## PyTorch data

PyTorch comes with a nice paradigm for dealing with data which we'll use here. A PyTorch <a href="Dataset\_(http://pytorch.org/docs/master/data.html#torch.utils.data.Dataset">Dataset\_(http://pytorch.org/docs/master/data.html#torch.utils.data.Dataset</a>) knows where to find data in its raw form (files on disk) and how to load individual examples into Python datastructures. A PyTorch <a href="DataLoader\_(http://pytorch.org/docs/master/data.html#torch.utils.data.DataLoader\_">DataLoader\_(http://pytorch.org/docs/master/data.html#torch.utils.data.DataLoader\_)</a> takes a dataset and offers a variety of ways to sample batches from that dataset.

Take a moment to browse through the CIFAR10 Dataset in 2\_pytorch/cifar10.py, read the DataLoader documentation linked above, and see how these are used in the section of train.py that loads data. Note that in the first part of the homework we subtracted a mean CIFAR10 image from every image before feeding it in to our models. Here we subtract a constant color instead. Both methods are seen in practice and work equally well.

PyTorch provides lots of vision datasets which can be imported directly from <a href="mailto:torchvision.datasets">torchvision.datasets</a> (<a href="http://pytorch.org/docs/master/torchvision/datasets.html">http://pytorch.org/docs/master/torchvision/datasets.html</a>). Also see <a href="mailto:torchtext">torchtext</a> (<a href="https://github.com/pytorch/text#datasets">https://github.com/pytorch/text#datasets</a>) for natural language datasets.

## ConvNet Classifier in PyTorch

In PyTorch Deep Learning building blocks are implemented in the neural network module <a href="torch.nn\_(http://pytorch.org/docs/master/nn.html">torch.nn\_(http://pytorch.org/docs/master/nn.html</a>) (usually imported as nn ). A PyTorch model is typically a subclass of <a href="nn.Module\_(http://pytorch.org/docs/master/nn.html#torch.nn.Module">nn.Module\_(http://pytorch.org/docs/master/nn.html#torch.nn.Module</a>) and thereby gains a multitude of features. Because your logistic regressor is an <a href="nn.Module">nn.Module</a> all of its parameters and sub-modules are accessible through the <a href="parameters">parameters</a>() and <a href="modules">modules</a>() methods.

Now implement a ConvNet classifier by filling in the marked sections of models/convnet.py.

The main driver for this question is <code>train.py</code>. It reads arguments and model hyperparameter from the command line, loads CIFAR10 data and the specified model (in this case, softmax). Using the optimizer initialized with appropriate hyperparameters, it trains the model and reports performance on test data.

Complete the following couple of sections in train.py:

- 1. Initialize an optimizer from the torch.optim package
- 2. Update the parameters in model using the optimizer initialized above

At this point all of the components required to train the softmax classifer are complete for the softmax classifier. Now run

```
$ run_convnet.sh
```

to train a model and save it to convnet.pt. This will also produce a convnet.log file which contains training details which we will visualize below.

**Note**: You may want to adjust the hyperparameters specified in run\_convnet.sh to get reasonable performance.

## Visualizing the PyTorch model

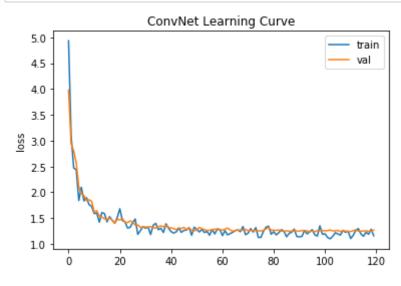
```
In [2]: # Assuming that you have completed training the classifer, let us plot the
# example to show a simple way to log and plot data from PyTorch.

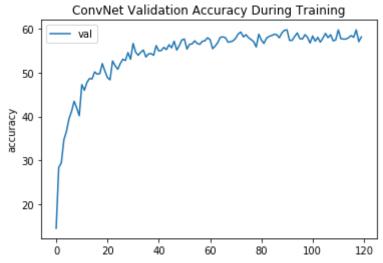
# we neeed matplotlib to plot the graphs for us!
import matplotlib
# This is needed to save images
matplotlib.use('Agg')
import matplotlib.pyplot as plt
%matplotlib inline
```

```
In [5]: # Parse the train and val losses one line at a time.
        import re
        # regexes to find train and val losses on a line
        float regex = r'[-+]?(\d+(\.\d*)?|\.\d+)([eE][-+]?\d+)?'
        train loss re = re.compile('.*Train Loss: ({})'.format(float regex))
        val_loss_re = re.compile('.*Val Loss: ({})'.format(float_regex))
        val_acc_re = re.compile('.*Val Acc: ({})'.format(float_regex))
        # extract one loss for each logged iteration
        train losses = []
        val losses = []
        val_accs = []
        # NOTE: You may need to change this file name.
        with open('convnet.log', 'r') as f:
            for line in f:
                train match = train loss re.match(line)
                val_match = val_loss_re.match(line)
                val acc match = val acc re.match(line)
                if train match:
                    train losses.append(float(train match.group(1)))
                if val match:
                    val losses.append(float(val match.group(1)))
                if val acc match:
                    val accs.append(float(val acc match.group(1)))
```

```
In [6]: fig = plt.figure()
    plt.plot(train_losses, label='train')
    plt.plot(val_losses, label='val')
    plt.title('ConvNet Learning Curve')
    plt.ylabel('loss')
    plt.legend()
    fig.savefig('convnet_lossvstrain.png')

fig = plt.figure()
    plt.plot(val_accs, label='val')
    plt.title('ConvNet Validation Accuracy During Training')
    plt.ylabel('accuracy')
    plt.legend()
    fig.savefig('convnet_valaccuracy.png')
```

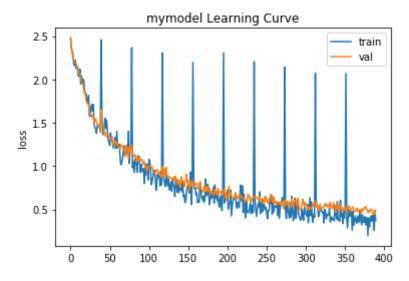


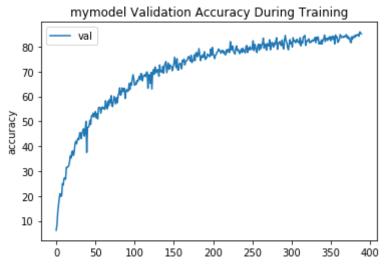


```
In [3]: # Parse the train and val losses one line at a time.
        import re
        # regexes to find train and val losses on a line
        float_regex = r'[-+]?(\d+(\.\d*)?|\.\d+)([eE][-+]?\d+)?'
        train_loss_re = re.compile('.*Train_Loss: ({})'.format(float_regex))
        val_loss_re = re.compile('.*Val Loss: ({})'.format(float_regex))
        val_acc_re = re.compile('.*Val Acc: ({})'.format(float_regex))
        # extract one loss for each logged iteration
        train_losses = []
        val_losses = []
        val accs = []
        # NOTE: You may need to change this file name.
        with open('mymodel.log', 'r') as f:
            for line in f:
                train_match = train_loss_re.match(line)
                val_match = val_loss_re.match(line)
                val_acc_match = val_acc_re.match(line)
                if train match:
                    train losses.append(float(train_match.group(1)))
                if val match:
                    val losses.append(float(val match.group(1)))
                if val acc match:
                    val_accs.append(float(val_acc_match.group(1)))
```

```
In [4]: fig = plt.figure()
    plt.plot(train_losses, label='train')
    plt.plot(val_losses, label='val')
    plt.title('mymodel Learning Curve')
    plt.ylabel('loss')
    plt.legend()
    fig.savefig('mymodel_lossvstrain.png')

fig = plt.figure()
    plt.plot(val_accs, label='val')
    plt.title('mymodel Validation Accuracy During Training')
    plt.ylabel('accuracy')
    plt.legend()
    fig.savefig('mymodel_valaccuracy.png')
```





```
In [ ]:
```