11]:
```
class ConvModel(nn.Module):
    def __init__(self):
        super(ConvModel, self).__init__()

        self.layer1 = nn.Sequential(
            nn.Conv2d(3, 16, kernel_size=(3,3), stride=1, padding=1),
            nn.ReLU(),
            nn.MaxPool2d(2),
            nn.Conv2d(16, 16, kernel_size=(3,3), stride=1, padding=1),
            nn.ReLU(),
            Flatten()
        )
        self.layer2 = nn.Sequential(
            nn.Linear(4096, 64),
            nn.ReLU(),
            nn.Linear(64, 10)
        )


    def forward(self, x):
        x = self.layer1(x)
        #x = x.view(512, 64)
        x = self.layer2(x)
        return(x)


model = ConvModel().to(device)

loss = nn.CrossEntropyLoss()
optimizer = optim.RMSprop(model.parameters(), lr=0.001, weight_decay=0.01)

metrics = train(model, train_loader, test_loader, loss, optimizer, training
```

```
  Epoch 0 @ step 0: Train Loss: 0.004280, Train Accuracy: 0.000125
  Epoch 0 @ step 1000: Train Loss: 1.814721, Train Accuracy: 0.340000
  Epoch 0 @ step 2000: Train Loss: 1.579486, Train Accuracy: 0.424500
  Epoch 0 @ step 3000: Train Loss: 1.523278, Train Accuracy: 0.447625
  Epoch 0 @ step 4000: Train Loss: 1.469823, Train Accuracy: 0.463625
  Epoch 0 @ step 5000: Train Loss: 1.431902, Train Accuracy: 0.481125
  Epoch 0 @ step 6000: Train Loss: 1.392955, Train Accuracy: 0.503750
Epoch 0 Test Loss: 1.453382, Test Accuracy: 0.473600, time: 23.8s
  Epoch 1 @ step 7000: Train Loss: 1.395619, Train Accuracy: 0.489875
  Epoch 1 @ step 8000: Train Loss: 1.374484, Train Accuracy: 0.499000
  Epoch 1 @ step 9000: Train Loss: 1.377012, Train Accuracy: 0.507250
  Epoch 1 @ step 10000: Train Loss: 1.353213, Train Accuracy: 0.512000
  Epoch 1 @ step 11000: Train Loss: 1.340086, Train Accuracy: 0.514000
  Epoch 1 @ step 12000: Train Loss: 1.364718, Train Accuracy: 0.504375
Epoch 1 Test Loss: 1.392499, Test Accuracy: 0.485300, time: 24.3s
  Epoch 2 @ step 13000: Train Loss: 1.333992, Train Accuracy: 0.526625
  Epoch 2 @ step 14000: Train Loss: 1.324994, Train Accuracy: 0.522375
  Epoch 2 @ step 15000: Train Loss: 1.328469, Train Accuracy: 0.519250
  Epoch 2 @ step 16000: Train Loss: 1.328187, Train Accuracy: 0.520750
  Epoch 2 @ step 17000: Train Loss: 1.327326, Train Accuracy: 0.521500
  Epoch 2 @ step 18000: Train Loss: 1.308332, Train Accuracy: 0.528625
Epoch 2 Test Loss: 1.273093, Test Accuracy: 0.551600, time: 23.7s
  Epoch 3 @ step 19000: Train Loss: 1.285880, Train Accuracy: 0.537375
  Epoch 3 @ step 20000: Train Loss: 1.290305, Train Accuracy: 0.532125
```

```
  Epoch 3 @ step 21000: Train Loss: 1.281676, Train Accuracy: 0.546875
  Epoch 3 @ step 22000: Train Loss: 1.292151, Train Accuracy: 0.538250
  Epoch 3 @ step 23000: Train Loss: 1.294391, Train Accuracy: 0.534250
  Epoch 3 @ step 24000: Train Loss: 1.302860, Train Accuracy: 0.532375
Epoch 3 Test Loss: 1.235892, Test Accuracy: 0.549600, time: 25.8s
  Epoch 4 @ step 25000: Train Loss: 1.290988, Train Accuracy: 0.534125
  Epoch 4 @ step 26000: Train Loss: 1.269605, Train Accuracy: 0.534625
  Epoch 4 @ step 27000: Train Loss: 1.296589, Train Accuracy: 0.538375
  Epoch 4 @ step 28000: Train Loss: 1.255024, Train Accuracy: 0.551250
  Epoch 4 @ step 29000: Train Loss: 1.269300, Train Accuracy: 0.538875
  Epoch 4 @ step 30000: Train Loss: 1.285277, Train Accuracy: 0.537625
  Epoch 4 @ step 31000: Train Loss: 1.267735, Train Accuracy: 0.545875
Epoch 4 Test Loss: 1.225984, Test Accuracy: 0.558800, time: 24.9s
Final Test Loss: 1.225984, Test Accuracy: 0.558800, Total time: 122.4s
```

In [12]:
```
plot_graphs("ConvModel", metrics)
```





Do you notice the improvement over the accuracy compared to that in Part 1?

Yes, there is around 17% improvement due to the more complex network having convolution.

Part 3 Open Design Competition (35 Points + 10 bonus points)

Try to beat the previous models by adding additional layers, changing parameters, etc. You should add at least one layer.

Possible changes include:

- Dropout
- Batch Normalization
- More layers
- Residual Connections (harder)
- Change layer size
- Pooling layers, stride
- Different optimizer
- Train for longer

Once you have a model you think is great, evaluate it against our hidden test data (see hidden_loader above) and upload the results to the leader board on gradescope. **The top 3 scorers will get a bonus 10 points.**

You can steal model structures found on the internet if you want. The only constraint is that **you must train the model from scratch**.

In [5]:
```
import torch.nn as nn
import torch.nn.functional as F
import torchvision.transforms as transforms
import torchvision
import torch.backends.cudnn as cudnn
import torch.optim as optim
device = 'cuda' if torch.cuda.is_available() else 'cpu'

import os
import sys
import time
import math
import numpy as np
import torch.nn.init as init


class Bottleneck(nn.Module):
    def __init__(self, last_planes, in_planes, out_planes, dense_depth, str
        super(Bottleneck, self).__init__()
        self.out_planes = out_planes
        self.dense_depth = dense_depth

        self.conv1 = nn.Conv2d(last_planes, in_planes, kernel_size=1, bias=
        self.bn1 = nn.BatchNorm2d(in_planes)
        self.conv2 = nn.Conv2d(in_planes, in_planes, kernel_size=3, stride=
        self.bn2 = nn.BatchNorm2d(in_planes)
        self.conv3 = nn.Conv2d(in_planes, out_planes+dense_depth, kernel_si
        self.bn3 = nn.BatchNorm2d(out_planes+dense_depth)

        self.shortcut = nn.Sequential()
        if first_layer:
            self.shortcut = nn.Sequential(
                nn.Conv2d(last_planes, out_planes+dense_depth, kernel_size=
                nn.BatchNorm2d(out_planes+dense_depth)
            )

    def forward(self, x):
        out = F.relu(self.bn1(self.conv1(x)))
        out = F.relu(self.bn2(self.conv2(out)))
        out = self.bn3(self.conv3(out))
        x = self.shortcut(x)
        d = self.out_planes
        out = torch.cat([x[:,:d,:,:]+out[:,:d,:,:], x[:,d:,:,:], out[:,d:,:
        out = F.relu(out)
        return out


class AwesomeModel(nn.Module):
    def __init__(self):
        super(AwesomeModel, self).__init__()
        in_planes= (96,192,384,768)
        out_planes = (256,512,1024,2048)
        num_blocks = (3,4,20,3)
        dense_depth = (16,32,24,128)

        self.conv1 = nn.Conv2d(3, 64, kernel_size=3, stride=1, padding=1, b
```

```
        self.bn1 = nn.BatchNorm2d(64)
        self.last_planes = 64
        self.layer1 = self._make_layer(in_planes[0], out_planes[0], num_blc
        self.layer2 = self._make_layer(in_planes[1], out_planes[1], num_blc
        self.layer3 = self._make_layer(in_planes[2], out_planes[2], num_blc
        self.layer4 = self._make_layer(in_planes[3], out_planes[3], num_blc
        self.linear = nn.Linear(out_planes[3]+(num_blocks[3]+1)*dense_depth

    def _make_layer(self, in_planes, out_planes, num_blocks, dense_depth, s
        strides = [stride] + [1]*(num_blocks-1)
        layers = []
        for i,stride in enumerate(strides):
            layers.append(Bottleneck(self.last_planes, in_planes, out_plane
            self.last_planes = out_planes + (i+2) * dense_depth
        return nn.Sequential(*layers)

    def forward(self, x):
        out = F.relu(self.bn1(self.conv1(x)))
        out = self.layer1(out)
        out = self.layer2(out)
        out = self.layer3(out)
        out = self.layer4(out)
        out = F.avg_pool2d(out, 4)
        out = out.view(out.size(0), -1)
        out = self.linear(out)
        return out


best_acc = 0  # best test accuracy
start_epoch = 0  # start from epoch 0 or last checkpoint epoch

# Data
print('==> Preparing data..')
transform_train = transforms.Compose([
    transforms.RandomCrop(32, padding=4),
    transforms.RandomHorizontalFlip(),
    transforms.ToTensor(),
    transforms.Normalize((0.4914, 0.4822, 0.4465), (0.2023, 0.1994, 0.2010)
])

transform_test = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize((0.4914, 0.4822, 0.4465), (0.2023, 0.1994, 0.2010)
])

batch_size = 64
trainset = torchvision.datasets.CIFAR10(root='./data', train=True, download
trainloader = torch.utils.data.DataLoader(trainset, batch_size=batch_size, 

testset = torchvision.datasets.CIFAR10(root='./data', train=False, download
testloader = torch.utils.data.DataLoader(testset, batch_size=batch_size, sh

# Model
print('==> Building model..')

model = AwesomeModel()
model = model.to(device)
```

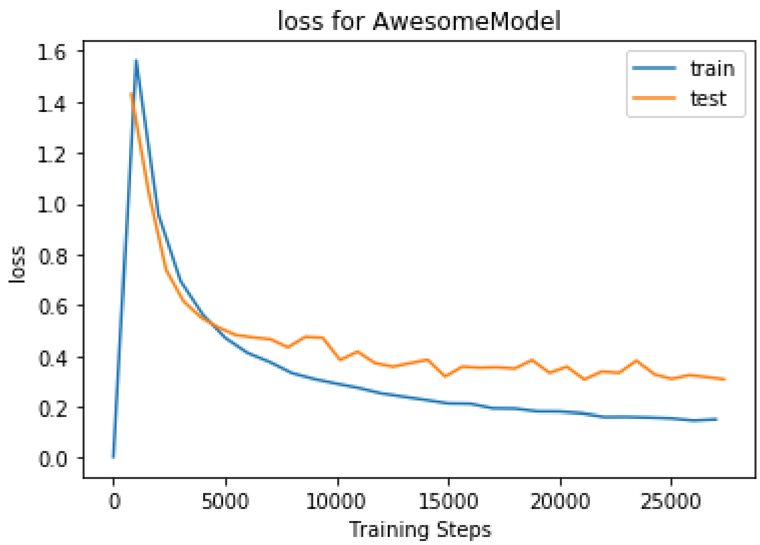
```
if device == 'cuda':
    model = torch.nn.DataParallel(model)
    cudnn.benchmark = True



criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(model.parameters(), lr=0.01, momentum=0.9, weight_dec

if False:
    # Load checkpoint.
    print('==> Resuming from checkpoint..')
    checkpoint = torch.load('./ckpt.t7')
    model.load_state_dict(checkpoint['model'])
    best_acc = checkpoint['acc']
    start_epoch = checkpoint['epoch']

training_epochs = 35
metrics = train(model, trainloader, testloader, criterion, optimizer, train
```

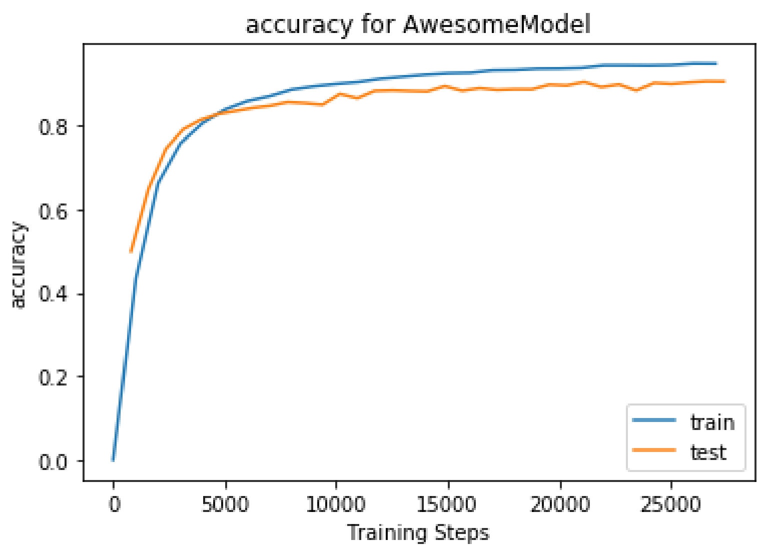
```
  Epoch 24 @ step 19000: Train Loss: 0.181935, Train Accuracy: 0.936438
Epoch 24 Test Loss: 0.333184, Test Accuracy: 0.898189, time: 464.1s
  Epoch 25 @ step 20000: Train Loss: 0.181344, Train Accuracy: 0.936906
Epoch 25 Test Loss: 0.357318, Test Accuracy: 0.896298, time: 463.7s
  Epoch 26 @ step 21000: Train Loss: 0.174920, Train Accuracy: 0.938438
Epoch 26 Test Loss: 0.307053, Test Accuracy: 0.904658, time: 464.3s
Epoch 27 Test Loss: 0.338248, Test Accuracy: 0.892416, time: 464.0s
  Epoch 28 @ step 22000: Train Loss: 0.160740, Train Accuracy: 0.944594
Epoch 28 Test Loss: 0.333181, Test Accuracy: 0.898786, time: 464.1s
  Epoch 29 @ step 23000: Train Loss: 0.161144, Train Accuracy: 0.944609
Epoch 29 Test Loss: 0.380991, Test Accuracy: 0.884256, time: 463.8s
  Epoch 30 @ step 24000: Train Loss: 0.158781, Train Accuracy: 0.944266
Epoch 30 Test Loss: 0.327186, Test Accuracy: 0.902369, time: 463.8s
  Epoch 31 @ step 25000: Train Loss: 0.155592, Train Accuracy: 0.945156
Epoch 31 Test Loss: 0.309503, Test Accuracy: 0.899980, time: 464.0s
Epoch 32 Test Loss: 0.324250, Test Accuracy: 0.903662, time: 463.8s
  Epoch 33 @ step 26000: Train Loss: 0.147245, Train Accuracy: 0.948938
Epoch 33 Test Loss: 0.316644, Test Accuracy: 0.906250, time: 463.6s
  Epoch 34 @ step 27000: Train Loss: 0.151895, Train Accuracy: 0.948641
Epoch 34 Test Loss: 0.307930, Test Accuracy: 0.905852, time: 463.5s
```

What changes did you make to improve your model?

Data Normalization, running for more Epochs(~140), pickeling(saving) the model every time the produces accuracy which is more than the current best result. Using Stochastic Gradient Descent as optimizer. In terms of the network I added more layers, batch 2d normalization, and average pooling.

In [6]:
```
plot_graphs("AwesomeModel", metrics)
```





After you get a nice model, download the test_file.zip and unzip it to get test_file.pt. In colab, you can explore your files from the left side bar. You can also download the files to your machine from there.

In [7]:
```
!wget http://courses.engr.illinois.edu/cs498aml/sp2019/homeworks/test_file.
!unzip test_file.zip
```

```
--2019-04-29 23:42:22--  http://courses.engr.illinois.edu/cs498aml/sp201
9/homeworks/test_file.zip (http://courses.engr.illinois.edu/cs498aml/sp20
19/homeworks/test_file.zip)
Resolving courses.engr.illinois.edu (courses.engr.illinois.edu)... 130.12
6.151.9
Connecting to courses.engr.illinois.edu (courses.engr.illinois.edu)|130.1
26.151.9|:80... connected.
HTTP request sent, awaiting response... 301 Moved Permanently
Location: https://courses.engr.illinois.edu/cs498aml/sp2019/homeworks/tes
t_file.zip (https://courses.engr.illinois.edu/cs498aml/sp2019/homeworks/t
est_file.zip) [following]
--2019-04-29 23:42:22--  https://courses.engr.illinois.edu/cs498aml/sp201
9/homeworks/test_file.zip (https://courses.engr.illinois.edu/cs498aml/sp2
019/homeworks/test_file.zip)
Connecting to courses.engr.illinois.edu (courses.engr.illinois.edu)|130.1
26.151.9|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 3841776 (3.7M) [application/x-zip-compressed]
Saving to: ‘test_file.zip’

test_file.zip       100%[===================>]   3.66M  13.0MB/s    in 0.
3s

2019-04-29 23:42:23 (13.0 MB/s) - ‘test_file.zip’ saved [3841776/3841776]

Archive:  test_file.zip
  inflating: test_file.pt
```

Then use your model to predict the label of the test images. Fill the remaining code below, where x has two dimensions (batch_size x one image size). Remember to reshpe x accordingly before feeding it into your model. The submission.txt should contain one predicted label (0~9) each line. Submit your submission.txt to the competition in gradscope.

In [8]:
```
import torch.utils.data as Data

test_file = './test_file.pt'
pred_file = './submission.txt'
f_pred = open(pred_file,'w')
tensor = torch.load(test_file)

torch_dataset = Data.TensorDataset(tensor)
test_loader = torch.utils.data.DataLoader(torch_dataset, 64, shuffle=False,

for ele in test_loader:
    x = ele[0]
    for image in x:
      image = image.reshape((1, 3, 32, 32))
      image = image.to(device)
      prediction = model(image)
      _, predicted = torch.max(prediction, dim=1)
      predicted = predicted.tolist()[0]
      f_pred.write(str(predicted))
      f_pred.write('\n')

f_pred.close()
print('Done!')
```

```
Done!
```

Report

Part 0: Imports and Basic Setup (5 Points)

Nothing to report for this part. You will be just scored for finishing the setup.

Part 1: Fully connected neural networks (25 Points)

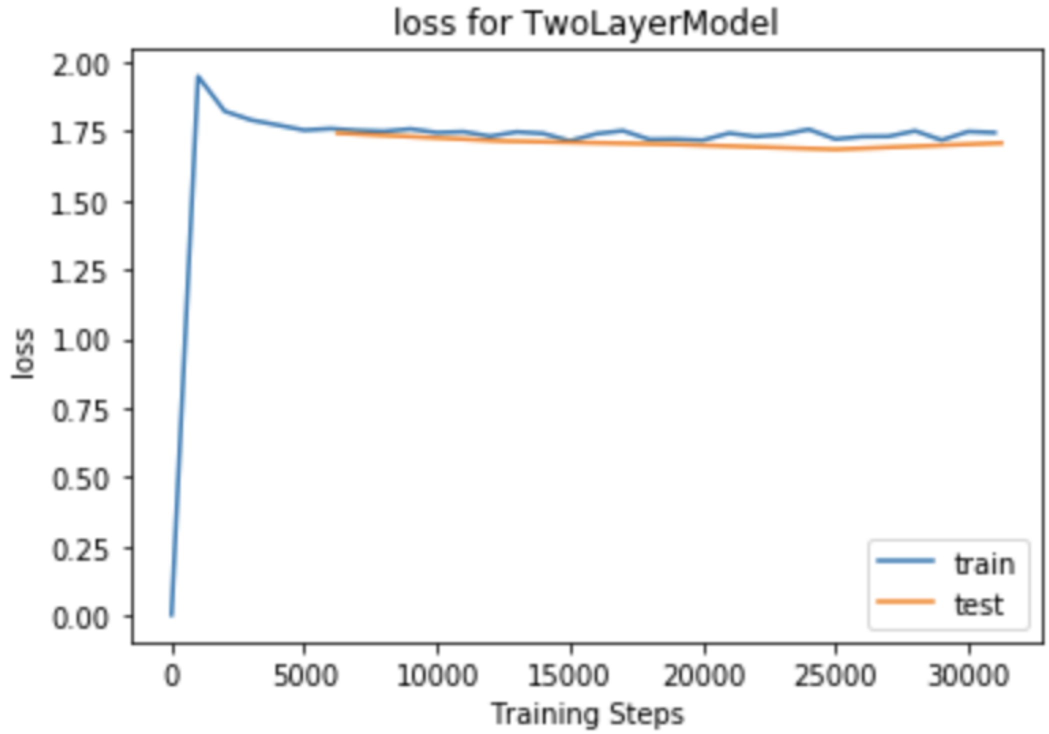
Test (on validation set) accuracy (5 Points):0.393000

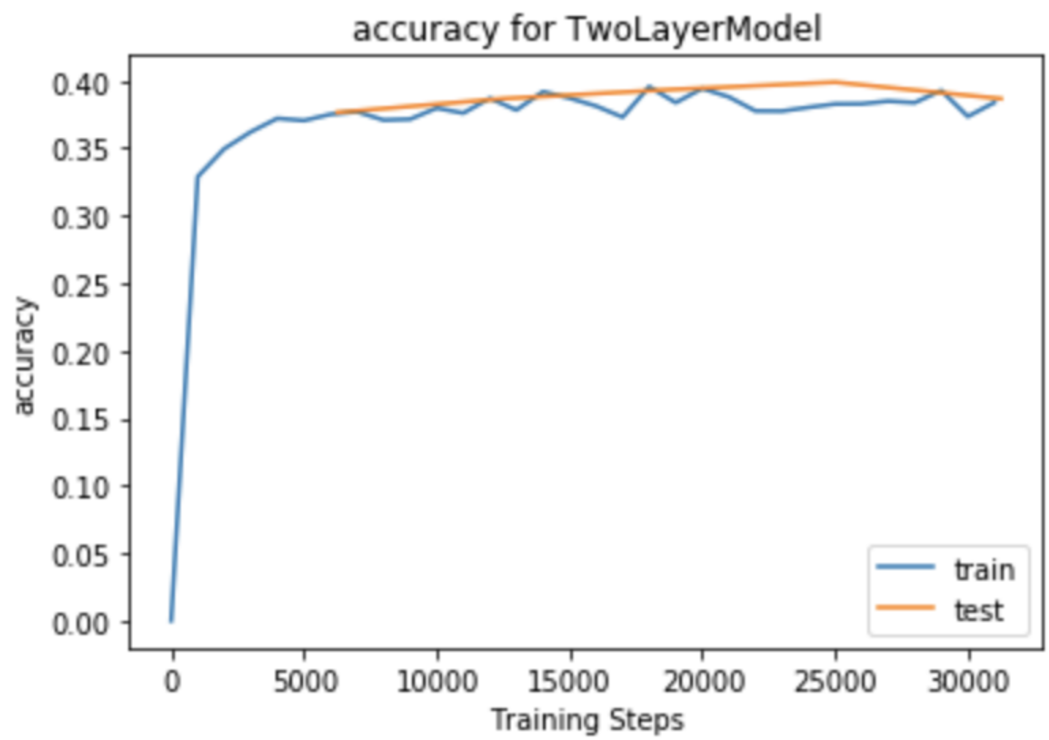
Test loss (5 Points):1.710990

Training time (5 Points):84.4s/epoch

Plots:

- For both accuracy and loss plots on validation set vs training steps please see above or:





Part 2: Convolution Network (Basic) (35 Points)

Tensor dimensions: A good way to debug your network for size mismatches is to print the dimension of output after every layers:

(10 Points)

Output dimension after 1st conv layer: tensor with size [8, 16, 32, 32]

Output dimension after 1st max pooling: tensor with size [8, 16, 16, 16]

Output dimension after 2nd conv layer: tensor with size [8, 16, 32, 32]

Output dimension after flatten layer: tensor with size [8, 4096]

Output dimension after 1st fully connected layer: [8, 64]

Output dimension after 2nd fully connected layer: [8, 10]

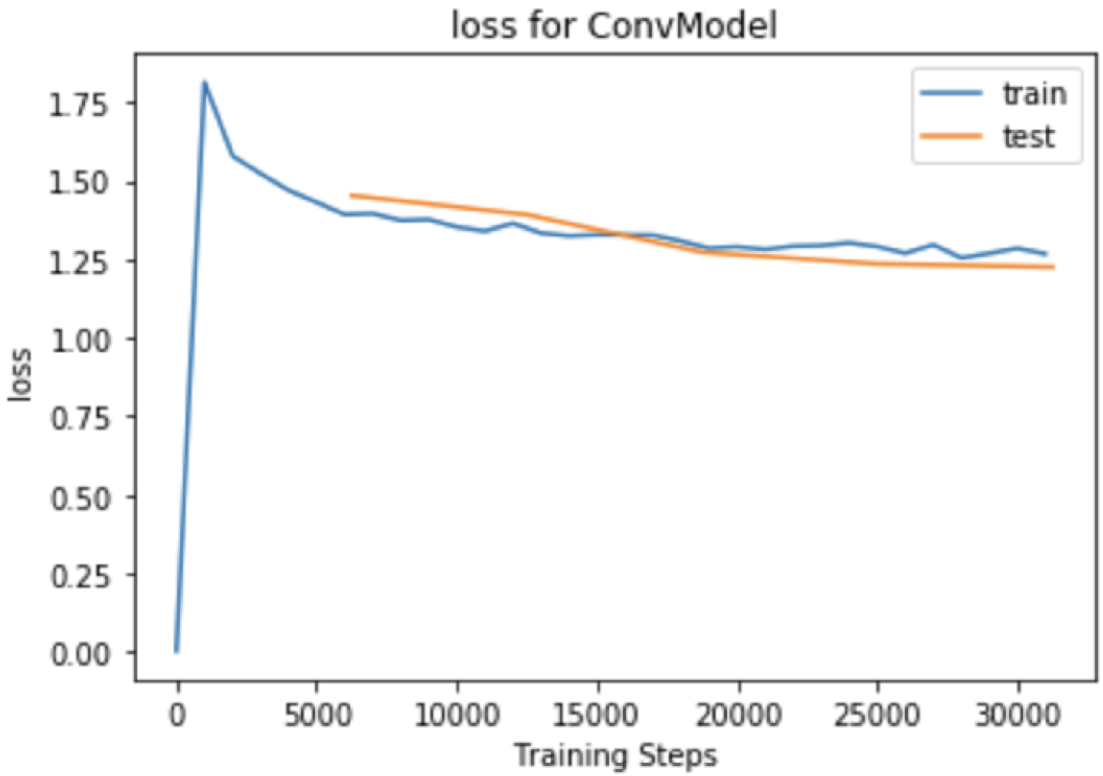
Test (on validation set) Accuracy (5 Points):0.544800

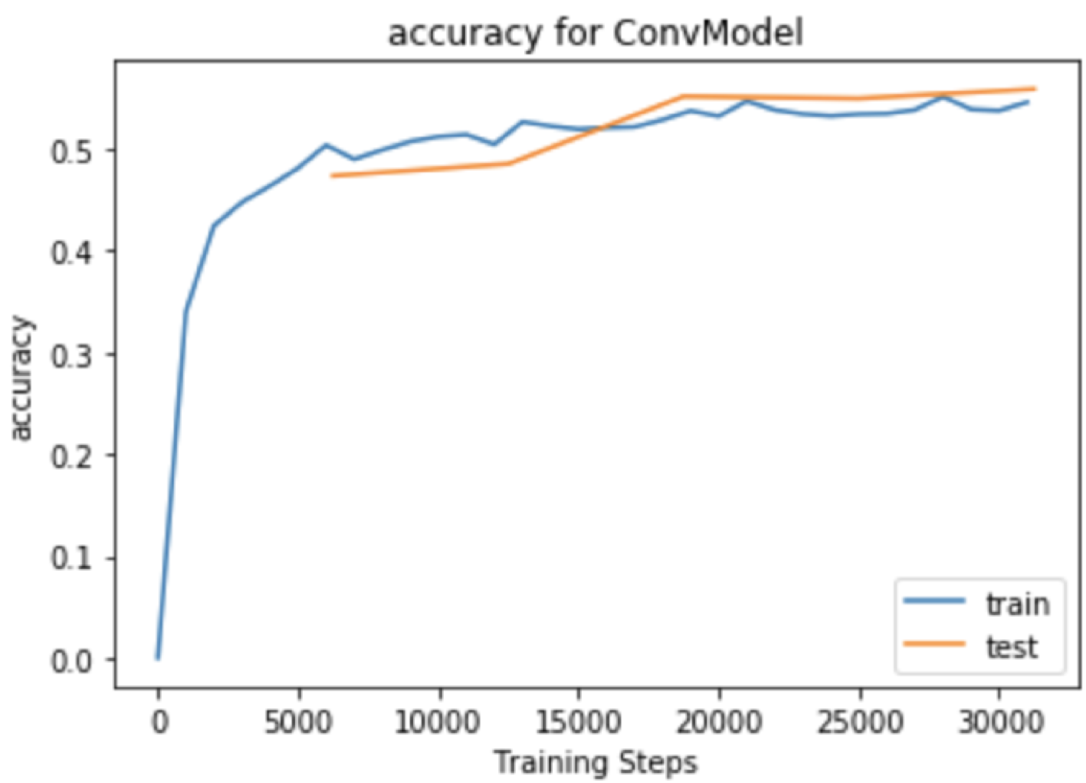
Test loss (5 Points):1.254007

Training time (5 Points):123.2s/epoch

Plots:

- For both accuracy and loss plots on validation set vs training steps please see above or:





Part 3: Convolution Network (Add one or more suggested changes) (35 Points)

Describe the additional changes implemented, your intuition for as to why it works, you may also describe other approaches you experimented with (10 Points):

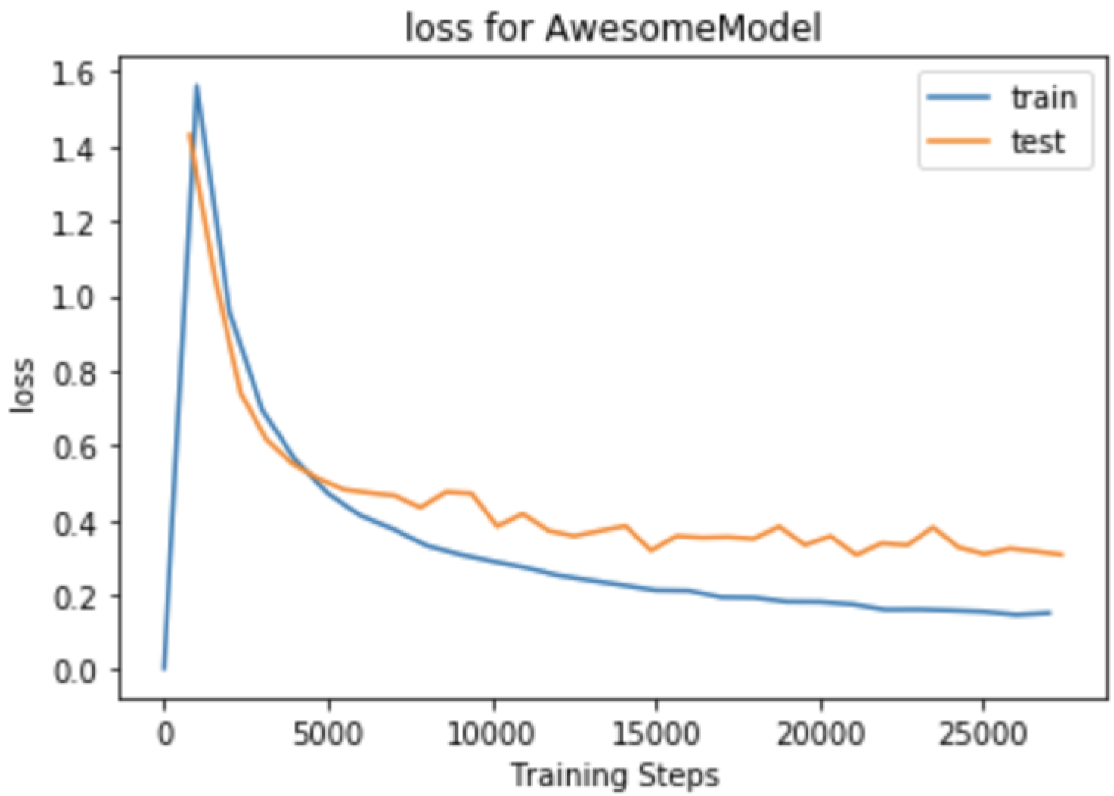
Test (on validation set) Accuracy (5 Points): 86.6%. Leader board name: yan

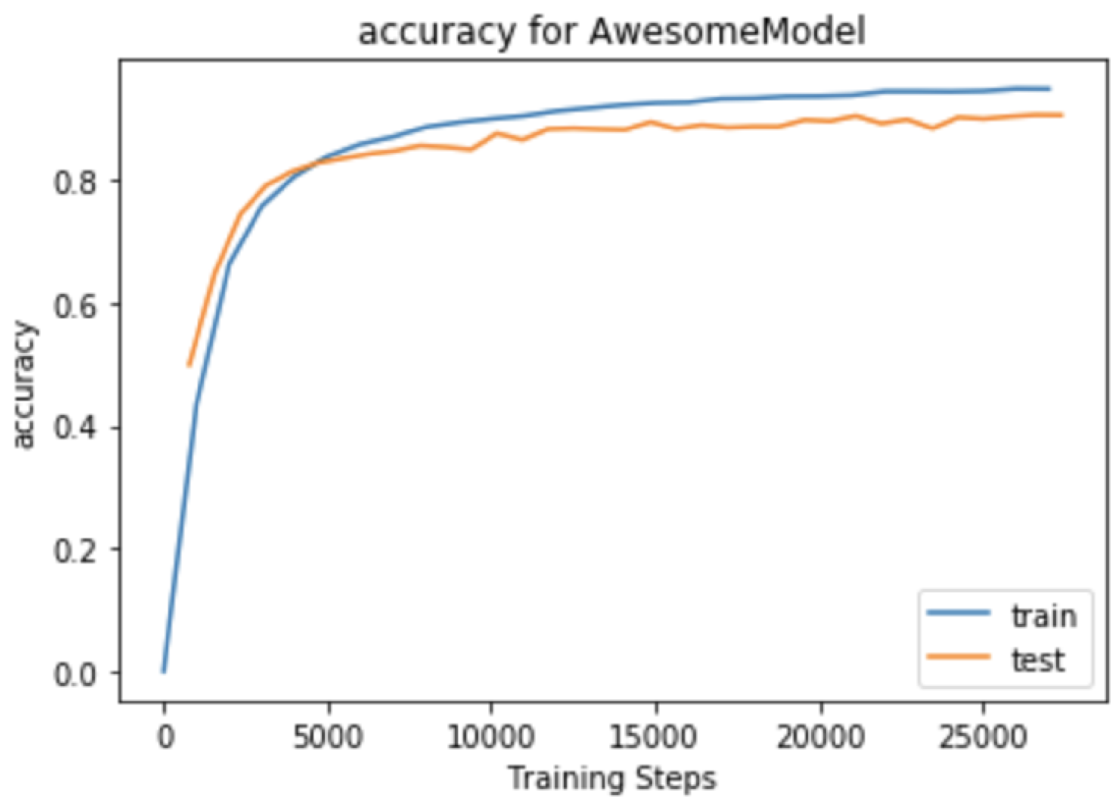
Test loss (5 Points):0.308

Training time (5 Points):463s/epoch Trained more than 140 epochs with model checkpoint saving.

Plots:

- For both accuracy and loss plots on validation set vs training steps please see above or:





10 bonus points will be awarded to top 3 scorers on leaderboard (in case of tie for 3rd position everyone tied for 3rd position will get the bonus)

On the following screenshot you can see the training including checkpoint saving the model in t7 format. This helped a lot in case of Google Colab resets my session :)

ble of contents Code snippets Files

JPLOAD REFRESH

..
data
sample_data
ckpt_118.t7
ckpt_137.t7

_137.t7

[6]

```
0it [00:00, ?it/s]==> Preparing data..
Downloading https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz to ./data/cifar-10-python.tar.gz
100%|██████████| 170352640/170498071 [00:22<00:00, 7916400.95it/s]Files already downloaded and verified
==> Building model..
==> Resuming from checkpoint..
170500096it [00:40, 7916400.95it/s]                          Epoch 118 @ step 0: Train Loss: 0.002016, Train Accuracy: 0.001000
Epoch 118 Test Loss: 0.194723, Test Accuracy: 0.943173, time: 934.7s
Saving..
  Epoch 119 @ step 1000: Train Loss: 0.034426, Train Accuracy: 0.989969
Epoch 119 Test Loss: 0.194826, Test Accuracy: 0.941680, time: 915.2s
  Epoch 120 @ step 2000: Train Loss: 0.033117, Train Accuracy: 0.990188
Epoch 120 Test Loss: 0.194389, Test Accuracy: 0.944865, time: 914.5s
Saving..
  Epoch 121 @ step 3000: Train Loss: 0.030885, Train Accuracy: 0.990938
Epoch 121 Test Loss: 0.194916, Test Accuracy: 0.944964, time: 915.3s
Saving..
Epoch 122 Test Loss: 0.207069, Test Accuracy: 0.942775, time: 915.2s
  Epoch 123 @ step 4000: Train Loss: 0.028969, Train Accuracy: 0.991797
Epoch 123 Test Loss: 0.200301, Test Accuracy: 0.944467, time: 914.4s
  Epoch 124 @ step 5000: Train Loss: 0.026556, Train Accuracy: 0.992672
Epoch 124 Test Loss: 0.203026, Test Accuracy: 0.944268, time: 914.8s
  Epoch 125 @ step 6000: Train Loss: 0.024552, Train Accuracy: 0.993125
Epoch 125 Test Loss: 0.205113, Test Accuracy: 0.945263, time: 912.8s
Saving..
  Epoch 126 @ step 7000: Train Loss: 0.022170, Train Accuracy: 0.994156
Epoch 126 Test Loss: 0.211654, Test Accuracy: 0.943471, time: 910.9s
Epoch 127 Test Loss: 0.210708, Test Accuracy: 0.945462, time: 912.7s
Saving..
  Epoch 128 @ step 8000: Train Loss: 0.021084, Train Accuracy: 0.994484
Epoch 128 Test Loss: 0.211940, Test Accuracy: 0.944467, time: 909.9s
  Epoch 129 @ step 9000: Train Loss: 0.021049, Train Accuracy: 0.994031
Epoch 129 Test Loss: 0.206148, Test Accuracy: 0.945064, time: 909.1s
  Epoch 130 @ step 10000: Train Loss: 0.020118, Train Accuracy: 0.994516
Epoch 130 Test Loss: 0.207158, Test Accuracy: 0.944865, time: 909.6s
Epoch 131 Test Loss: 0.211263, Test Accuracy: 0.945462, time: 907.3s
  Epoch 132 @ step 11000: Train Loss: 0.018848, Train Accuracy: 0.995109
Epoch 132 Test Loss: 0.207890, Test Accuracy: 0.945462, time: 909.2s
  Epoch 133 @ step 12000: Train Loss: 0.018894, Train Accuracy: 0.994859
Epoch 133 Test Loss: 0.211911, Test Accuracy: 0.945263, time: 909.0s
  Epoch 134 @ step 13000: Train Loss: 0.017514, Train Accuracy: 0.995625
Epoch 134 Test Loss: 0.221171, Test Accuracy: 0.943571, time: 907.5s
  Epoch 135 @ step 14000: Train Loss: 0.016227, Train Accuracy: 0.995875
Epoch 135 Test Loss: 0.212094, Test Accuracy: 0.945462, time: 907.6s
Epoch 136 Test Loss: 0.214949, Test Accuracy: 0.944765, time: 905.7s
  Epoch 137 @ step 15000: Train Loss: 0.015378, Train Accuracy: 0.995953
Epoch 137 Test Loss: 0.210566, Test Accuracy: 0.946158, time: 906.4s
Saving..
  Epoch 138 @ step 16000: Train Loss: 0.014540, Train Accuracy: 0.996359
---------------------------------------------------------------------------
```

In [0]: