What's this PyTorch business?

You've written a lot of code in this assignment to provide a whole host of neural network functionality. Dropout, Batch Norm, and 2D convolutions are some of the workhorses of deep learning in computer vision. You've also worked hard to make your code efficient and vectorized.

For the last part of this assignment, though, we're going to leave behind your beautiful codebase and instead migrate to one of two popular deep learning frameworks: in this instance, PyTorch (or TensorFlow, if you choose to use that notebook).

Part I. Preparation

First, we load the CIFAR-10 dataset. This might take a couple minutes the first time you do it, but the files should stay cached after that.

In previous parts of the assignment we had to write our own code to download the CIFAR-10 dataset, preprocess it, and iterate through it in minibatches; PyTorch provides convenient tools to automate this process for us.

```
using device: cuda
```

Part II. Barebones PyTorch

PyTorch ships with high-level APIs to help us define model architectures conveniently, which we will cover in Part II of this tutorial. In this section, we will start with the barebone PyTorch elements to understand the autograd engine better. After this exercise, you will come to appreciate the high-level model API more.

We will start with a simple fully-connected ReLU network with two hidden layers and no biases for CIFAR classification. This implementation computes the forward pass using operations on PyTorch Tensors, and uses PyTorch autograd to compute gradients. It is important that you understand every line, because you will write a harder version after the example.

When we create a PyTorch Tensor with `requires_grad=True`, then operations involving that Tensor will not just compute values; they will also build up a computational graph in the background, allowing us to easily backpropagate through the graph to compute gradients of some Tensors with respect to a downstream loss. Concretely if x is a Tensor with `x.requires_grad == True` then after backpropagation `x.grad` will be another Tensor holding the gradient of x with respect to the scalar loss at the end.

```
Before flattening:  tensor([[[[ 0,  1],
          [ 2,  3],
          [ 4,  5]]],


        [[[ 6,  7],
          [ 8,  9],
          [10, 11]]]])
After flattening:  tensor([[ 0,  1,  2,  3,  4,  5],
        [ 6,  7,  8,  9, 10, 11]])
```

```
torch.Size([64, 10])
```

Barebones PyTorch: Three-Layer ConvNet

Here you will complete the implementation of the function `three_layer_convnet`, which will perform the forward pass of a three-layer convolutional network. Like above, we can immediately test our implementation by passing zeros through the network. The network should have the following architecture:

1. A convolutional layer (with bias) with `channel_1` filters, each with shape `KW1 x KH1`, and zero-padding of two
2. ReLU nonlinearity
3. A convolutional layer (with bias) with `channel_2` filters, each with shape `KW2 x KH2`, and zero-padding of one
4. ReLU nonlinearity
5. Fully-connected layer with bias, producing scores for C classes.

Note that we have **no softmax activation** here after our fully-connected layer: this is because PyTorch's cross entropy loss performs a softmax activation for you, and by bundling that step in makes computation more efficient.

a softmax activation for you, and by bundling that step in makes computation more efficient.

HINT: For convolutions: http://pytorch.org/docs/stable/nn.html#torch.nn.functional.conv2d; pay attention to the shapes of convolutional filters!

In [6]:

```
def three_layer_convnet(x, params):
    """
    Performs the forward pass of a three-layer convolutional network with the
    architecture defined above.

    Inputs:
    - x: A PyTorch Tensor of shape (N, 3, H, W) giving a minibatch of images
    - params: A list of PyTorch Tensors giving the weights and biases for the
      network; should contain the following:
      - conv_w1: PyTorch Tensor of shape (channel_1, 3, KH1, KW1) giving weights
        for the first convolutional layer
      - conv_b1: PyTorch Tensor of shape (channel_1,) giving biases for the first
        convolutional layer
      - conv_w2: PyTorch Tensor of shape (channel_2, channel_1, KH2, KW2) giving
        weights for the second convolutional layer
      - conv_b2: PyTorch Tensor of shape (channel_2,) giving biases for the second
        convolutional layer
      - fc_w: PyTorch Tensor giving weights for the fully-connected layer. Can you
        figure out what the shape should be?
      - fc_b: PyTorch Tensor giving biases for the fully-connected layer. Can you
        figure out what the shape should be?

    Returns:
    - scores: PyTorch Tensor of shape (N, C) giving classification scores for x
    """
    conv_w1, conv_b1, conv_w2, conv_b2, fc_w, fc_b = params
    scores = None
    ################################################################################
    # TODO: Implement the forward pass for the three-layer ConvNet.                #
    ################################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

    # (32 + 2 * 2 - 5)/1 + 1 = 32
    # (32 + 2 * 1 - 3)/1 + 1 = 32

    # zero-padding of two
    conv1 = F.conv2d(x, weight = conv_w1, bias = conv_b1, padding = 2)
    relu1 = F.relu(conv1)

    # zero-padding of one
    conv2 = F.conv2d(relu1, weight = conv_w2, bias = conv_b2, padding = 1)
    relu2 = F.relu(conv2)

    relu2_flat = flatten(relu2)
    scores = relu2_flat.mm(fc_w) + fc_b

    # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    ################################################################################
    #                                END OF YOUR CODE                              #
    ################################################################################
    return scores
```

After defining the forward pass of the ConvNet above, run the following cell to test your implementation.

When you run this function, scores should have shape (64, 10).

```
torch.Size([64, 10])
```

Barebones PyTorch: Initialization

Let's write a couple utility methods to initialize the weight matrices for our models.

- `random_weight(shape)` initializes a weight tensor with the Kaiming normalization method.
- `zero_weight(shape)` initializes a weight tensor with all zeros. Useful for instantiating bias parameters.

The `random_weight` function uses the Kaiming normal initialization method, described in:

He et al, *Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification*, ICCV 2015, https://arxiv.org/abs/1502.01852

Out[8]:

```
tensor([[ 0.8353,  0.0717,  0.8552, -0.1880,  0.3146],
        [ 0.1567, -0.3085, -0.2543, -0.6643, -0.9352],
        [-0.0133,  0.1022, -0.4872,  0.5114, -0.8374]], device='cuda:0',
       requires_grad=True)
```

Barebones PyTorch: Check Accuracy

When training the model we will use the following function to check the accuracy of our model on the training or validation sets.

When checking accuracy we don't need to compute any gradients; as a result we don't need PyTorch to build a computational graph for us when we compute scores. To prevent a graph from being built we scope our computation under a `torch.no_grad()` context manager.

BareBones PyTorch: Training Loop

We can now set up a basic training loop to train our network. We will train the model using stochastic gradient descent without momentum. We will use `torch.functional.cross_entropy` to compute the loss; you can read about it here.

The training loop takes as input the neural network function, a list of initialized parameters (`[w1, w2]` in our example), and learning rate.

BareBones PyTorch: Train a Two-Layer Network

Now we are ready to run the training loop. We need to explicitly allocate tensors for the fully connected weights, `w1` and `w2`.

Each minibatch of CIFAR has 64 examples, so the tensor shape is `[64, 3, 32, 32]`.

After flattening, `x` shape should be `[64, 3 * 32 * 32]`. This will be the size of the first dimension of `w1`. The second dimension of `w1` is the hidden layer size, which will also be the first dimension of `w2`.

Finally, the output of the network is a 10-dimensional vector that represents the probability distribution over 10 classes.

You don't need to tune any hyperparameters but you should see accuracies above 40% after training for one epoch.

In [11]:

```
hidden_layer_size = 4000
learning_rate = 1e-2

w1 = random_weight((3 * 32 * 32, hidden_layer_size))
w2 = random_weight((hidden_layer_size, 10))

train_part2(two_layer_fc, [w1, w2], learning_rate)
```

```
Iteration 0, loss = 3.4906
Checking accuracy on the val set
Got 157 / 1000 correct (15.70%)

Iteration 100, loss = 2.6464
Checking accuracy on the val set
Got 326 / 1000 correct (32.60%)

Iteration 200, loss = 1.9548
Checking accuracy on the val set
Got 388 / 1000 correct (38.80%)

Iteration 300, loss = 1.9776
Checking accuracy on the val set
Got 380 / 1000 correct (38.00%)

Iteration 400, loss = 2.3733
Checking accuracy on the val set
Got 409 / 1000 correct (40.90%)
```

```
Iteration 500, loss = 1.8391
Checking accuracy on the val set
Got 441 / 1000 correct (44.10%)

Iteration 600, loss = 1.9783
Checking accuracy on the val set
Got 375 / 1000 correct (37.50%)

Iteration 700, loss = 1.4147
Checking accuracy on the val set
Got 438 / 1000 correct (43.80%)
```

BareBones PyTorch: Training a ConvNet

In the below you should use the functions defined above to train a three-layer convolutional network on CIFAR. The network should have the following architecture:

1. Convolutional layer (with bias) with 32 5x5 filters, with zero-padding of 2
2. ReLU
3. Convolutional layer (with bias) with 16 3x3 filters, with zero-padding of 1
4. ReLU
5. Fully-connected layer (with bias) to compute scores for 10 classes

You should initialize your weight matrices using the `random_weight` function defined above, and you should initialize your bias vectors using the `zero_weight` function above.

You don't need to tune any hyperparameters, but if everything works correctly you should achieve an accuracy above 42% after one epoch.

In [12]:

```
learning_rate = 3e-3

channel_1 = 32
channel_2 = 16

conv_w1 = None
conv_b1 = None
conv_w2 = None
conv_b2 = None
fc_w = None
fc_b = None

################################################################################
# TODO: Initialize the parameters of a three-layer ConvNet.                    #
################################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

# Basically just change tensor.zeros to random_weights and adopt the same implementation
# in the function three_layer_convnet_test

conv_w1 = random_weight((channel_1, 3, 5, 5))
conv_b1 = zero_weight((channel_1,))
conv_w2 = random_weight((channel_2, channel_1, 3, 3))
conv_b2 = zero_weight((channel_2,))
fc_w = random_weight((channel_2 * 32 * 32, 10))
fc_b = zero_weight((10,))

# *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
################################################################################
#                                END OF YOUR CODE                              #
################################################################################

params = [conv_w1, conv_b1, conv_w2, conv_b2, fc_w, fc_b]
train_part2(three_layer_convnet, params, learning_rate)
```

```
Iteration 0, loss = 2.4838
Checking accuracy on the val set
Got 110 / 1000 correct (11.00%)

Iteration 100, loss = 2.1007
Checking accuracy on the val set
Got 321 / 1000 correct (32.10%)
```

```
Iteration 200, loss = 1.7121
Checking accuracy on the val set
Got 387 / 1000 correct (38.70%)

Iteration 300, loss = 1.7689
Checking accuracy on the val set
Got 419 / 1000 correct (41.90%)

Iteration 400, loss = 1.5850
Checking accuracy on the val set
Got 454 / 1000 correct (45.40%)

Iteration 500, loss = 1.5140
Checking accuracy on the val set
Got 453 / 1000 correct (45.30%)

Iteration 600, loss = 1.5323
Checking accuracy on the val set
Got 456 / 1000 correct (45.60%)

Iteration 700, loss = 1.4435
Checking accuracy on the val set
Got 472 / 1000 correct (47.20%)
```

Part III. PyTorch Module API

Barebone PyTorch requires that we track all the parameter tensors by hand. This is fine for small networks with a few tensors, but it would be extremely inconvenient and error-prone to track tens or hundreds of tensors in larger networks.

PyTorch provides the `nn.Module` API for you to define arbitrary network architectures, while tracking every learnable parameters for you. In Part II, we implemented SGD ourselves. PyTorch also provides the `torch.optim` package that implements all the common optimizers, such as RMSProp, Adagrad, and Adam. It even supports approximate second-order methods like L-BFGS! You can refer to the doc for the exact specifications of each optimizer.

To use the Module API, follow the steps below:

1. Subclass `nn.Module`. Give your network class an intuitive name like `TwoLayerFC`.
2. In the constructor `__init__()`, define all the layers you need as class attributes. Layer objects like `nn.Linear` and `nn.Conv2d` are themselves `nn.Module` subclasses and contain learnable parameters, so that you don't have to instantiate the raw tensors yourself. `nn.Module` will track these internal parameters for you. Refer to the doc to learn more about the dozens of builtin layers. **Warning**: don't forget to call the `super().__init__()` first!
3. In the `forward()` method, define the *connectivity* of your network. You should use the attributes defined in `__init__` as function calls that take tensor as input and output the "transformed" tensor. Do *not* create any new layers with learnable parameters in `forward()`! All of them must be declared upfront in `__init__`.

After you define your Module subclass, you can instantiate it as an object and call it just like the NN forward function in part II.

Module API: Two-Layer Network

Here is a concrete example of a 2-layer fully connected network:

In [13]:

```
class TwoLayerFC(nn.Module):
    def __init__(self, input_size, hidden_size, num_classes):
        super().__init__()
        # assign layer objects to class attributes
        self.fc1 = nn.Linear(input_size, hidden_size)
        # nn.init package contains convenient initialization methods
        # http://pytorch.org/docs/master/nn.html#torch-nn-init
        nn.init.kaiming_normal_(self.fc1.weight)
        self.fc2 = nn.Linear(hidden_size, num_classes)
        nn.init.kaiming_normal_(self.fc2.weight)

    def forward(self, x):
        # forward always defines connectivity
        x = flatten(x)
        scores = self.fc2(F.relu(self.fc1(x)))
```

```
        return scores

def test_TwoLayerFC():
    input_size = 50
    x = torch.zeros((64, input_size), dtype=dtype)  # minibatch size 64, feature dimension 50
    model = TwoLayerFC(input_size, 42, 10)
    scores = model(x)
    print(scores.size())  # you should see [64, 10]
test_TwoLayerFC()
```

```
torch.Size([64, 10])
```

Module API: Three-Layer ConvNet

It's your turn to implement a 3-layer ConvNet followed by a fully connected layer. The network architecture should be the same as in Part II:

1. Convolutional layer with `channel_1` 5x5 filters with zero-padding of 2
2. ReLU
3. Convolutional layer with `channel_2` 3x3 filters with zero-padding of 1
4. ReLU
5. Fully-connected layer to `num_classes` classes

You should initialize the weight matrices of the model using the Kaiming normal initialization method.

HINT: http://pytorch.org/docs/stable/nn.html#conv2d

After you implement the three-layer ConvNet, the `test_ThreeLayerConvNet` function will run your implementation; it should print `(64, 10)` for the shape of the output scores.

In [14]:

```
class ThreeLayerConvNet(nn.Module):
    def __init__(self, in_channel, channel_1, channel_2, num_classes):
        super().__init__()
        ########################################################################
        # TODO: Set up the layers you need for a three-layer ConvNet with the  #
        # architecture defined above.                                          #
        ########################################################################
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

        self.conv1 = nn.Conv2d(in_channel, channel_1, 5, padding = 2)
        nn.init.kaiming_normal_(self.conv1.weight)
        #nn.init.constant_(self.conv1.bias, 0)

        self.conv2 = nn.Conv2d(channel_1, channel_2, 3, padding = 1)
        nn.init.kaiming_normal_(self.conv2.weight)
        #nn.init.constant_(self.conv2.bias, 0)

        self.fc = nn.Linear(channel_2 * 32 * 32, num_classes)
        nn.init.kaiming_normal_(self.fc.weight)
        #nn.init.constant_(self.fc.bias, 0)

        # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
        ########################################################################
        #                            END OF YOUR CODE                          #
        ########################################################################

    def forward(self, x):
        scores = None
        ########################################################################
        # TODO: Implement the forward function for a 3-layer ConvNet. you      #
        # should use the layers you defined in __init__ and specify the        #
        # connectivity of those layers in forward()                            #
        ########################################################################
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

        # Before moving to Fully-connected layer, flatten the outcome from the second Relu layer
        scores = self.fc(flatten(F.relu(self.conv2(F.relu(self.conv1(x))))))

        # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
        ########################################################################
        #                              END OF YOUR CODE                        #
        ########################################################################
```

```
        return scores


def test_ThreeLayerConvNet():
    x = torch.zeros((64, 3, 32, 32), dtype=dtype)  # minibatch size 64, image size [3, 32, 32]
    model = ThreeLayerConvNet(in_channel=3, channel_1=12, channel_2=8, num_classes=10)
    scores = model(x)
    print(scores.size())  # you should see [64, 10]
test_ThreeLayerConvNet()
```

```
torch.Size([64, 10])
```

Module API: Check Accuracy

Given the validation or test set, we can check the classification accuracy of a neural network.

This version is slightly different from the one in part II. You don't manually pass in the parameters anymore.

In [15]:

```
def check_accuracy_part34(loader, model):
    if loader.dataset.train:
        print('Checking accuracy on validation set')
    else:
        print('Checking accuracy on test set')
    num_correct = 0
    num_samples = 0
    model.eval()  # set model to evaluation mode
    with torch.no_grad():
        for x, y in loader:
            x = x.to(device=device, dtype=dtype)  # move to device, e.g. GPU
            y = y.to(device=device, dtype=torch.long)
            scores = model(x)
            _, preds = scores.max(1)
            num_correct += (preds == y).sum()
            num_samples += preds.size(0)
        acc = float(num_correct) / num_samples
        print('Got %d / %d correct (%.2f)' % (num_correct, num_samples, 100 * acc))
```

Module API: Training Loop

We also use a slightly different training loop. Rather than updating the values of the weights ourselves, we use an Optimizer object from the `torch.optim` package, which abstract the notion of an optimization algorithm and provides implementations of most of the algorithms commonly used to optimize neural networks.

In [16]:

```
def train_part34(model, optimizer, epochs=1):
    """
    Train a model on CIFAR-10 using the PyTorch Module API.

    Inputs:
    - model: A PyTorch Module giving the model to train.
    - optimizer: An Optimizer object we will use to train the model
    - epochs: (Optional) A Python integer giving the number of epochs to train for

    Returns: Nothing, but prints model accuracies during training.
    """
    model = model.to(device=device)  # move the model parameters to CPU/GPU
    for e in range(epochs):
        for t, (x, y) in enumerate(loader_train):
            model.train()  # put model to training mode
            x = x.to(device=device, dtype=dtype)  # move to device, e.g. GPU
            y = y.to(device=device, dtype=torch.long)

            scores = model(x)
            loss = F.cross_entropy(scores, y)

            # Zero out all of the gradients for the variables which the optimizer
            # will update.
            optimizer.zero_grad()

            # This is the backwards pass: compute the gradient of the loss with
            # respect to each  parameter of the model
```

```
            # respect to each parameter of the model.
            loss.backward()

            # Actually update the parameters of the model using the gradients
            # computed by the backwards pass.
            optimizer.step()

            if t % print_every == 0:
                print('Iteration %d, loss = %.4f' % (t, loss.item()))
                check_accuracy_part34(loader_val, model)
                print()
```

Module API: Train a Two-Layer Network

Now we are ready to run the training loop. In contrast to part II, we don't explicitly allocate parameter tensors anymore.

Simply pass the input size, hidden layer size, and number of classes (i.e. output size) to the constructor of `TwoLayerFC`.

You also need to define an optimizer that tracks all the learnable parameters inside `TwoLayerFC`.

You don't need to tune any hyperparameters, but you should see model accuracies above 40% after training for one epoch.

In [17]:

```
hidden_layer_size = 4000
learning_rate = 1e-2
model = TwoLayerFC(3 * 32 * 32, hidden_layer_size, 10)
optimizer = optim.SGD(model.parameters(), lr=learning_rate)

train_part34(model, optimizer)
```

```
Iteration 0, loss = 2.9949
Checking accuracy on validation set
Got 121 / 1000 correct (12.10)

Iteration 100, loss = 2.3486
Checking accuracy on validation set
Got 324 / 1000 correct (32.40)

Iteration 200, loss = 2.1595
Checking accuracy on validation set
Got 373 / 1000 correct (37.30)

Iteration 300, loss = 1.5870
Checking accuracy on validation set
Got 384 / 1000 correct (38.40)

Iteration 400, loss = 1.7430
Checking accuracy on validation set
Got 425 / 1000 correct (42.50)

Iteration 500, loss = 2.2017
Checking accuracy on validation set
Got 405 / 1000 correct (40.50)

Iteration 600, loss = 1.6490
Checking accuracy on validation set
Got 431 / 1000 correct (43.10)

Iteration 700, loss = 1.7141
Checking accuracy on validation set
Got 445 / 1000 correct (44.50)
```

Module API: Train a Three-Layer ConvNet

You should now use the Module API to train a three-layer ConvNet on CIFAR. This should look very similar to training the two-layer network! You don't need to tune any hyperparameters, but you should achieve above above 45% after training for one epoch.

You should train the model using stochastic gradient descent without momentum.

In [18]:

```
learning_rate = 3e-3
```

```
channel_1 = 32
channel_2 = 16

model = None
optimizer = None
################################################################################
# TODO: Instantiate your ThreeLayerConvNet model and a corresponding optimizer #
################################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

model = ThreeLayerConvNet(3, channel_1, channel_2, 10)
optimizer = optim.SGD(model.parameters(), lr=learning_rate)

# *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
################################################################################
#                                END OF YOUR CODE
################################################################################

train_part34(model, optimizer)
```

```
Iteration 0, loss = 3.2324
Checking accuracy on validation set
Got 132 / 1000 correct (13.20)

Iteration 100, loss = 1.6502
Checking accuracy on validation set
Got 357 / 1000 correct (35.70)

Iteration 200, loss = 1.7441
Checking accuracy on validation set
Got 403 / 1000 correct (40.30)

Iteration 300, loss = 1.5787
Checking accuracy on validation set
Got 438 / 1000 correct (43.80)

Iteration 400, loss = 1.8331
Checking accuracy on validation set
Got 462 / 1000 correct (46.20)

Iteration 500, loss = 1.8362
Checking accuracy on validation set
Got 468 / 1000 correct (46.80)

Iteration 600, loss = 1.6090
Checking accuracy on validation set
Got 459 / 1000 correct (45.90)

Iteration 700, loss = 1.4880
Checking accuracy on validation set
Got 472 / 1000 correct (47.20)
```

Part IV. PyTorch Sequential API

Part III introduced the PyTorch Module API, which allows you to define arbitrary learnable layers and their connectivity.

For simple models like a stack of feed forward layers, you still need to go through 3 steps: subclass `nn.Module`, assign layers to class attributes in `__init__`, and call each layer one by one in `forward()`. Is there a more convenient way?

Fortunately, PyTorch provides a container Module called `nn.Sequential`, which merges the above steps into one. It is not as flexible as `nn.Module`, because you cannot specify more complex topology than a feed-forward stack, but it's good enough for many use cases.

Sequential API: Two-Layer Network

Let's see how to rewrite our two-layer fully connected network example with `nn.Sequential`, and train it using the training loop defined above.

Again, you don't need to tune any hyperparameters here, but you shoud achieve above 40% accuracy after one epoch of training.

In [19]:

```
# We need to wrap `flatten` function in a module in order to stack it
# in nn.Sequential
class Flatten(nn.Module):
    def forward(self, x):
        return flatten(x)

hidden_layer_size = 4000
learning_rate = 1e-2

model = nn.Sequential(
    Flatten(),
    nn.Linear(3 * 32 * 32, hidden_layer_size),
    nn.ReLU(),
    nn.Linear(hidden_layer_size, 10),
)

# you can use Nesterov momentum in optim.SGD
optimizer = optim.SGD(model.parameters(), lr=learning_rate,
                      momentum=0.9, nesterov=True)

train_part34(model, optimizer)
```

```
Iteration 0, loss = 2.3438
Checking accuracy on validation set
Got 157 / 1000 correct (15.70)

Iteration 100, loss = 1.8731
Checking accuracy on validation set
Got 382 / 1000 correct (38.20)

Iteration 200, loss = 1.8784
Checking accuracy on validation set
Got 426 / 1000 correct (42.60)

Iteration 300, loss = 1.6531
Checking accuracy on validation set
Got 410 / 1000 correct (41.00)

Iteration 400, loss = 1.6222
Checking accuracy on validation set
Got 433 / 1000 correct (43.30)

Iteration 500, loss = 1.4940
Checking accuracy on validation set
Got 459 / 1000 correct (45.90)

Iteration 600, loss = 1.5447
Checking accuracy on validation set
Got 431 / 1000 correct (43.10)

Iteration 700, loss = 2.0133
Checking accuracy on validation set
Got 464 / 1000 correct (46.40)
```

Sequential API: Three-Layer ConvNet

Here you should use `nn.Sequential` to define and train a three-layer ConvNet with the same architecture we used in Part III:

1. Convolutional layer (with bias) with 32 5x5 filters, with zero-padding of 2
2. ReLU
3. Convolutional layer (with bias) with 16 3x3 filters, with zero-padding of 1
4. ReLU
5. Fully-connected layer (with bias) to compute scores for 10 classes

You should initialize your weight matrices using the `random_weight` function defined above, and you should initialize your bias vectors using the `zero_weight` function above.

You should optimize your model using stochastic gradient descent with Nesterov momentum 0.9.

Again, you don't need to tune any hyperparameters but you should see accuracy above 55% after one epoch of training.

In [20]:

```
channel_1 = 32
```

```
channel_1 = 32
channel_2 = 16
learning_rate = 1e-2

model = None
optimizer = None

################################################################################
# TODO: Rewrite the 2-layer ConvNet with bias from Part III with the           #
# Sequential API.                                                              #
################################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

# From Piazza, it is OK to use default initialization. No need to do explicit initialization

model = nn.Sequential(
    nn.Conv2d(3, channel_1, 5, padding = 2),
    nn.ReLU(),
    nn.Conv2d(channel_1, channel_2, 3, padding = 1),
    nn.ReLU(),
    Flatten(),
    nn.Linear(channel_2 * 32 * 32, 10)
)

optimizer = optim.SGD(model.parameters(), lr=learning_rate,
                      momentum=0.9, nesterov=True)

# *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
################################################################################
#                                END OF YOUR CODE
################################################################################

train_part34(model, optimizer)
```

```
Iteration 0, loss = 2.2971
Checking accuracy on validation set
Got 100 / 1000 correct (10.00)

Iteration 100, loss = 1.7188
Checking accuracy on validation set
Got 422 / 1000 correct (42.20)

Iteration 200, loss = 1.6543
Checking accuracy on validation set
Got 475 / 1000 correct (47.50)

Iteration 300, loss = 1.2017
Checking accuracy on validation set
Got 519 / 1000 correct (51.90)

Iteration 400, loss = 1.4025
Checking accuracy on validation set
Got 535 / 1000 correct (53.50)

Iteration 500, loss = 1.1097
Checking accuracy on validation set
Got 540 / 1000 correct (54.00)

Iteration 600, loss = 1.0994
Checking accuracy on validation set
Got 574 / 1000 correct (57.40)

Iteration 700, loss = 1.0963
Checking accuracy on validation set
Got 578 / 1000 correct (57.80)
```

Part V. CIFAR-10 open-ended challenge

In this section, you can experiment with whatever ConvNet architecture you'd like on CIFAR-10.

Now it's your job to experiment with architectures, hyperparameters, loss functions, and optimizers to train a model that achieves **at least 70%** accuracy on the CIFAR-10 **validation** set within 10 epochs. You can use the check_accuracy and train functions from above. You can use either `nn.Module` or `nn.Sequential` API.

Describe what you did at the end of this notebook.

Here are the official API documentation for each component. One note: what we call in the class "spatial batch norm" is called "BatchNorm2D" in PyTorch.

- Layers in torch.nn package: http://pytorch.org/docs/stable/nn.html
- Activations: http://pytorch.org/docs/stable/nn.html#non-linear-activations
- Loss functions: http://pytorch.org/docs/stable/nn.html#loss-functions
- Optimizers: http://pytorch.org/docs/stable/optim.html

Things you might try:

- **Filter size**: Above we used 5x5; would smaller filters be more efficient?
- **Number of filters**: Above we used 32 filters. Do more or fewer do better?
- **Pooling vs Strided Convolution**: Do you use max pooling or just stride convolutions?
- **Batch normalization**: Try adding spatial batch normalization after convolution layers and vanilla batch normalization after affine layers. Do your networks train faster?
- **Network architecture**: The network above has two layers of trainable parameters. Can you do better with a deep network? Good architectures to try include:
  - [conv-relu-pool]xN -> [affine]xM -> [softmax or SVM]
  - [conv-relu-conv-relu-pool]xN -> [affine]xM -> [softmax or SVM]
  - [batchnorm-relu-conv]xN -> [affine]xM -> [softmax or SVM]
- **Global Average Pooling**: Instead of flattening and then having multiple affine layers, perform convolutions until your image gets small (7x7 or so) and then perform an average pooling operation to get to a 1x1 image picture (1, 1 , Filter#), which is then reshaped into a (Filter#) vector. This is used in Google's Inception Network (See Table 1 for their architecture).
- **Regularization**: Add l2 weight regularization, or perhaps use Dropout.

Tips for training

For each network architecture that you try, you should tune the learning rate and other hyperparameters. When doing this there are a couple important things to keep in mind:

- If the parameters are working well, you should see improvement within a few hundred iterations
- Remember the coarse-to-fine approach for hyperparameter tuning: start by testing a large range of hyperparameters for just a few training iterations to find the combinations of parameters that are working at all.
- Once you have found some sets of parameters that seem to work, search more finely around these parameters. You may need to train for more epochs.
- You should use the validation set for hyperparameter search, and save your test set for evaluating your architecture on the best parameters as selected by the validation set.

Going above and beyond

If you are feeling adventurous there are many other features you can implement to try and improve your performance. You are **not required** to implement any of these, but don't miss the fun if you have time!

- Alternative optimizers: you can try Adam, Adagrad, RMSprop, etc.
- Alternative activation functions such as leaky ReLU, parametric ReLU, ELU, or MaxOut.
- Model ensembles
- Data augmentation
- New Architectures
  - ResNets where the input from the previous layer is added to the output.
  - DenseNets where inputs into previous layers are concatenated together.
  - This blog has an in-depth overview

Have fun and happy training!

In [24]:

```
################################################################################
# TODO:                                                                        #
# Experiment with any architectures, optimizers, and hyperparameters.          #
# Achieve AT LEAST 70% accuracy on the *validation set* within 10 epochs.      #
#                                                                              #
# Note that you can use the check_accuracy function to evaluate on either      #
# the test set or the validation set, by passing either loader_test or         #
# loader_val as the second argument to check_accuracy. You should not touch    #
# the test set until you have finished your architecture and  hyperparameter   #
# tuning, and only run the test set once at the end to report a final value.   #
```

```
################################################################################
model = None
optimizer = None

# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

# (32 + 2 * 2 - 5)/1 + 1 = 32
layer1 = nn.Sequential(
    nn.Conv2d(3, 16, kernel_size=5, padding=2),
    nn.ReLU(),
)

# (32 + 2 * 2 - 5)/1 + 1 = 32
# (32 - 2)/2 + 1 = 16
layer2 = nn.Sequential(
    nn.Conv2d(16, 32, kernel_size=3, padding=1),
    nn.ReLU(),
    nn.MaxPool2d(2)
)


# (16 + 2 * 1 - 3)/1 + 1 = 16
layer3 = nn.Sequential(
    nn.Conv2d(32, 48, kernel_size=3, padding=1),
    nn.ReLU(),
)

# (16 + 2 * 1 - 3)/1 + 1 = 16
# (16 - 2)/2 + 1 = 8
layer4 = nn.Sequential(
    nn.Conv2d(48, 64, kernel_size=3, padding=1),
    nn.ReLU(),
    nn.MaxPool2d(2)
)


fc = nn.Linear(64*8*8, 10)

model = nn.Sequential(
    layer1,
    layer2,
    layer3,
    layer4,
    Flatten(),
    fc
)

learning_rate = 1e-3

optimizer = optim.Adam(model.parameters(), lr=learning_rate)

# Print training status every epoch
print_every = 1000

# *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
################################################################################
#                                END OF YOUR CODE
################################################################################

# You should get at least 70% accuracy
train_part34(model, optimizer, epochs=10)
```

```
Iteration 0, loss = 2.2974
Checking accuracy on validation set
Got 98 / 1000 correct (9.80)

Iteration 0, loss = 0.9447
Checking accuracy on validation set
Got 585 / 1000 correct (58.50)

Iteration 0, loss = 1.0508
Checking accuracy on validation set
Got 684 / 1000 correct (68.40)

Iteration 0, loss = 0.7837
Checking accuracy on validation set
Got 716 / 1000 correct (71.60)
```

```
Iteration 0, loss = 0.5664
Checking accuracy on validation set
Got 750 / 1000 correct (75.00)

Iteration 0, loss = 0.5874
Checking accuracy on validation set
Got 737 / 1000 correct (73.70)

Iteration 0, loss = 0.5890
Checking accuracy on validation set
Got 740 / 1000 correct (74.00)

Iteration 0, loss = 0.3552
Checking accuracy on validation set
Got 743 / 1000 correct (74.30)

Iteration 0, loss = 0.3969
Checking accuracy on validation set
Got 753 / 1000 correct (75.30)

Iteration 0, loss = 0.2919
Checking accuracy on validation set
Got 744 / 1000 correct (74.40)
```

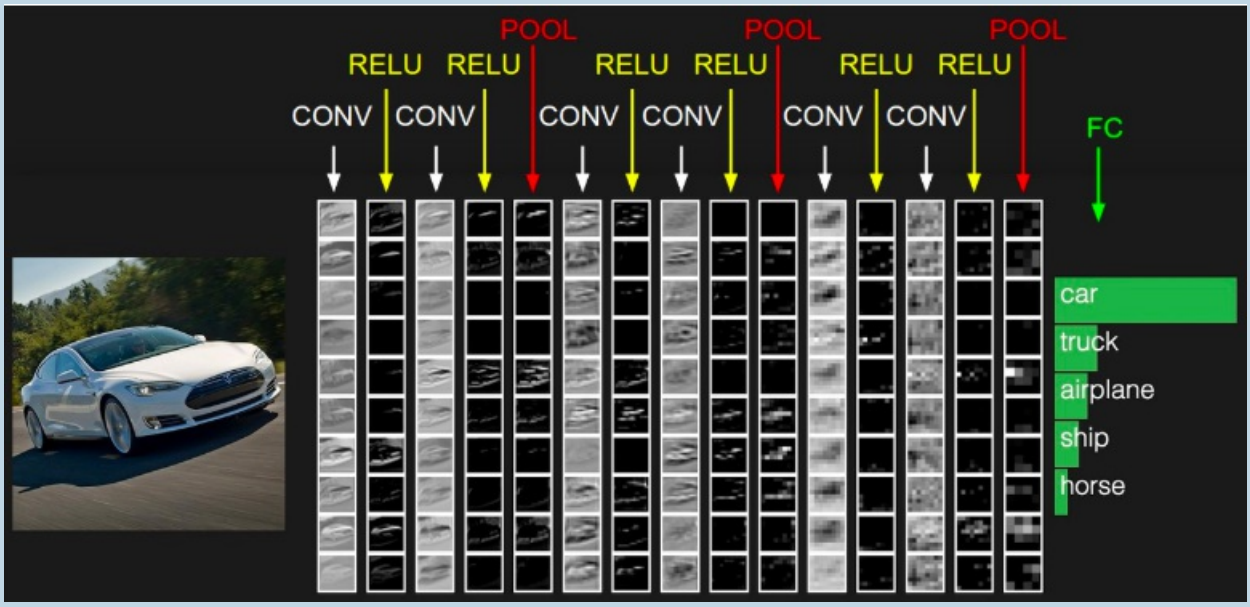
Describe what you did

In the cell below you should write an explanation of what you did, any additional features that you implemented, and/or any graphs that you made in the process of training and evaluating your network.

TODO:

I constructed a 5-layer convolutional network, the first four layers have similar structure as the example in the class slide, and the last layer is a fully-connected layer. They can be represented as below.

[(conv -> relu) -> (conv -> relu -> pool)] * 2 -> fc



Test set -- run this only once

Now that we've gotten a result we're happy with, we test our final model on the test set (which you should store in best_model). Think about how this compares to your validation set accuracy.

In [25]:

```
best_model = model
```

```
check_accuracy_part34(loader_test, best_model)
```

```
Checking accuracy on test set
Got 7327 / 10000 correct (73.27)
```