FullyConnectedNets

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1 Fully-Connected Neural Nets

In the previous homework you implemented a fully-connected two-layer neural network on CIFAR-10. The implementation was simple but not very modular since the loss and gradient were computed in a single monolithic function. This is manageable for a simple two-layer network, but would become impractical as we move to bigger models. Ideally we want to build networks using a more modular design so that we can implement different layer types in isolation and then snap them together into models with different architectures.

In this exercise we will implement fully-connected networks using a more modular approach. For each layer we will implement a `forward` and a `backward` function. The `forward` function will receive inputs, weights, and other parameters and will return both an output and a `cache` object storing data needed for the backward pass, like this:

```python
def layer_forward(x, w):
  """ Receive inputs x and weights w """
  # Do some computations ...
  z = # ... some intermediate value
  # Do some more computations ...
  out = # the output

  cache = (x, w, z, out) # Values we need to compute gradients

  return out, cache
```

The backward pass will receive upstream derivatives and the `cache` object, and will return gradients with respect to the inputs and weights, like this:

```python
def layer_backward(dout, cache):
  """
  Receive dout (derivative of loss with respect to outputs) and cache,
  and compute derivative with respect to inputs.
  """
  # Unpack cache values
  x, w, z, out = cache

  # Use values in cache to compute derivatives
  dx = # Derivative of loss with respect to x
  dw = # Derivative of loss with respect to w
```

```
return dx, dw
```

After implementing a bunch of layers this way, we will be able to easily combine them to build classifiers with different architectures.

In addition to implementing fully-connected networks of arbitrary depth, we will also explore different update rules for optimization, and introduce Dropout as a regularizer and Batch/Layer Normalization as a tool to more efficiently optimize deep networks.

[1]:
```
# As usual, a bit of setup
from __future__ import print_function
import time
import numpy as np
import matplotlib.pyplot as plt
from cs231n.classifiers.fc_net import *
from cs231n.data_utils import get_CIFAR10_data
from cs231n.gradient_check import eval_numerical_gradient,␣
↪eval_numerical_gradient_array
from cs231n.solver import Solver

%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'

# for auto-reloading external modules
# see http://stackoverflow.com/questions/1907993/
↪autoreload-of-modules-in-ipython
%load_ext autoreload
%autoreload 2

def rel_error(x, y):
  """ returns relative error """
  return np.max(np.abs(x - y) / (np.maximum(1e-8, np.abs(x) + np.abs(y))))
```

[2]:
```
# Load the (preprocessed) CIFAR10 data.

data = get_CIFAR10_data()
for k, v in list(data.items()):
  print(('%s: ' % k, v.shape))
```

```
('X_train: ', (49000, 3, 32, 32))
('y_train: ', (49000,))
('X_val: ', (1000, 3, 32, 32))
('y_val: ', (1000,))
('X_test: ', (1000, 3, 32, 32))
('y_test: ', (1000,))
```

2 Affine layer: forward

Open the file cs231n/layers.py and implement the affine_forward function.

Once you are done you can test your implementaion by running the following:

[3]:
```
# Test the affine_forward function

num_inputs = 2
input_shape = (4, 5, 6)
output_dim = 3

input_size = num_inputs * np.prod(input_shape)
weight_size = output_dim * np.prod(input_shape)

x = np.linspace(-0.1, 0.5, num=input_size).reshape(num_inputs, *input_shape)
w = np.linspace(-0.2, 0.3, num=weight_size).reshape(np.prod(input_shape),␣
 ↪output_dim)
b = np.linspace(-0.3, 0.1, num=output_dim)

out, _ = affine_forward(x, w, b)
correct_out = np.array([[ 1.49834967,  1.70660132,  1.91485297],
                        [ 3.25553199,  3.5141327,   3.77273342]])

# Compare your output with ours. The error should be around e-9 or less.
print('Testing affine_forward function:')
print('difference: ', rel_error(out, correct_out))
```

```
Testing affine_forward function:
difference:  9.769849468192957e-10
```

3 Affine layer: backward

Now implement the affine_backward function and test your implementation using numeric gradient checking.

[4]:
```
# Test the affine_backward function
np.random.seed(231)
x = np.random.randn(10, 2, 3)
w = np.random.randn(6, 5)
b = np.random.randn(5)
dout = np.random.randn(10, 5)

dx_num = eval_numerical_gradient_array(lambda x: affine_forward(x, w, b)[0], x,␣
 ↪dout)
dw_num = eval_numerical_gradient_array(lambda w: affine_forward(x, w, b)[0], w,␣
 ↪dout)
```

```
db_num = eval_numerical_gradient_array(lambda b: affine_forward(x, w, b)[0], b,␣
 ↪dout)

_, cache = affine_forward(x, w, b)
dx, dw, db = affine_backward(dout, cache)

# The error should be around e-10 or less
print('Testing affine_backward function:')
print('dx error: ', rel_error(dx_num, dx))
print('dw error: ', rel_error(dw_num, dw))
print('db error: ', rel_error(db_num, db))
```

```
Testing affine_backward function:
dx error:  5.399100368651805e-11
dw error:  9.904211865398145e-11
db error:  2.4122867568119087e-11
```

4 ReLU activation: forward

Implement the forward pass for the ReLU activation function in the `relu_forward` function and test your implementation using the following:

[5]:
```
# Test the relu_forward function

x = np.linspace(-0.5, 0.5, num=12).reshape(3, 4)

out, _ = relu_forward(x)
correct_out = np.array([[ 0.,          0.,          0.,          0.,         ],
                        [ 0.,          0.,          0.04545455,  0.13636364,],
                        [ 0.22727273,  0.31818182,  0.40909091,  0.5,        ]])

# Compare your output with ours. The error should be on the order of e-8
print('Testing relu_forward function:')
print('difference: ', rel_error(out, correct_out))
```

```
Testing relu_forward function:
difference:  4.999999798022158e-08
```

5 ReLU activation: backward

Now implement the backward pass for the ReLU activation function in the `relu_backward` function and test your implementation using numeric gradient checking:

[6]:
```
np.random.seed(231)
x = np.random.randn(10, 10)
dout = np.random.randn(*x.shape)
```

```
dx_num = eval_numerical_gradient_array(lambda x: relu_forward(x)[0], x, dout)

_, cache = relu_forward(x)
dx = relu_backward(dout, cache)

# The error should be on the order of e-12
print('Testing relu_backward function:')
print('dx error: ', rel_error(dx_num, dx))
```

```
Testing relu_backward function:
dx error:  3.2756349136310288e-12
```

5.1 Inline Question 1:

We've only asked you to implement ReLU, but there are a number of different activation functions that one could use in neural networks, each with its pros and cons. In particular, an issue commonly seen with activation functions is getting zero (or close to zero) gradient flow during backpropagation. Which of the following activation functions have this problem? If you consider these functions in the one dimensional case, what types of input would lead to this behaviour? 1. Sigmoid 2. ReLU 3. Leaky ReLU 4. ELU (Exponential Linear Unit) ## Answer:

La función Sigmoide tiene el problema que puede saturar a las neuronas, y cuando esto se da, el aprendizaje de dicha neurona se vuelve muy lento, o simplemente no se da. Esto sucede cuando el valor de activación está muy cerca de cero o uno (x tendiendo a infinito o menos infinito), y en esos casos el gradiente tiende a cero.

ReLu no tiene ese problema para cuando x>=0, pero cuando x es negativa, dichas neuronas no pueden aprender (neuronas muertas). A ELU le sucede igual cunado x tiende a menos infinito, ya que en dicho caso el gradiente tiende a cero.

En el caso de Leaky ReLU, para x<0, no tenemos el problema de las neuronas muertas ya que el gradiente, si bien pequeño, no es cero ni tiende a cero.

5.2 Inline Question 2:

How would you implement the backward pass of a LeakyReLU layer, with slope parameter `alpha`?

You don't need to make it work. Just write **one line of code** with the important part in the space below. Assume the same variable names as in the ReLU functions of `layers.py`.

5.3 Answer:

dx = dout

dx[x <=0] = alpha * dx

6 "Sandwich" layers

There are some common patterns of layers that are frequently used in neural nets. For example, affine layers are frequently followed by a ReLU nonlinearity. To make these common patterns easy, we define several convenience layers in the file `cs231n/layer_utils.py`.

For now take a look at the `affine_relu_forward` and `affine_relu_backward` functions, and run the following to numerically gradient check the backward pass:

[7]:
```python
from cs231n.layer_utils import affine_relu_forward, affine_relu_backward
np.random.seed(231)
x = np.random.randn(2, 3, 4)
w = np.random.randn(12, 10)
b = np.random.randn(10)
dout = np.random.randn(2, 10)

out, cache = affine_relu_forward(x, w, b)
dx, dw, db = affine_relu_backward(dout, cache)

dx_num = eval_numerical_gradient_array(lambda x: affine_relu_forward(x, w,␣
 ↪b)[0], x, dout)
dw_num = eval_numerical_gradient_array(lambda w: affine_relu_forward(x, w,␣
 ↪b)[0], w, dout)
db_num = eval_numerical_gradient_array(lambda b: affine_relu_forward(x, w,␣
 ↪b)[0], b, dout)

# Relative error should be around e-10 or less
print('Testing affine_relu_forward and affine_relu_backward:')
print('dx error: ', rel_error(dx_num, dx))
print('dw error: ', rel_error(dw_num, dw))
print('db error: ', rel_error(db_num, db))
```

```
Testing affine_relu_forward and affine_relu_backward:
dx error:  2.299579177309368e-11
dw error:  8.162011105764925e-11
db error:  7.826724021458994e-12
```

7 Loss layers: Softmax and SVM

You implemented these loss functions in the last assignment, so we'll give them to you for free here. You should still make sure you understand how they work by looking at the implementations in `cs231n/layers.py`.

You can make sure that the implementations are correct by running the following:

[8]:
```python
np.random.seed(231)
num_classes, num_inputs = 10, 50
x = 0.001 * np.random.randn(num_inputs, num_classes)
y = np.random.randint(num_classes, size=num_inputs)

dx_num = eval_numerical_gradient(lambda x: svm_loss(x, y)[0], x, verbose=False)
loss, dx = svm_loss(x, y)
```

```
# Test svm_loss function. Loss should be around 9 and dx error should be around␣
↪the order of e-9
print('Testing svm_loss:')
print('loss: ', loss)
print('dx error: ', rel_error(dx_num, dx))

dx_num = eval_numerical_gradient(lambda x: softmax_loss(x, y)[0], x,␣
↪verbose=False)
loss, dx = softmax_loss(x, y)

# Test softmax_loss function. Loss should be close to 2.3 and dx error should␣
↪be around e-8
print('\nTesting softmax_loss:')
print('loss: ', loss)
print('dx error: ', rel_error(dx_num, dx))
```

```
Testing svm_loss:
loss:  8.999602749096233
dx error:  1.4021566006651672e-09

Testing softmax_loss:
loss:  2.302545844500738
dx error:  9.384673161989355e-09
```

8 Two-layer network

In the previous assignment you implemented a two-layer neural network in a single monolithic class. Now that you have implemented modular versions of the necessary layers, you will reimplement the two layer network using these modular implementations.

Open the file `cs231n/classifiers/fc_net.py` and complete the implementation of the `TwoLayerNet` class. This class will serve as a model for the other networks you will implement in this assignment, so read through it to make sure you understand the API. You can run the cell below to test your implementation.

[9]:
```
np.random.seed(231)
N, D, H, C = 3, 5, 50, 7
X = np.random.randn(N, D)
y = np.random.randint(C, size=N)

std = 1e-3
model = TwoLayerNet(input_dim=D, hidden_dim=H, num_classes=C, weight_scale=std)

print('Testing initialization ... ')
W1_std = abs(model.params['W1'].std() - std)
b1 = model.params['b1']
W2_std = abs(model.params['W2'].std() - std)
```

```
b2 = model.params['b2']
assert W1_std < std / 10, 'First layer weights do not seem right'
assert np.all(b1 == 0), 'First layer biases do not seem right'
assert W2_std < std / 10, 'Second layer weights do not seem right'
assert np.all(b2 == 0), 'Second layer biases do not seem right'

print('Testing test-time forward pass ... ')
model.params['W1'] = np.linspace(-0.7, 0.3, num=D*H).reshape(D, H)
model.params['b1'] = np.linspace(-0.1, 0.9, num=H)
model.params['W2'] = np.linspace(-0.3, 0.4, num=H*C).reshape(H, C)
model.params['b2'] = np.linspace(-0.9, 0.1, num=C)
X = np.linspace(-5.5, 4.5, num=N*D).reshape(D, N).T
scores = model.loss(X)
correct_scores = np.asarray(
  [[11.53165108,  12.2917344,   13.05181771,  13.81190102,  14.57198434, 15.
↪33206765,  16.09215096],
   [12.05769098,  12.74614105,  13.43459113,  14.1230412,   14.81149128, 15.
↪49994135,  16.18839143],
   [12.58373087,  13.20054771,  13.81736455,  14.43418138,  15.05099822, 15.
↪66781506,  16.2846319 ]])
scores_diff = np.abs(scores - correct_scores).sum()
assert scores_diff < 1e-6, 'Problem with test-time forward pass'

print('Testing training loss (no regularization)')
y = np.asarray([0, 5, 1])
loss, grads = model.loss(X, y)
correct_loss = 3.4702243556
assert abs(loss - correct_loss) < 1e-10, 'Problem with training-time loss'

model.reg = 1.0
loss, grads = model.loss(X, y)
correct_loss = 26.5948426952
assert abs(loss - correct_loss) < 1e-10, 'Problem with regularization loss'

# Errors should be around e-7 or less
for reg in [0.0, 0.7]:
  print('Running numeric gradient check with reg = ', reg)
  model.reg = reg
  loss, grads = model.loss(X, y)

  for name in sorted(grads):
    f = lambda _: model.loss(X, y)[0]
    grad_num = eval_numerical_gradient(f, model.params[name], verbose=False)
    print('%s relative error: %.2e' % (name, rel_error(grad_num, grads[name])))
```

```
Testing initialization …
Testing test-time forward pass …
```

```
Testing training loss (no regularization)
Running numeric gradient check with reg =  0.0
W1 relative error: 1.83e-08
W2 relative error: 3.12e-10
b1 relative error: 9.83e-09
b2 relative error: 4.33e-10
Running numeric gradient check with reg =  0.7
W1 relative error: 2.53e-07
W2 relative error: 2.85e-08
b1 relative error: 1.56e-08
b2 relative error: 7.76e-10
```

9 Solver

In the previous assignment, the logic for training models was coupled to the models themselves. Following a more modular design, for this assignment we have split the logic for training models into a separate class.

Open the file `cs231n/solver.py` and read through it to familiarize yourself with the API. After doing so, use a `Solver` instance to train a `TwoLayerNet` that achieves at least `50%` accuracy on the validation set.

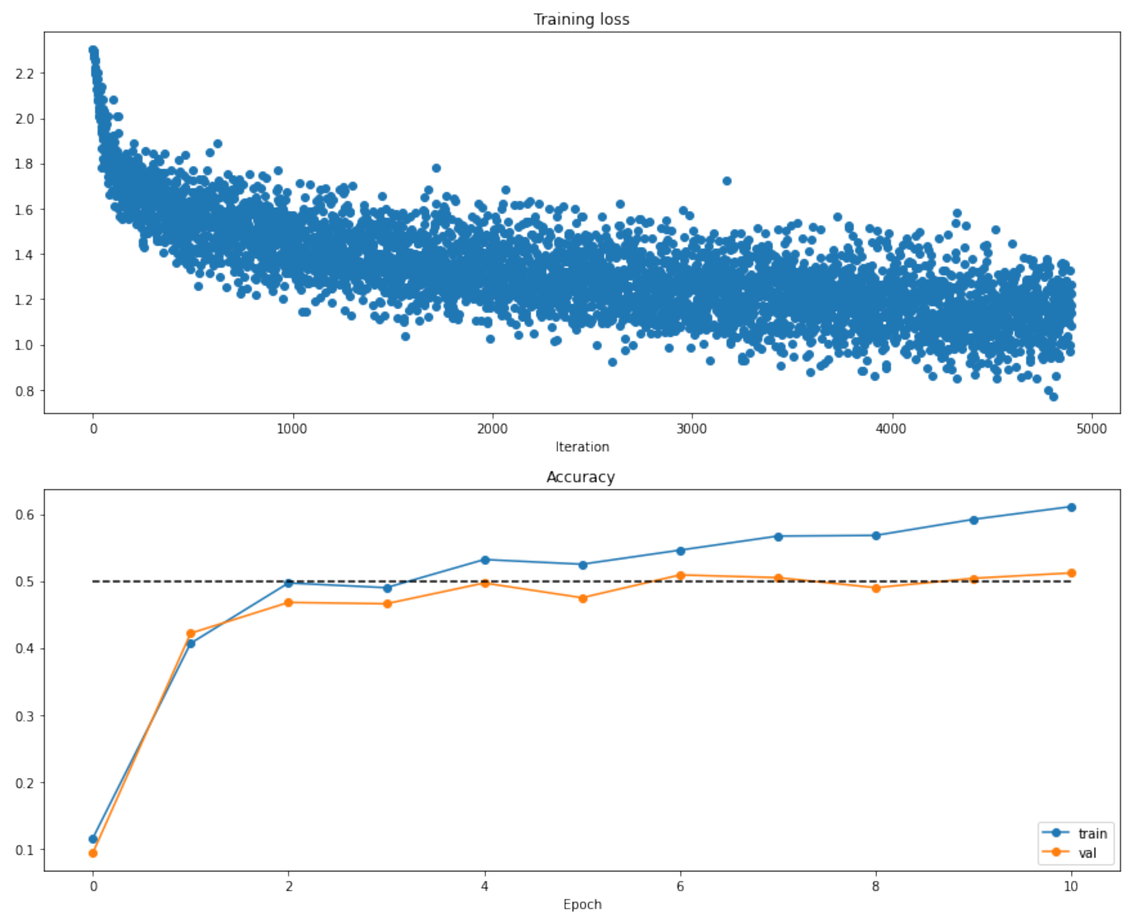
[10]:
```
model = TwoLayerNet()
solver = None

##############################################################################
# TODO: Use a Solver instance to train a TwoLayerNet that achieves at least  #
# 50% accuracy on the validation set.                                        #
##############################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

solver = Solver(model, data,update_rule='sgd',optim_config={'learning_rate':␣
 ↪1e-3,},lr_decay=0.95,num_epochs=10, batch_size=100,print_every=100)
solver.train()

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

```
(Iteration 1 / 4900) loss: 2.304060
(Epoch 0 / 10) train acc: 0.116000; val_acc: 0.094000
(Iteration 101 / 4900) loss: 1.829613
(Iteration 201 / 4900) loss: 1.857390
(Iteration 301 / 4900) loss: 1.744448
(Iteration 401 / 4900) loss: 1.420187
(Epoch 1 / 10) train acc: 0.407000; val_acc: 0.422000
(Iteration 501 / 4900) loss: 1.565913
```

```
(Iteration 601 / 4900) loss: 1.700510
(Iteration 701 / 4900) loss: 1.732213
(Iteration 801 / 4900) loss: 1.688361
(Iteration 901 / 4900) loss: 1.439529
(Epoch 2 / 10) train acc: 0.497000; val_acc: 0.468000
(Iteration 1001 / 4900) loss: 1.385772
(Iteration 1101 / 4900) loss: 1.278401
(Iteration 1201 / 4900) loss: 1.641580
(Iteration 1301 / 4900) loss: 1.438847
(Iteration 1401 / 4900) loss: 1.172536
(Epoch 3 / 10) train acc: 0.490000; val_acc: 0.466000
(Iteration 1501 / 4900) loss: 1.346286
(Iteration 1601 / 4900) loss: 1.268492
(Iteration 1701 / 4900) loss: 1.318215
(Iteration 1801 / 4900) loss: 1.395750
(Iteration 1901 / 4900) loss: 1.338233
(Epoch 4 / 10) train acc: 0.532000; val_acc: 0.497000
(Iteration 2001 / 4900) loss: 1.343165
(Iteration 2101 / 4900) loss: 1.393173
(Iteration 2201 / 4900) loss: 1.276734
(Iteration 2301 / 4900) loss: 1.287951
(Iteration 2401 / 4900) loss: 1.352778
(Epoch 5 / 10) train acc: 0.525000; val_acc: 0.475000
(Iteration 2501 / 4900) loss: 1.390234
(Iteration 2601 / 4900) loss: 1.276361
(Iteration 2701 / 4900) loss: 1.111768
(Iteration 2801 / 4900) loss: 1.271688
(Iteration 2901 / 4900) loss: 1.272039
(Epoch 6 / 10) train acc: 0.546000; val_acc: 0.509000
(Iteration 3001 / 4900) loss: 1.304489
(Iteration 3101 / 4900) loss: 1.346667
(Iteration 3201 / 4900) loss: 1.325510
(Iteration 3301 / 4900) loss: 1.392728
(Iteration 3401 / 4900) loss: 1.402001
(Epoch 7 / 10) train acc: 0.567000; val_acc: 0.505000
(Iteration 3501 / 4900) loss: 1.319024
(Iteration 3601 / 4900) loss: 1.153287
(Iteration 3701 / 4900) loss: 1.180922
(Iteration 3801 / 4900) loss: 1.093164
(Iteration 3901 / 4900) loss: 1.135902
(Epoch 8 / 10) train acc: 0.568000; val_acc: 0.490000
(Iteration 4001 / 4900) loss: 1.191735
(Iteration 4101 / 4900) loss: 1.359396
(Iteration 4201 / 4900) loss: 1.227283
(Iteration 4301 / 4900) loss: 1.024113
(Iteration 4401 / 4900) loss: 1.327583
(Epoch 9 / 10) train acc: 0.592000; val_acc: 0.504000
(Iteration 4501 / 4900) loss: 0.963330
```

```
(Iteration 4601 / 4900) loss: 1.445619
(Iteration 4701 / 4900) loss: 1.007542
(Iteration 4801 / 4900) loss: 1.005175
(Epoch 10 / 10) train acc: 0.611000; val_acc: 0.512000
```

[11]:
```
# Run this cell to visualize training loss and train / val accuracy

plt.subplot(2, 1, 1)
plt.title('Training loss')
plt.plot(solver.loss_history, 'o')
plt.xlabel('Iteration')

plt.subplot(2, 1, 2)
plt.title('Accuracy')
plt.plot(solver.train_acc_history, '-o', label='train')
plt.plot(solver.val_acc_history, '-o', label='val')
plt.plot([0.5] * len(solver.val_acc_history), 'k--')
plt.xlabel('Epoch')
plt.legend(loc='lower right')
plt.gcf().set_size_inches(15, 12)
plt.show()
```



10 Multilayer network

Next you will implement a fully-connected network with an arbitrary number of hidden layers.

Read through the `FullyConnectedNet` class in the file `cs231n/classifiers/fc_net.py`.

Implement the initialization, the forward pass, and the backward pass. For the moment don't worry about implementing dropout or batch/layer normalization; we will add those features soon.

10.1 Initial loss and gradient check

As a sanity check, run the following to check the initial loss and to gradient check the network both with and without regularization. Do the initial losses seem reasonable?

For gradient checking, you should expect to see errors around 1e-7 or less.

[12]:
```
np.random.seed(231)
N, D, H1, H2, C = 2, 15, 20, 30, 10
X = np.random.randn(N, D)
y = np.random.randint(C, size=(N,))

for reg in [0, 3.14]:
  print('Running check with reg = ', reg)
  model = FullyConnectedNet([H1, H2], input_dim=D, num_classes=C,
                            reg=reg, weight_scale=5e-2, dtype=np.float64)

  loss, grads = model.loss(X, y)
  print('Initial loss: ', loss)

  # Most of the errors should be on the order of e-7 or smaller.
  # NOTE: It is fine however to see an error for W2 on the order of e-5
  # for the check when reg = 0.0
  for name in sorted(grads):
    f = lambda _: model.loss(X, y)[0]
    grad_num = eval_numerical_gradient(f, model.params[name], verbose=False,
 ↪h=1e-5)
    print('%s relative error: %.2e' % (name, rel_error(grad_num, grads[name])))
```

```
Running check with reg =  0
Initial loss:  2.3004790897684924
W1 relative error: 1.48e-07
W2 relative error: 2.21e-05
W3 relative error: 3.53e-07
b1 relative error: 5.38e-09
b2 relative error: 2.09e-09
b3 relative error: 5.80e-11
Running check with reg =  3.14
```

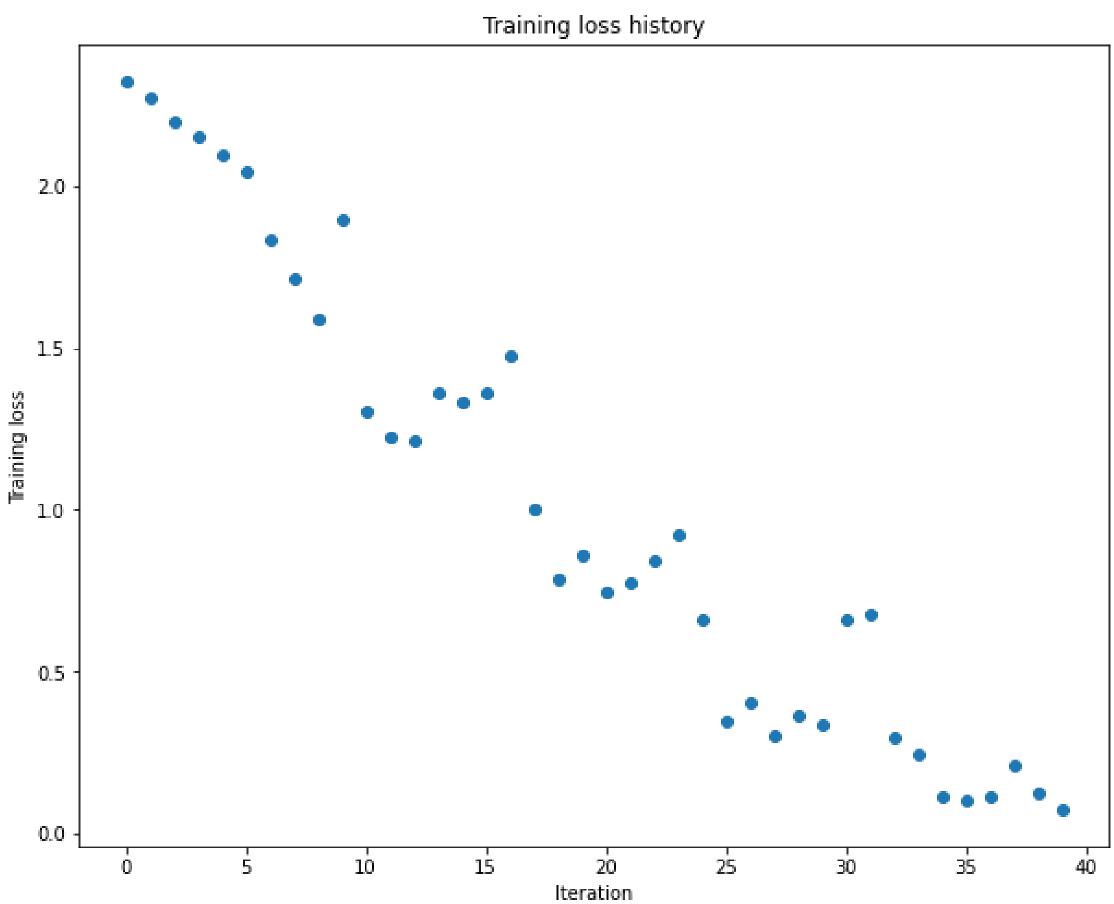
```
Initial loss:  7.052114776533016
W1 relative error: 7.36e-09
W2 relative error: 6.87e-08
W3 relative error: 3.48e-08
b1 relative error: 1.48e-08
b2 relative error: 1.72e-09
b3 relative error: 1.80e-10
```

As another sanity check, make sure you can overfit a small dataset of 50 images. First we will try a three-layer network with 100 units in each hidden layer. In the following cell, tweak the **learning rate** and **weight initialization scale** to overfit and achieve 100% training accuracy within 20 epochs.

[13]:
```python
# TODO: Use a three-layer Net to overfit 50 training examples by
# tweaking just the learning rate and initialization scale.

num_train = 50
small_data = {
  'X_train': data['X_train'][:num_train],
  'y_train': data['y_train'][:num_train],
  'X_val': data['X_val'],
  'y_val': data['y_val'],
}

weight_scale = 7.5e-3   # Experiment with this!
learning_rate = 1e-2  # Experiment with this!
model = FullyConnectedNet([100, 100],
              weight_scale=weight_scale, dtype=np.float64)
solver = Solver(model, small_data,
                print_every=10, num_epochs=20, batch_size=25,
                update_rule='sgd',
                optim_config={
                  'learning_rate': learning_rate,
                }
         )
solver.train()

plt.plot(solver.loss_history, 'o')
plt.title('Training loss history')
plt.xlabel('Iteration')
plt.ylabel('Training loss')
plt.show()
```

```
(Iteration 1 / 40) loss: 2.324703
(Epoch 0 / 20) train acc: 0.140000; val_acc: 0.098000
(Epoch 1 / 20) train acc: 0.240000; val_acc: 0.125000
(Epoch 2 / 20) train acc: 0.380000; val_acc: 0.146000
(Epoch 3 / 20) train acc: 0.380000; val_acc: 0.169000
(Epoch 4 / 20) train acc: 0.380000; val_acc: 0.159000
```

```
(Epoch 5 / 20) train acc: 0.480000; val_acc: 0.177000
(Iteration 11 / 40) loss: 1.305169
(Epoch 6 / 20) train acc: 0.480000; val_acc: 0.188000
(Epoch 7 / 20) train acc: 0.540000; val_acc: 0.179000
(Epoch 8 / 20) train acc: 0.620000; val_acc: 0.158000
(Epoch 9 / 20) train acc: 0.740000; val_acc: 0.204000
(Epoch 10 / 20) train acc: 0.800000; val_acc: 0.189000
(Iteration 21 / 40) loss: 0.744108
(Epoch 11 / 20) train acc: 0.900000; val_acc: 0.190000
(Epoch 12 / 20) train acc: 0.880000; val_acc: 0.194000
(Epoch 13 / 20) train acc: 0.860000; val_acc: 0.197000
(Epoch 14 / 20) train acc: 1.000000; val_acc: 0.215000
(Epoch 15 / 20) train acc: 0.820000; val_acc: 0.170000
(Iteration 31 / 40) loss: 0.661105
(Epoch 16 / 20) train acc: 0.920000; val_acc: 0.199000
(Epoch 17 / 20) train acc: 0.980000; val_acc: 0.199000
(Epoch 18 / 20) train acc: 0.960000; val_acc: 0.207000
(Epoch 19 / 20) train acc: 1.000000; val_acc: 0.187000
(Epoch 20 / 20) train acc: 1.000000; val_acc: 0.202000
```

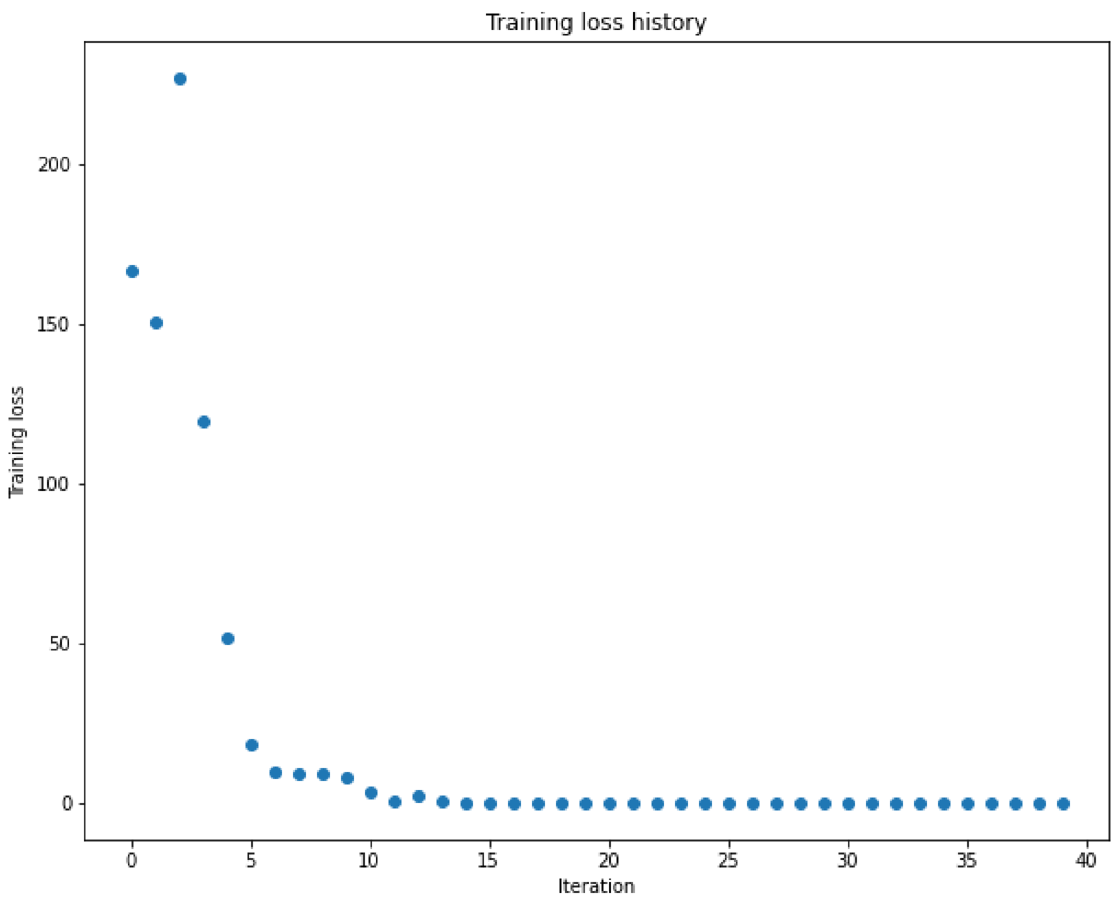


Now try to use a five-layer network with 100 units on each layer to overfit 50 training examples. Again, you will have to adjust the learning rate and weight initialization scale, but you should be able to achieve 100% training accuracy within 20 epochs.

[14]:
```python
# TODO: Use a five-layer Net to overfit 50 training examples by
# tweaking just the learning rate and initialization scale.

num_train = 50
small_data = {
  'X_train': data['X_train'][:num_train],
  'y_train': data['y_train'][:num_train],
  'X_val': data['X_val'],
  'y_val': data['y_val'],
}

learning_rate = 2e-3  # Experiment with this!
weight_scale = 1e-1   # Experiment with this!
model = FullyConnectedNet([100, 100, 100, 100],
                weight_scale=weight_scale, dtype=np.float64)
solver = Solver(model, small_data,
                print_every=10, num_epochs=20, batch_size=25,
                update_rule='sgd',
                optim_config={
                  'learning_rate': learning_rate,
                }
         )
solver.train()

plt.plot(solver.loss_history, 'o')
plt.title('Training loss history')
plt.xlabel('Iteration')
plt.ylabel('Training loss')
plt.show()
```

```
(Iteration 1 / 40) loss: 166.501707
(Epoch 0 / 20) train acc: 0.100000; val_acc: 0.107000
(Epoch 1 / 20) train acc: 0.320000; val_acc: 0.101000
(Epoch 2 / 20) train acc: 0.160000; val_acc: 0.122000
(Epoch 3 / 20) train acc: 0.380000; val_acc: 0.106000
(Epoch 4 / 20) train acc: 0.520000; val_acc: 0.111000
(Epoch 5 / 20) train acc: 0.760000; val_acc: 0.113000
(Iteration 11 / 40) loss: 3.343141
(Epoch 6 / 20) train acc: 0.840000; val_acc: 0.122000
(Epoch 7 / 20) train acc: 0.920000; val_acc: 0.113000
(Epoch 8 / 20) train acc: 0.940000; val_acc: 0.125000
(Epoch 9 / 20) train acc: 0.960000; val_acc: 0.125000
(Epoch 10 / 20) train acc: 0.980000; val_acc: 0.121000
(Iteration 21 / 40) loss: 0.039138
```

```
(Epoch 11 / 20) train acc: 0.980000; val_acc: 0.123000
(Epoch 12 / 20) train acc: 1.000000; val_acc: 0.121000
(Epoch 13 / 20) train acc: 1.000000; val_acc: 0.121000
(Epoch 14 / 20) train acc: 1.000000; val_acc: 0.121000
(Epoch 15 / 20) train acc: 1.000000; val_acc: 0.121000
(Iteration 31 / 40) loss: 0.000644
(Epoch 16 / 20) train acc: 1.000000; val_acc: 0.121000
(Epoch 17 / 20) train acc: 1.000000; val_acc: 0.121000
(Epoch 18 / 20) train acc: 1.000000; val_acc: 0.121000
(Epoch 19 / 20) train acc: 1.000000; val_acc: 0.121000
(Epoch 20 / 20) train acc: 1.000000; val_acc: 0.121000
```



10.2 Inline Question 3:

Did you notice anything about the comparative difficulty of training the three-layer net vs training the five layer net? In particular, based on your experience, which network seemed more sensitive to the initialization scale? Why do you think that is the case?

10.3 Answer:

Es más fácil sobreajustar a ejemplos de entrenamiento la red con más parámetros, lo que ocasionará peor performance en un conjunto de datos no vistos. Se puede observar este comportamiento en los resultados anteriores, con el dataset de validación.

La red de 3 capas es más sensible a la inicialización, dado que son menos parámetros a ajustar y aprender.

11 Update rules

So far we have used vanilla stochastic gradient descent (SGD) as our update rule. More sophisticated update rules can make it easier to train deep networks. We will implement a few of the most commonly used update rules and compare them to vanilla SGD.

12 SGD+Momentum

Stochastic gradient descent with momentum is a widely used update rule that tends to make deep networks converge faster than vanilla stochastic gradient descent. See the Momentum Update section at http://cs231n.github.io/neural-networks-3/#sgd for more information.

Open the file `cs231n/optim.py` and read the documentation at the top of the file to make sure you understand the API. Implement the SGD+momentum update rule in the function `sgd_momentum` and run the following to check your implementation. You should see errors less than e-8.

[15]:
```
from cs231n.optim import sgd_momentum

N, D = 4, 5
w = np.linspace(-0.4, 0.6, num=N*D).reshape(N, D)
dw = np.linspace(-0.6, 0.4, num=N*D).reshape(N, D)
v = np.linspace(0.6, 0.9, num=N*D).reshape(N, D)

config = {'learning_rate': 1e-3, 'velocity': v}
next_w, _ = sgd_momentum(w, dw, config=config)

expected_next_w = np.asarray([
  [ 0.1406,      0.20738947,  0.27417895,  0.34096842,  0.40775789],
  [ 0.47454737,  0.54133684,  0.60812632,  0.67491579,  0.74170526],
  [ 0.80849474,  0.87528421,  0.94207368,  1.00886316,  1.07565263],
  [ 1.14244211,  1.20923158,  1.27602105,  1.34281053,  1.4096    ]])
expected_velocity = np.asarray([
  [ 0.5406,      0.55475789,  0.56891579, 0.58307368,  0.59723158],
  [ 0.61138947,  0.62554737,  0.63970526,  0.65386316,  0.66802105],
  [ 0.68217895,  0.69633684,  0.71049474,  0.72465263,  0.73881053],
  [ 0.75296842,  0.76712632,  0.78128421,  0.79544211,  0.8096    ]])

# Should see relative errors around e-8 or less
print('next_w error: ', rel_error(next_w, expected_next_w))
```

```python
print('velocity error: ', rel_error(expected_velocity, config['velocity']))
```

```
next_w error:  8.882347033505819e-09
velocity error:  4.269287743278663e-09
```

Once you have done so, run the following to train a six-layer network with both SGD and SGD+momentum. You should see the SGD+momentum update rule converge faster.

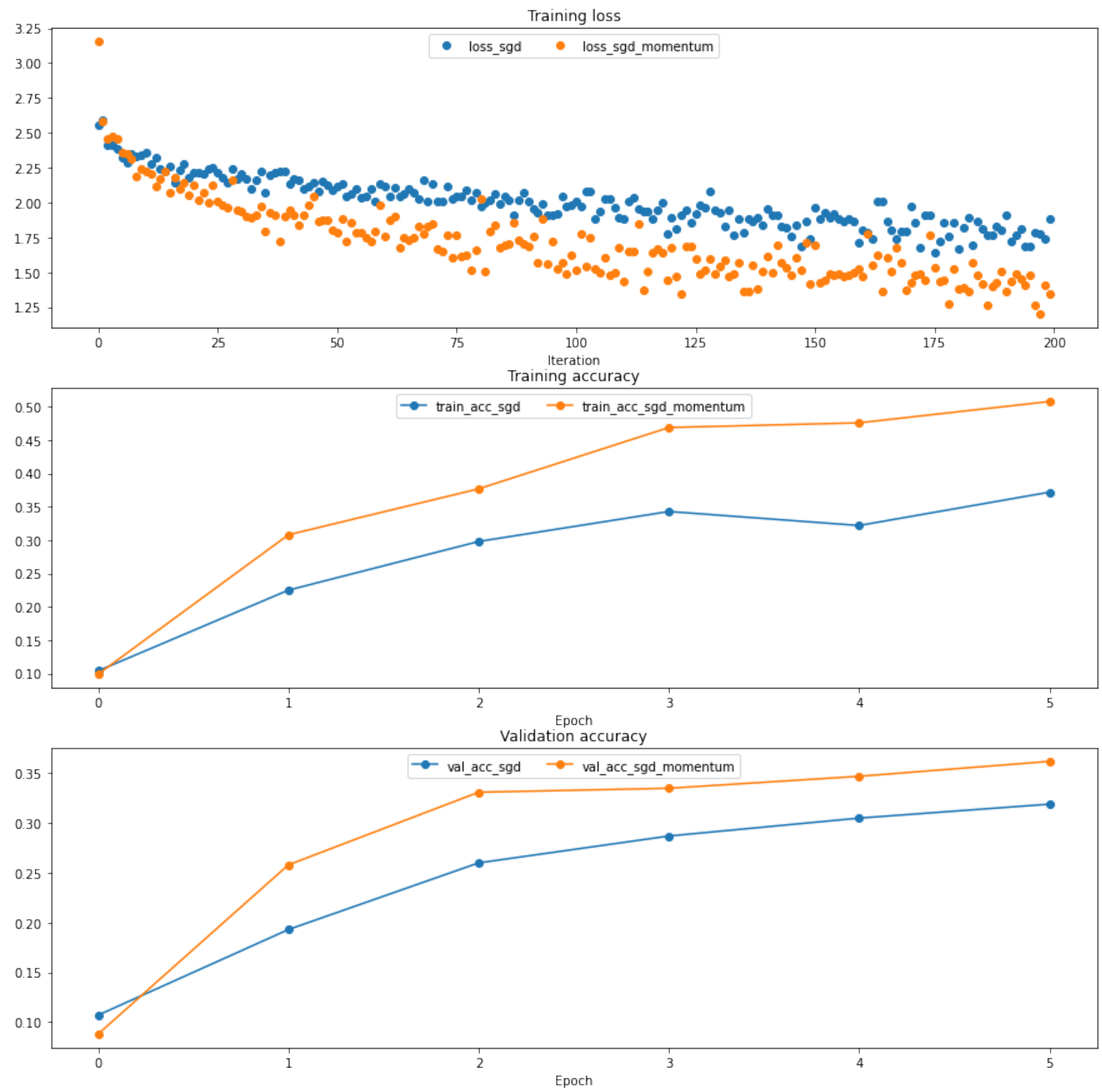
[16]:
```python
num_train = 4000
small_data = {
  'X_train': data['X_train'][:num_train],
  'y_train': data['y_train'][:num_train],
  'X_val': data['X_val'],
  'y_val': data['y_val'],
}

solvers = {}

for update_rule in ['sgd', 'sgd_momentum']:
  print('running with ', update_rule)
  model = FullyConnectedNet([100, 100, 100, 100, 100], weight_scale=5e-2)

  solver = Solver(model, small_data,
                  num_epochs=5, batch_size=100,
                  update_rule=update_rule,
                  optim_config={
                    'learning_rate': 5e-3,
                  },
                  verbose=True)
  solvers[update_rule] = solver
  solver.train()
  print()

plt.subplot(3, 1, 1)
plt.title('Training loss')
plt.xlabel('Iteration')

plt.subplot(3, 1, 2)
plt.title('Training accuracy')
plt.xlabel('Epoch')

plt.subplot(3, 1, 3)
plt.title('Validation accuracy')
plt.xlabel('Epoch')

for update_rule, solver in solvers.items():
  plt.subplot(3, 1, 1)
  plt.plot(solver.loss_history, 'o', label="loss_%s" % update_rule)
```

```python
  plt.subplot(3, 1, 2)
  plt.plot(solver.train_acc_history, '-o', label="train_acc_%s" % update_rule)

  plt.subplot(3, 1, 3)
  plt.plot(solver.val_acc_history, '-o', label="val_acc_%s" % update_rule)

for i in [1, 2, 3]:
  plt.subplot(3, 1, i)
  plt.legend(loc='upper center', ncol=4)
plt.gcf().set_size_inches(15, 15)
plt.show()
```

```
running with  sgd
(Iteration 1 / 200) loss: 2.559978
(Epoch 0 / 5) train acc: 0.104000; val_acc: 0.107000
(Iteration 11 / 200) loss: 2.356069
(Iteration 21 / 200) loss: 2.214091
(Iteration 31 / 200) loss: 2.205927
(Epoch 1 / 5) train acc: 0.225000; val_acc: 0.193000
(Iteration 41 / 200) loss: 2.132095
(Iteration 51 / 200) loss: 2.118950
(Iteration 61 / 200) loss: 2.116443
(Iteration 71 / 200) loss: 2.132549
(Epoch 2 / 5) train acc: 0.298000; val_acc: 0.260000
(Iteration 81 / 200) loss: 1.977227
(Iteration 91 / 200) loss: 2.007528
(Iteration 101 / 200) loss: 2.004762
(Iteration 111 / 200) loss: 1.885342
(Epoch 3 / 5) train acc: 0.343000; val_acc: 0.287000
(Iteration 121 / 200) loss: 1.891517
(Iteration 131 / 200) loss: 1.923677
(Iteration 141 / 200) loss: 1.957744
(Iteration 151 / 200) loss: 1.966736
(Epoch 4 / 5) train acc: 0.322000; val_acc: 0.305000
(Iteration 161 / 200) loss: 1.801483
(Iteration 171 / 200) loss: 1.973780
(Iteration 181 / 200) loss: 1.666572
(Iteration 191 / 200) loss: 1.909494
(Epoch 5 / 5) train acc: 0.372000; val_acc: 0.319000

running with  sgd_momentum
(Iteration 1 / 200) loss: 3.153777
(Epoch 0 / 5) train acc: 0.099000; val_acc: 0.088000
(Iteration 11 / 200) loss: 2.227203
(Iteration 21 / 200) loss: 2.125706
(Iteration 31 / 200) loss: 1.932679
(Epoch 1 / 5) train acc: 0.308000; val_acc: 0.258000
```

```
(Iteration 41 / 200) loss: 1.946330
(Iteration 51 / 200) loss: 1.780464
(Iteration 61 / 200) loss: 1.753502
(Iteration 71 / 200) loss: 1.844626
(Epoch 2 / 5) train acc: 0.377000; val_acc: 0.331000
(Iteration 81 / 200) loss: 2.028390
(Iteration 91 / 200) loss: 1.685415
(Iteration 101 / 200) loss: 1.513204
(Iteration 111 / 200) loss: 1.431671
(Epoch 3 / 5) train acc: 0.469000; val_acc: 0.335000
(Iteration 121 / 200) loss: 1.678510
(Iteration 131 / 200) loss: 1.545366
(Iteration 141 / 200) loss: 1.617381
(Iteration 151 / 200) loss: 1.693830
(Epoch 4 / 5) train acc: 0.476000; val_acc: 0.347000
(Iteration 161 / 200) loss: 1.466674
(Iteration 171 / 200) loss: 1.425210
(Iteration 181 / 200) loss: 1.377764
(Iteration 191 / 200) loss: 1.363371
(Epoch 5 / 5) train acc: 0.508000; val_acc: 0.362000
```

```
<ipython-input-16-a73acf083950>:39: MatplotlibDeprecationWarning: Adding an axes
using the same arguments as a previous axes currently reuses the earlier
instance.  In a future version, a new instance will always be created and
returned.  Meanwhile, this warning can be suppressed, and the future behavior
ensured, by passing a unique label to each axes instance.
  plt.subplot(3, 1, 1)
<ipython-input-16-a73acf083950>:42: MatplotlibDeprecationWarning: Adding an axes
using the same arguments as a previous axes currently reuses the earlier
instance.  In a future version, a new instance will always be created and
returned.  Meanwhile, this warning can be suppressed, and the future behavior
ensured, by passing a unique label to each axes instance.
  plt.subplot(3, 1, 2)
<ipython-input-16-a73acf083950>:45: MatplotlibDeprecationWarning: Adding an axes
using the same arguments as a previous axes currently reuses the earlier
instance.  In a future version, a new instance will always be created and
returned.  Meanwhile, this warning can be suppressed, and the future behavior
ensured, by passing a unique label to each axes instance.
  plt.subplot(3, 1, 3)
<ipython-input-16-a73acf083950>:49: MatplotlibDeprecationWarning: Adding an axes
using the same arguments as a previous axes currently reuses the earlier
instance.  In a future version, a new instance will always be created and
returned.  Meanwhile, this warning can be suppressed, and the future behavior
ensured, by passing a unique label to each axes instance.
  plt.subplot(3, 1, i)
```



13 RMSProp and Adam

RMSProp [1] and Adam [2] are update rules that set per-parameter learning rates by using a running average of the second moments of gradients.

In the file `cs231n/optim.py`, implement the RMSProp update rule in the `rmsprop` function and implement the Adam update rule in the `adam` function, and check your implementations using the tests below.

NOTE: Please implement the *complete* Adam update rule (with the bias correction mechanism), not the first simplified version mentioned in the course notes.

[1] Tijmen Tieleman and Geoffrey Hinton. "Lecture 6.5-rmsprop: Divide the gradient by a running average of its recent magnitude." COURSERA: Neural Networks for Machine Learning 4 (2012).

[2] Diederik Kingma and Jimmy Ba, "Adam: A Method for Stochastic Optimization", ICLR 2015.

[17]:
```
# Test RMSProp implementation
from cs231n.optim import rmsprop

N, D = 4, 5
w = np.linspace(-0.4, 0.6, num=N*D).reshape(N, D)
dw = np.linspace(-0.6, 0.4, num=N*D).reshape(N, D)
cache = np.linspace(0.6, 0.9, num=N*D).reshape(N, D)

config = {'learning_rate': 1e-2, 'cache': cache}
next_w, _ = rmsprop(w, dw, config=config)

expected_next_w = np.asarray([
  [-0.39223849, -0.34037513, -0.28849239, -0.23659121, -0.18467247],
  [-0.132737,   -0.08078555, -0.02881884,  0.02316247,  0.07515774],
  [ 0.12716641,  0.17918792,  0.23122175,  0.28326742,  0.33532447],
  [ 0.38739248,  0.43947102,  0.49155973,  0.54365823,  0.59576619]])
expected_cache = np.asarray([
  [ 0.5976,      0.6126277,   0.6277108,   0.64284931,  0.65804321],
  [ 0.67329252,  0.68859723,  0.70395734,  0.71937285,  0.73484377],
  [ 0.75037008,  0.7659518,   0.78158892,  0.79728144,  0.81302936],
  [ 0.82883269,  0.84469141,  0.86060554,  0.87657507,  0.8926    ]])

# You should see relative errors around e-7 or less
print('next_w error: ', rel_error(expected_next_w, next_w))
print('cache error: ', rel_error(expected_cache, config['cache']))
```

```
next_w error:  9.524687511038133e-08
cache error:  2.6477955807156126e-09
```

[18]:
```
# Test Adam implementation
from cs231n.optim import adam

N, D = 4, 5
w = np.linspace(-0.4, 0.6, num=N*D).reshape(N, D)
dw = np.linspace(-0.6, 0.4, num=N*D).reshape(N, D)
m = np.linspace(0.6, 0.9, num=N*D).reshape(N, D)
v = np.linspace(0.7, 0.5, num=N*D).reshape(N, D)

config = {'learning_rate': 1e-2, 'm': m, 'v': v, 't': 5}
next_w, _ = adam(w, dw, config=config)

expected_next_w = np.asarray([
  [-0.40094747, -0.34836187, -0.29577703, -0.24319299, -0.19060977],
  [-0.1380274,  -0.08544591, -0.03286534,  0.01971428,  0.0722929],
  [ 0.1248705,   0.17744702,  0.23002243,  0.28259667,  0.33516969],
  [ 0.38774145,  0.44031188,  0.49288093,  0.54544852,  0.59801459]])
```

```
expected_v = np.asarray([
  [ 0.69966,     0.68908382,  0.67851319,  0.66794809,  0.65738853,],
  [ 0.64683452,  0.63628604,  0.6257431,   0.61520571,  0.60467385,],
  [ 0.59414753,  0.58362676,  0.57311152,  0.56260183,  0.55209767,],
  [ 0.54159906,  0.53110598,  0.52061845,  0.51013645,  0.49966,   ]])
expected_m = np.asarray([
  [ 0.48,        0.49947368,  0.51894737,  0.53842105,  0.55789474],
  [ 0.57736842,  0.59684211,  0.61631579,  0.63578947,  0.65526316],
  [ 0.67473684,  0.69421053,  0.71368421,  0.73315789,  0.75263158],
  [ 0.77210526,  0.79157895,  0.81105263,  0.83052632,  0.85      ]])

# You should see relative errors around e-7 or less
print('next_w error: ', rel_error(expected_next_w, next_w))
print('v error: ', rel_error(expected_v, config['v']))
print('m error: ', rel_error(expected_m, config['m']))
```

```
next_w error:  1.1395691798535431e-07
v error:  4.208314038113071e-09
m error:  4.214963193114416e-09
```

Once you have debugged your RMSProp and Adam implementations, run the following to train a pair of deep networks using these new update rules:

[19]:
```
learning_rates = {'rmsprop': 1e-4, 'adam': 1e-3}
for update_rule in ['adam', 'rmsprop']:
  print('running with ', update_rule)
  model = FullyConnectedNet([100, 100, 100, 100, 100], weight_scale=5e-2)

  solver = Solver(model, small_data,
                  num_epochs=5, batch_size=100,
                  update_rule=update_rule,
                  optim_config={
                    'learning_rate': learning_rates[update_rule]
                  },
                  verbose=True)
  solvers[update_rule] = solver
  solver.train()
  print()

plt.subplot(3, 1, 1)
plt.title('Training loss')
plt.xlabel('Iteration')

plt.subplot(3, 1, 2)
plt.title('Training accuracy')
plt.xlabel('Epoch')

plt.subplot(3, 1, 3)
```

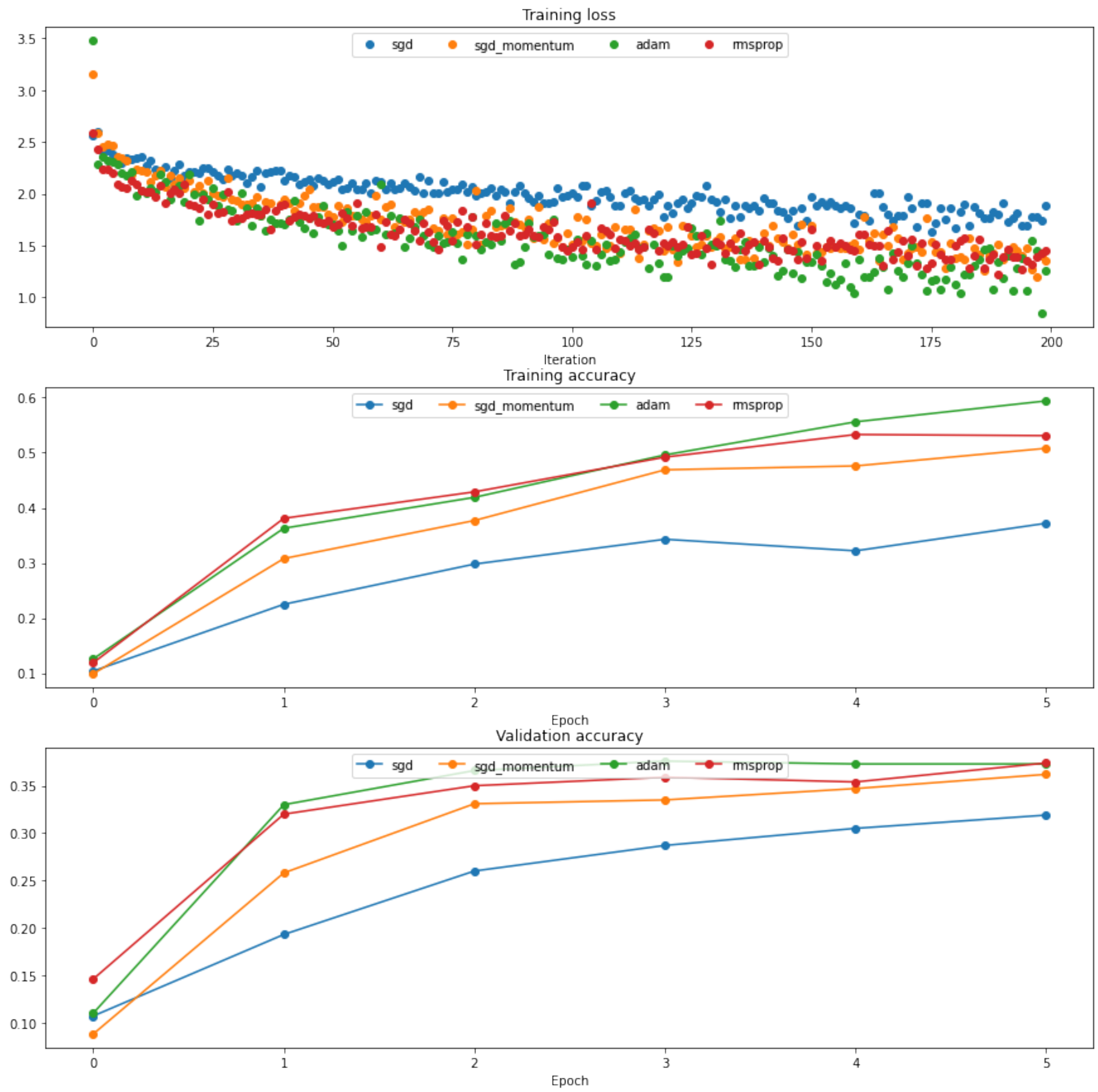
```python
plt.title('Validation accuracy')
plt.xlabel('Epoch')

for update_rule, solver in list(solvers.items()):
  plt.subplot(3, 1, 1)
  plt.plot(solver.loss_history, 'o', label=update_rule)

  plt.subplot(3, 1, 2)
  plt.plot(solver.train_acc_history, '-o', label=update_rule)

  plt.subplot(3, 1, 3)
  plt.plot(solver.val_acc_history, '-o', label=update_rule)

for i in [1, 2, 3]:
  plt.subplot(3, 1, i)
  plt.legend(loc='upper center', ncol=4)
plt.gcf().set_size_inches(15, 15)
plt.show()
```

```
running with  adam
(Iteration 1 / 200) loss: 3.476928
(Epoch 0 / 5) train acc: 0.126000; val_acc: 0.110000
(Iteration 11 / 200) loss: 2.027712
(Iteration 21 / 200) loss: 2.183358
(Iteration 31 / 200) loss: 1.744257
(Epoch 1 / 5) train acc: 0.363000; val_acc: 0.330000
(Iteration 41 / 200) loss: 1.707951
(Iteration 51 / 200) loss: 1.703834
(Iteration 61 / 200) loss: 2.094758
(Iteration 71 / 200) loss: 1.505614
(Epoch 2 / 5) train acc: 0.419000; val_acc: 0.366000
(Iteration 81 / 200) loss: 1.593840
(Iteration 91 / 200) loss: 1.492122
(Iteration 101 / 200) loss: 1.393159
(Iteration 111 / 200) loss: 1.441610
(Epoch 3 / 5) train acc: 0.496000; val_acc: 0.376000
(Iteration 121 / 200) loss: 1.196205
(Iteration 131 / 200) loss: 1.500585
(Iteration 141 / 200) loss: 1.336431
(Iteration 151 / 200) loss: 1.343462
(Epoch 4 / 5) train acc: 0.556000; val_acc: 0.373000
(Iteration 161 / 200) loss: 1.366904
(Iteration 171 / 200) loss: 1.335568
(Iteration 181 / 200) loss: 1.130025
(Iteration 191 / 200) loss: 1.187725
(Epoch 5 / 5) train acc: 0.594000; val_acc: 0.373000

running with  rmsprop
```

```
(Iteration 1 / 200) loss: 2.589166
(Epoch 0 / 5) train acc: 0.119000; val_acc: 0.146000
(Iteration 11 / 200) loss: 2.032921
(Iteration 21 / 200) loss: 1.897277
(Iteration 31 / 200) loss: 1.770793
(Epoch 1 / 5) train acc: 0.381000; val_acc: 0.320000
(Iteration 41 / 200) loss: 1.895731
(Iteration 51 / 200) loss: 1.681091
(Iteration 61 / 200) loss: 1.487204
(Iteration 71 / 200) loss: 1.629973
(Epoch 2 / 5) train acc: 0.429000; val_acc: 0.350000
(Iteration 81 / 200) loss: 1.506686
(Iteration 91 / 200) loss: 1.610742
(Iteration 101 / 200) loss: 1.486124
(Iteration 111 / 200) loss: 1.559454
(Epoch 3 / 5) train acc: 0.492000; val_acc: 0.359000
(Iteration 121 / 200) loss: 1.496860
(Iteration 131 / 200) loss: 1.531552
(Iteration 141 / 200) loss: 1.550195
(Iteration 151 / 200) loss: 1.657838
(Epoch 4 / 5) train acc: 0.533000; val_acc: 0.354000
(Iteration 161 / 200) loss: 1.603105
(Iteration 171 / 200) loss: 1.405372
(Iteration 181 / 200) loss: 1.503740
(Iteration 191 / 200) loss: 1.385278
(Epoch 5 / 5) train acc: 0.531000; val_acc: 0.374000
```

```
<ipython-input-19-c31f2247ce3b>:30: MatplotlibDeprecationWarning: Adding an axes
using the same arguments as a previous axes currently reuses the earlier
instance.  In a future version, a new instance will always be created and
returned.  Meanwhile, this warning can be suppressed, and the future behavior
ensured, by passing a unique label to each axes instance.
  plt.subplot(3, 1, 1)
<ipython-input-19-c31f2247ce3b>:33: MatplotlibDeprecationWarning: Adding an axes
using the same arguments as a previous axes currently reuses the earlier
instance.  In a future version, a new instance will always be created and
returned.  Meanwhile, this warning can be suppressed, and the future behavior
ensured, by passing a unique label to each axes instance.
  plt.subplot(3, 1, 2)
<ipython-input-19-c31f2247ce3b>:36: MatplotlibDeprecationWarning: Adding an axes
using the same arguments as a previous axes currently reuses the earlier
instance.  In a future version, a new instance will always be created and
returned.  Meanwhile, this warning can be suppressed, and the future behavior
ensured, by passing a unique label to each axes instance.
  plt.subplot(3, 1, 3)
<ipython-input-19-c31f2247ce3b>:40: MatplotlibDeprecationWarning: Adding an axes
using the same arguments as a previous axes currently reuses the earlier
```

```
instance.  In a future version, a new instance will always be created and
returned.  Meanwhile, this warning can be suppressed, and the future behavior
ensured, by passing a unique label to each axes instance.
  plt.subplot(3, 1, i)
```



13.1 Inline Question 4:

AdaGrad, like RMSprop and Adam, is a per-parameter optimization method that uses the following update rule:

```
cache += dw**2
w += - learning_rate * dw / (np.sqrt(cache) + eps)
```

John notices that when he was training a network with AdaGrad that the updates became very small, and that his network was learning slowly. Using your knowledge of the AdaGrad update rule, why do you think the updates would become very small? Would RMSprop have the same issue? What about Adam? Justify.

13.2 Answer:

Los tres métodos son parte de la familia de métodos de optimización con Learning Rate adaptativo.

En el caso de AdaGrad, el learning rate luego de muchas iteraciones se vuelve muy pequeño, por lo que el aprendizaje se enlentece. La forma de actualizar el learning rate, dividiendo siempre por la suma de los cuadrados de los gradientes calculados hasta ese momento, hace que siempre disminuya, volviendolo muy pequeño.

RMSProp actualiza el learning rate ponderando el cálculo del cuadrado del gradiente del paso anterior con el cuadrado del gradiente en dicho paso (ponderación realizada con el parámetro decay rate). De esta manera, el learning rate no tiene porque disminuir hasta volverse muy pequeño.

Adam tampoco tiene el problema de AdaGrad, ya que la división del learning rate en cada paso se realiza con la misma idea que RMSProp. Además, para mantener una inercia en el movimiento del que iba teniendo, se multiplica por el "primer momento" (ponderacion del gradiente con el gradiente anterior), en vez que por el gradiente en dicho punto. Esto último es independiente del learning rate, pero es la diferencia sustancial con RMSProp.

14 Train a good model!

Train the best fully-connected model that you can on CIFAR-10, storing your best model in the `best_model` variable. We require you to get at least 50% accuracy on the validation set using a fully-connected net.

If you are careful it should be possible to get accuracies above 55%, but we don't require it for this part and won't assign extra credit for doing so. Later in the assignment we will ask you to train the best convolutional network that you can on CIFAR-10, and we would prefer that you spend your effort working on convolutional nets rather than fully-connected nets.

You might find it useful to complete the `BatchNormalization.ipynb` and `Dropout.ipynb` notebooks before completing this part, since those techniques can help you train powerful models.

[23]:
```
best_model = None
################################################################################
# TODO: Train the best FullyConnectedNet that you can on CIFAR-10. You might   #
# find batch/layer normalization and dropout useful. Store your best model in  #
# the best_model variable.                                                     #
################################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

best_acc = -1

for drOut in [0.5, 0.9]:
        model = FullyConnectedNet([100, 100, 100, 100, 100], weight_scale=5e-2,␣
 ↪normalization = 'batchnorm', dropout = drOut)
        solver = Solver(model, data,
```

```
                      num_epochs=5, batch_size=100,
                      update_rule='adam',
                      optim_config={
                        'learning_rate': 5e-3,
                      },
                      verbose=True)
        solvers[update_rule] = solver
        solver.train()
        if solver.val_acc_history[-1] > best_acc:
            best_acc = solver.val_acc_history[-1]
            best_model = model

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

```
(Iteration 1 / 2450) loss: 2.267681
(Epoch 0 / 5) train acc: 0.099000; val_acc: 0.115000
(Iteration 11 / 2450) loss: 2.300138
(Iteration 21 / 2450) loss: 2.321648
(Iteration 31 / 2450) loss: 2.259934
(Iteration 41 / 2450) loss: 2.242060
(Iteration 51 / 2450) loss: 2.242353
(Iteration 61 / 2450) loss: 2.197359
(Iteration 71 / 2450) loss: 2.209563
(Iteration 81 / 2450) loss: 2.010295
(Iteration 91 / 2450) loss: 2.197425
(Iteration 101 / 2450) loss: 1.981836
(Iteration 111 / 2450) loss: 2.108379
(Iteration 121 / 2450) loss: 2.010417
(Iteration 131 / 2450) loss: 2.083258
(Iteration 141 / 2450) loss: 2.208658
(Iteration 151 / 2450) loss: 2.059224
(Iteration 161 / 2450) loss: 1.992993
(Iteration 171 / 2450) loss: 2.109613
(Iteration 181 / 2450) loss: 2.009898
(Iteration 191 / 2450) loss: 2.069989
(Iteration 201 / 2450) loss: 2.143241
(Iteration 211 / 2450) loss: 2.046433
(Iteration 221 / 2450) loss: 1.868004
(Iteration 231 / 2450) loss: 1.958076
(Iteration 241 / 2450) loss: 2.049822
(Iteration 251 / 2450) loss: 1.927111
(Iteration 261 / 2450) loss: 1.904266
(Iteration 271 / 2450) loss: 2.141049
(Iteration 281 / 2450) loss: 1.886779
(Iteration 291 / 2450) loss: 2.085457
```

```
(Iteration 301 / 2450) loss: 1.888010
(Iteration 311 / 2450) loss: 1.925098
(Iteration 321 / 2450) loss: 1.876229
(Iteration 331 / 2450) loss: 1.877353
(Iteration 341 / 2450) loss: 1.986933
(Iteration 351 / 2450) loss: 2.127018
(Iteration 361 / 2450) loss: 1.911489
(Iteration 371 / 2450) loss: 1.913146
(Iteration 381 / 2450) loss: 2.003284
(Iteration 391 / 2450) loss: 1.981713
(Iteration 401 / 2450) loss: 2.098961
(Iteration 411 / 2450) loss: 2.018379
(Iteration 421 / 2450) loss: 1.945340
(Iteration 431 / 2450) loss: 1.936231
(Iteration 441 / 2450) loss: 1.994619
(Iteration 451 / 2450) loss: 1.883160
(Iteration 461 / 2450) loss: 1.983976
(Iteration 471 / 2450) loss: 2.006366
(Iteration 481 / 2450) loss: 2.075239
(Epoch 1 / 5) train acc: 0.307000; val_acc: 0.329000
(Iteration 491 / 2450) loss: 1.871037
(Iteration 501 / 2450) loss: 1.788184
(Iteration 511 / 2450) loss: 1.929516
(Iteration 521 / 2450) loss: 2.013125
(Iteration 531 / 2450) loss: 1.946705
(Iteration 541 / 2450) loss: 2.021497
(Iteration 551 / 2450) loss: 2.084534
(Iteration 561 / 2450) loss: 1.764839
(Iteration 571 / 2450) loss: 1.877782
(Iteration 581 / 2450) loss: 1.893676
(Iteration 591 / 2450) loss: 1.881500
(Iteration 601 / 2450) loss: 1.982966
(Iteration 611 / 2450) loss: 1.837882
(Iteration 621 / 2450) loss: 1.840168
(Iteration 631 / 2450) loss: 1.961790
(Iteration 641 / 2450) loss: 1.867868
(Iteration 651 / 2450) loss: 1.897548
(Iteration 661 / 2450) loss: 1.897872
(Iteration 671 / 2450) loss: 2.174696
(Iteration 681 / 2450) loss: 2.002532
(Iteration 691 / 2450) loss: 1.947519
(Iteration 701 / 2450) loss: 1.731061
(Iteration 711 / 2450) loss: 1.931713
(Iteration 721 / 2450) loss: 1.774519
(Iteration 731 / 2450) loss: 1.878108
(Iteration 741 / 2450) loss: 1.817742
(Iteration 751 / 2450) loss: 1.933674
(Iteration 761 / 2450) loss: 1.786246
```

```
(Iteration 771 / 2450) loss: 1.894575
(Iteration 781 / 2450) loss: 1.881932
(Iteration 791 / 2450) loss: 1.874568
(Iteration 801 / 2450) loss: 1.876252
(Iteration 811 / 2450) loss: 1.871839
(Iteration 821 / 2450) loss: 1.820029
(Iteration 831 / 2450) loss: 1.914848
(Iteration 841 / 2450) loss: 1.877307
(Iteration 851 / 2450) loss: 1.892637
(Iteration 861 / 2450) loss: 1.981469
(Iteration 871 / 2450) loss: 1.769118
(Iteration 881 / 2450) loss: 1.780921
(Iteration 891 / 2450) loss: 1.867317
(Iteration 901 / 2450) loss: 1.778289
(Iteration 911 / 2450) loss: 2.043600
(Iteration 921 / 2450) loss: 1.998614
(Iteration 931 / 2450) loss: 1.974940
(Iteration 941 / 2450) loss: 1.980312
(Iteration 951 / 2450) loss: 1.820140
(Iteration 961 / 2450) loss: 1.976247
(Iteration 971 / 2450) loss: 2.011847
(Epoch 2 / 5) train acc: 0.375000; val_acc: 0.362000
(Iteration 981 / 2450) loss: 1.934528
(Iteration 991 / 2450) loss: 1.941811
(Iteration 1001 / 2450) loss: 1.883698
(Iteration 1011 / 2450) loss: 1.758031
(Iteration 1021 / 2450) loss: 1.919450
(Iteration 1031 / 2450) loss: 1.824338
(Iteration 1041 / 2450) loss: 1.919201
(Iteration 1051 / 2450) loss: 1.785010
(Iteration 1061 / 2450) loss: 1.863965
(Iteration 1071 / 2450) loss: 1.869940
(Iteration 1081 / 2450) loss: 1.859113
(Iteration 1091 / 2450) loss: 1.826528
(Iteration 1101 / 2450) loss: 1.904383
(Iteration 1111 / 2450) loss: 1.893273
(Iteration 1121 / 2450) loss: 1.820200
(Iteration 1131 / 2450) loss: 1.838461
(Iteration 1141 / 2450) loss: 1.778176
(Iteration 1151 / 2450) loss: 1.888015
(Iteration 1161 / 2450) loss: 1.802767
(Iteration 1171 / 2450) loss: 1.867055
(Iteration 1181 / 2450) loss: 1.886893
(Iteration 1191 / 2450) loss: 1.894463
(Iteration 1201 / 2450) loss: 1.919154
(Iteration 1211 / 2450) loss: 1.900411
(Iteration 1221 / 2450) loss: 1.845119
(Iteration 1231 / 2450) loss: 1.921927
```

```
(Iteration 1241 / 2450) loss: 1.701614
(Iteration 1251 / 2450) loss: 1.932239
(Iteration 1261 / 2450) loss: 2.010717
(Iteration 1271 / 2450) loss: 1.830600
(Iteration 1281 / 2450) loss: 1.882096
(Iteration 1291 / 2450) loss: 2.032261
(Iteration 1301 / 2450) loss: 1.767264
(Iteration 1311 / 2450) loss: 1.783849
(Iteration 1321 / 2450) loss: 1.889049
(Iteration 1331 / 2450) loss: 1.798526
(Iteration 1341 / 2450) loss: 1.879413
(Iteration 1351 / 2450) loss: 1.989595
(Iteration 1361 / 2450) loss: 1.834174
(Iteration 1371 / 2450) loss: 1.927016
(Iteration 1381 / 2450) loss: 1.848488
(Iteration 1391 / 2450) loss: 1.974419
(Iteration 1401 / 2450) loss: 1.880473
(Iteration 1411 / 2450) loss: 1.796976
(Iteration 1421 / 2450) loss: 1.884294
(Iteration 1431 / 2450) loss: 1.793358
(Iteration 1441 / 2450) loss: 1.846915
(Iteration 1451 / 2450) loss: 1.829015
(Iteration 1461 / 2450) loss: 1.870508
(Epoch 3 / 5) train acc: 0.378000; val_acc: 0.389000
(Iteration 1471 / 2450) loss: 1.792035
(Iteration 1481 / 2450) loss: 1.898763
(Iteration 1491 / 2450) loss: 1.862157
(Iteration 1501 / 2450) loss: 1.965981
(Iteration 1511 / 2450) loss: 1.882577
(Iteration 1521 / 2450) loss: 1.792362
(Iteration 1531 / 2450) loss: 1.772196
(Iteration 1541 / 2450) loss: 1.795697
(Iteration 1551 / 2450) loss: 1.882389
(Iteration 1561 / 2450) loss: 1.783817
(Iteration 1571 / 2450) loss: 1.799311
(Iteration 1581 / 2450) loss: 1.920072
(Iteration 1591 / 2450) loss: 1.764659
(Iteration 1601 / 2450) loss: 1.853558
(Iteration 1611 / 2450) loss: 1.842382
(Iteration 1621 / 2450) loss: 1.677482
(Iteration 1631 / 2450) loss: 1.990709
(Iteration 1641 / 2450) loss: 1.864365
(Iteration 1651 / 2450) loss: 1.849521
(Iteration 1661 / 2450) loss: 1.823341
(Iteration 1671 / 2450) loss: 1.901579
(Iteration 1681 / 2450) loss: 1.967088
(Iteration 1691 / 2450) loss: 1.707663
(Iteration 1701 / 2450) loss: 1.834097
```

```
(Iteration 1711 / 2450) loss: 1.738177
(Iteration 1721 / 2450) loss: 1.743959
(Iteration 1731 / 2450) loss: 1.800020
(Iteration 1741 / 2450) loss: 1.813305
(Iteration 1751 / 2450) loss: 1.823377
(Iteration 1761 / 2450) loss: 1.724991
(Iteration 1771 / 2450) loss: 1.716529
(Iteration 1781 / 2450) loss: 1.862297
(Iteration 1791 / 2450) loss: 1.661732
(Iteration 1801 / 2450) loss: 1.642575
(Iteration 1811 / 2450) loss: 1.898179
(Iteration 1821 / 2450) loss: 1.779054
(Iteration 1831 / 2450) loss: 1.715117
(Iteration 1841 / 2450) loss: 1.826146
(Iteration 1851 / 2450) loss: 1.831942
(Iteration 1861 / 2450) loss: 1.715724
(Iteration 1871 / 2450) loss: 1.651334
(Iteration 1881 / 2450) loss: 1.929140
(Iteration 1891 / 2450) loss: 1.966258
(Iteration 1901 / 2450) loss: 1.871918
(Iteration 1911 / 2450) loss: 1.755508
(Iteration 1921 / 2450) loss: 1.848613
(Iteration 1931 / 2450) loss: 1.711912
(Iteration 1941 / 2450) loss: 1.750943
(Iteration 1951 / 2450) loss: 1.729060
(Epoch 4 / 5) train acc: 0.407000; val_acc: 0.407000
(Iteration 1961 / 2450) loss: 1.708416
(Iteration 1971 / 2450) loss: 1.763089
(Iteration 1981 / 2450) loss: 1.887343
(Iteration 1991 / 2450) loss: 1.761518
(Iteration 2001 / 2450) loss: 1.853698
(Iteration 2011 / 2450) loss: 1.835174
(Iteration 2021 / 2450) loss: 1.831693
(Iteration 2031 / 2450) loss: 1.924796
(Iteration 2041 / 2450) loss: 1.743020
(Iteration 2051 / 2450) loss: 2.010957
(Iteration 2061 / 2450) loss: 1.852592
(Iteration 2071 / 2450) loss: 1.884347
(Iteration 2081 / 2450) loss: 1.983970
(Iteration 2091 / 2450) loss: 1.722125
(Iteration 2101 / 2450) loss: 1.646762
(Iteration 2111 / 2450) loss: 1.887745
(Iteration 2121 / 2450) loss: 1.841743
(Iteration 2131 / 2450) loss: 1.677059
(Iteration 2141 / 2450) loss: 1.805035
(Iteration 2151 / 2450) loss: 1.688518
(Iteration 2161 / 2450) loss: 1.891521
(Iteration 2171 / 2450) loss: 1.712456
```

```
(Iteration 2181 / 2450) loss: 1.877210
(Iteration 2191 / 2450) loss: 1.888699
(Iteration 2201 / 2450) loss: 1.765696
(Iteration 2211 / 2450) loss: 1.765956
(Iteration 2221 / 2450) loss: 1.720107
(Iteration 2231 / 2450) loss: 1.886132
(Iteration 2241 / 2450) loss: 1.771209
(Iteration 2251 / 2450) loss: 1.773066
(Iteration 2261 / 2450) loss: 1.869972
(Iteration 2271 / 2450) loss: 1.746719
(Iteration 2281 / 2450) loss: 1.812851
(Iteration 2291 / 2450) loss: 1.705789
(Iteration 2301 / 2450) loss: 1.800205
(Iteration 2311 / 2450) loss: 1.676957
(Iteration 2321 / 2450) loss: 1.797283
(Iteration 2331 / 2450) loss: 1.705066
(Iteration 2341 / 2450) loss: 1.637096
(Iteration 2351 / 2450) loss: 1.825960
(Iteration 2361 / 2450) loss: 1.737063
(Iteration 2371 / 2450) loss: 1.794648
(Iteration 2381 / 2450) loss: 1.721396
(Iteration 2391 / 2450) loss: 1.794456
(Iteration 2401 / 2450) loss: 1.887536
(Iteration 2411 / 2450) loss: 1.797733
(Iteration 2421 / 2450) loss: 1.899574
(Iteration 2431 / 2450) loss: 1.759573
(Iteration 2441 / 2450) loss: 1.592436
(Epoch 5 / 5) train acc: 0.402000; val_acc: 0.404000
(Iteration 1 / 2450) loss: 2.346818
(Epoch 0 / 5) train acc: 0.116000; val_acc: 0.112000
(Iteration 11 / 2450) loss: 2.170935
(Iteration 21 / 2450) loss: 2.096881
(Iteration 31 / 2450) loss: 1.907986
(Iteration 41 / 2450) loss: 2.022211
(Iteration 51 / 2450) loss: 1.869376
(Iteration 61 / 2450) loss: 1.844939
(Iteration 71 / 2450) loss: 1.875005
(Iteration 81 / 2450) loss: 1.873745
(Iteration 91 / 2450) loss: 1.804783
(Iteration 101 / 2450) loss: 1.734438
(Iteration 111 / 2450) loss: 1.822506
(Iteration 121 / 2450) loss: 1.703965
(Iteration 131 / 2450) loss: 1.738629
(Iteration 141 / 2450) loss: 1.665303
(Iteration 151 / 2450) loss: 1.841956
(Iteration 161 / 2450) loss: 1.718961
(Iteration 171 / 2450) loss: 1.746617
(Iteration 181 / 2450) loss: 1.900681
```

```
(Iteration 191 / 2450) loss: 1.703202
(Iteration 201 / 2450) loss: 1.855079
(Iteration 211 / 2450) loss: 1.774299
(Iteration 221 / 2450) loss: 1.700632
(Iteration 231 / 2450) loss: 1.791218
(Iteration 241 / 2450) loss: 1.800784
(Iteration 251 / 2450) loss: 1.801141
(Iteration 261 / 2450) loss: 1.612283
(Iteration 271 / 2450) loss: 1.675324
(Iteration 281 / 2450) loss: 1.835972
(Iteration 291 / 2450) loss: 1.761025
(Iteration 301 / 2450) loss: 1.643570
(Iteration 311 / 2450) loss: 1.763820
(Iteration 321 / 2450) loss: 1.821115
(Iteration 331 / 2450) loss: 1.700573
(Iteration 341 / 2450) loss: 1.695574
(Iteration 351 / 2450) loss: 1.738003
(Iteration 361 / 2450) loss: 1.567748
(Iteration 371 / 2450) loss: 1.768705
(Iteration 381 / 2450) loss: 1.592987
(Iteration 391 / 2450) loss: 1.798365
(Iteration 401 / 2450) loss: 1.574736
(Iteration 411 / 2450) loss: 1.688126
(Iteration 421 / 2450) loss: 1.689769
(Iteration 431 / 2450) loss: 1.663456
(Iteration 441 / 2450) loss: 1.843118
(Iteration 451 / 2450) loss: 1.521161
(Iteration 461 / 2450) loss: 1.685265
(Iteration 471 / 2450) loss: 1.575740
(Iteration 481 / 2450) loss: 1.680296
(Epoch 1 / 5) train acc: 0.451000; val_acc: 0.453000
(Iteration 491 / 2450) loss: 1.637750
(Iteration 501 / 2450) loss: 1.558981
(Iteration 511 / 2450) loss: 1.567754
(Iteration 521 / 2450) loss: 1.889158
(Iteration 531 / 2450) loss: 1.675525
(Iteration 541 / 2450) loss: 1.722899
(Iteration 551 / 2450) loss: 1.463143
(Iteration 561 / 2450) loss: 1.509441
(Iteration 571 / 2450) loss: 1.537315
(Iteration 581 / 2450) loss: 1.621834
(Iteration 591 / 2450) loss: 1.419395
(Iteration 601 / 2450) loss: 1.539763
(Iteration 611 / 2450) loss: 1.644981
(Iteration 621 / 2450) loss: 1.565988
(Iteration 631 / 2450) loss: 1.465074
(Iteration 641 / 2450) loss: 1.532844
(Iteration 651 / 2450) loss: 1.544501
```

```
(Iteration 661 / 2450) loss: 1.563435
(Iteration 671 / 2450) loss: 1.602261
(Iteration 681 / 2450) loss: 1.690961
(Iteration 691 / 2450) loss: 1.560265
(Iteration 701 / 2450) loss: 1.667593
(Iteration 711 / 2450) loss: 1.525292
(Iteration 721 / 2450) loss: 1.583047
(Iteration 731 / 2450) loss: 1.557381
(Iteration 741 / 2450) loss: 1.857377
(Iteration 751 / 2450) loss: 1.572024
(Iteration 761 / 2450) loss: 1.550533
(Iteration 771 / 2450) loss: 1.595838
(Iteration 781 / 2450) loss: 1.480404
(Iteration 791 / 2450) loss: 1.636589
(Iteration 801 / 2450) loss: 1.585442
(Iteration 811 / 2450) loss: 1.446723
(Iteration 821 / 2450) loss: 1.593582
(Iteration 831 / 2450) loss: 1.613958
(Iteration 841 / 2450) loss: 1.687240
(Iteration 851 / 2450) loss: 1.600756
(Iteration 861 / 2450) loss: 1.428398
(Iteration 871 / 2450) loss: 1.380056
(Iteration 881 / 2450) loss: 1.540354
(Iteration 891 / 2450) loss: 1.636370
(Iteration 901 / 2450) loss: 1.553064
(Iteration 911 / 2450) loss: 1.523979
(Iteration 921 / 2450) loss: 1.540286
(Iteration 931 / 2450) loss: 1.501209
(Iteration 941 / 2450) loss: 1.437417
(Iteration 951 / 2450) loss: 1.582534
(Iteration 961 / 2450) loss: 1.617017
(Iteration 971 / 2450) loss: 1.632531
(Epoch 2 / 5) train acc: 0.496000; val_acc: 0.471000
(Iteration 981 / 2450) loss: 1.425461
(Iteration 991 / 2450) loss: 1.483605
(Iteration 1001 / 2450) loss: 1.461814
(Iteration 1011 / 2450) loss: 1.678430
(Iteration 1021 / 2450) loss: 1.576477
(Iteration 1031 / 2450) loss: 1.402389
(Iteration 1041 / 2450) loss: 1.394487
(Iteration 1051 / 2450) loss: 1.611997
(Iteration 1061 / 2450) loss: 1.721859
(Iteration 1071 / 2450) loss: 1.664372
(Iteration 1081 / 2450) loss: 1.430824
(Iteration 1091 / 2450) loss: 1.552279
(Iteration 1101 / 2450) loss: 1.451865
(Iteration 1111 / 2450) loss: 1.567770
(Iteration 1121 / 2450) loss: 1.641650
```

```
(Iteration 1131 / 2450) loss: 1.401029
(Iteration 1141 / 2450) loss: 1.300896
(Iteration 1151 / 2450) loss: 1.474157
(Iteration 1161 / 2450) loss: 1.679849
(Iteration 1171 / 2450) loss: 1.402036
(Iteration 1181 / 2450) loss: 1.426092
(Iteration 1191 / 2450) loss: 1.367008
(Iteration 1201 / 2450) loss: 1.647249
(Iteration 1211 / 2450) loss: 1.430722
(Iteration 1221 / 2450) loss: 1.461595
(Iteration 1231 / 2450) loss: 1.838923
(Iteration 1241 / 2450) loss: 1.633648
(Iteration 1251 / 2450) loss: 1.482048
(Iteration 1261 / 2450) loss: 1.564166
(Iteration 1271 / 2450) loss: 1.371805
(Iteration 1281 / 2450) loss: 1.655390
(Iteration 1291 / 2450) loss: 1.306323
(Iteration 1301 / 2450) loss: 1.547724
(Iteration 1311 / 2450) loss: 1.442265
(Iteration 1321 / 2450) loss: 1.677312
(Iteration 1331 / 2450) loss: 1.499055
(Iteration 1341 / 2450) loss: 1.496297
(Iteration 1351 / 2450) loss: 1.287934
(Iteration 1361 / 2450) loss: 1.596922
(Iteration 1371 / 2450) loss: 1.456486
(Iteration 1381 / 2450) loss: 1.392592
(Iteration 1391 / 2450) loss: 1.650231
(Iteration 1401 / 2450) loss: 1.351794
(Iteration 1411 / 2450) loss: 1.644830
(Iteration 1421 / 2450) loss: 1.360258
(Iteration 1431 / 2450) loss: 1.506661
(Iteration 1441 / 2450) loss: 1.449078
(Iteration 1451 / 2450) loss: 1.503618
(Iteration 1461 / 2450) loss: 1.404226
(Epoch 3 / 5) train acc: 0.504000; val_acc: 0.498000
(Iteration 1471 / 2450) loss: 1.387132
(Iteration 1481 / 2450) loss: 1.413202
(Iteration 1491 / 2450) loss: 1.499719
(Iteration 1501 / 2450) loss: 1.458759
(Iteration 1511 / 2450) loss: 1.668739
(Iteration 1521 / 2450) loss: 1.414708
(Iteration 1531 / 2450) loss: 1.588477
(Iteration 1541 / 2450) loss: 1.439648
(Iteration 1551 / 2450) loss: 1.555774
(Iteration 1561 / 2450) loss: 1.320230
(Iteration 1571 / 2450) loss: 1.478380
(Iteration 1581 / 2450) loss: 1.509159
(Iteration 1591 / 2450) loss: 1.464611
```

```
(Iteration 1601 / 2450) loss: 1.595486
(Iteration 1611 / 2450) loss: 1.408847
(Iteration 1621 / 2450) loss: 1.411437
(Iteration 1631 / 2450) loss: 1.595340
(Iteration 1641 / 2450) loss: 1.409516
(Iteration 1651 / 2450) loss: 1.347525
(Iteration 1661 / 2450) loss: 1.556752
(Iteration 1671 / 2450) loss: 1.608628
(Iteration 1681 / 2450) loss: 1.396919
(Iteration 1691 / 2450) loss: 1.427067
(Iteration 1701 / 2450) loss: 1.429831
(Iteration 1711 / 2450) loss: 1.293095
(Iteration 1721 / 2450) loss: 1.277452
(Iteration 1731 / 2450) loss: 1.403717
(Iteration 1741 / 2450) loss: 1.441291
(Iteration 1751 / 2450) loss: 1.327197
(Iteration 1761 / 2450) loss: 1.360472
(Iteration 1771 / 2450) loss: 1.432724
(Iteration 1781 / 2450) loss: 1.343094
(Iteration 1791 / 2450) loss: 1.591028
(Iteration 1801 / 2450) loss: 1.612885
(Iteration 1811 / 2450) loss: 1.250747
(Iteration 1821 / 2450) loss: 1.335752
(Iteration 1831 / 2450) loss: 1.440876
(Iteration 1841 / 2450) loss: 1.465240
(Iteration 1851 / 2450) loss: 1.359440
(Iteration 1861 / 2450) loss: 1.445729
(Iteration 1871 / 2450) loss: 1.423682
(Iteration 1881 / 2450) loss: 1.494437
(Iteration 1891 / 2450) loss: 1.427285
(Iteration 1901 / 2450) loss: 1.423571
(Iteration 1911 / 2450) loss: 1.399600
(Iteration 1921 / 2450) loss: 1.409437
(Iteration 1931 / 2450) loss: 1.611101
(Iteration 1941 / 2450) loss: 1.395752
(Iteration 1951 / 2450) loss: 1.390253
(Epoch 4 / 5) train acc: 0.489000; val_acc: 0.501000
(Iteration 1961 / 2450) loss: 1.506916
(Iteration 1971 / 2450) loss: 1.535468
(Iteration 1981 / 2450) loss: 1.552048
(Iteration 1991 / 2450) loss: 1.474483
(Iteration 2001 / 2450) loss: 1.520628
(Iteration 2011 / 2450) loss: 1.622077
(Iteration 2021 / 2450) loss: 1.225345
(Iteration 2031 / 2450) loss: 1.583378
(Iteration 2041 / 2450) loss: 1.480470
(Iteration 2051 / 2450) loss: 1.365159
(Iteration 2061 / 2450) loss: 1.405189
```

```
(Iteration 2071 / 2450) loss: 1.341781
(Iteration 2081 / 2450) loss: 1.348699
(Iteration 2091 / 2450) loss: 1.549894
(Iteration 2101 / 2450) loss: 1.222793
(Iteration 2111 / 2450) loss: 1.309708
(Iteration 2121 / 2450) loss: 1.178667
(Iteration 2131 / 2450) loss: 1.462421
(Iteration 2141 / 2450) loss: 1.340377
(Iteration 2151 / 2450) loss: 1.261710
(Iteration 2161 / 2450) loss: 1.477761
(Iteration 2171 / 2450) loss: 1.496405
(Iteration 2181 / 2450) loss: 1.520072
(Iteration 2191 / 2450) loss: 1.326987
(Iteration 2201 / 2450) loss: 1.424918
(Iteration 2211 / 2450) loss: 1.556797
(Iteration 2221 / 2450) loss: 1.439127
(Iteration 2231 / 2450) loss: 1.356689
(Iteration 2241 / 2450) loss: 1.510355
(Iteration 2251 / 2450) loss: 1.381279
(Iteration 2261 / 2450) loss: 1.108373
(Iteration 2271 / 2450) loss: 1.595991
(Iteration 2281 / 2450) loss: 1.426170
(Iteration 2291 / 2450) loss: 1.434308
(Iteration 2301 / 2450) loss: 1.587357
(Iteration 2311 / 2450) loss: 1.411812
(Iteration 2321 / 2450) loss: 1.426311
(Iteration 2331 / 2450) loss: 1.473602
(Iteration 2341 / 2450) loss: 1.330380
(Iteration 2351 / 2450) loss: 1.439326
(Iteration 2361 / 2450) loss: 1.404886
(Iteration 2371 / 2450) loss: 1.509758
(Iteration 2381 / 2450) loss: 1.221464
(Iteration 2391 / 2450) loss: 1.376966
(Iteration 2401 / 2450) loss: 1.433394
(Iteration 2411 / 2450) loss: 1.372459
(Iteration 2421 / 2450) loss: 1.393666
(Iteration 2431 / 2450) loss: 1.444407
(Iteration 2441 / 2450) loss: 1.302475
(Epoch 5 / 5) train acc: 0.546000; val_acc: 0.518000
```

15 Test your model!

Run your best model on the validation and test sets. You should achieve above 50% accuracy on the validation set.

[24]:
```python
y_test_pred = np.argmax(best_model.loss(data['X_test']), axis=1)
y_val_pred = np.argmax(best_model.loss(data['X_val']), axis=1)
```

```python
print('Validation set accuracy: ', (y_val_pred == data['y_val']).mean())
print('Test set accuracy: ', (y_test_pred == data['y_test']).mean())
```

```
Validation set accuracy:  0.518
Test set accuracy:  0.507
```

[ ]:

```python

```

BatchNormalization

November 17, 2020

1 Batch Normalization

One way to make deep networks easier to train is to use more sophisticated optimization procedures such as SGD+momentum, RMSProp, or Adam. Another strategy is to change the architecture of the network to make it easier to train. One idea along these lines is batch normalization which was proposed by [1] in 2015.

The idea is relatively straightforward. Machine learning methods tend to work better when their input data consists of uncorrelated features with zero mean and unit variance. When training a neural network, we can preprocess the data before feeding it to the network to explicitly decorrelate its features; this will ensure that the first layer of the network sees data that follows a nice distribution. However, even if we preprocess the input data, the activations at deeper layers of the network will likely no longer be decorrelated and will no longer have zero mean or unit variance since they are output from earlier layers in the network. Even worse, during the training process the distribution of features at each layer of the network will shift as the weights of each layer are updated.

The authors of [1] hypothesize that the shifting distribution of features inside deep neural networks may make training deep networks more difficult. To overcome this problem, [1] proposes to insert batch normalization layers into the network. At training time, a batch normalization layer uses a minibatch of data to estimate the mean and standard deviation of each feature. These estimated means and standard deviations are then used to center and normalize the features of the minibatch. A running average of these means and standard deviations is kept during training, and at test time these running averages are used to center and normalize features.

It is possible that this normalization strategy could reduce the representational power of the network, since it may sometimes be optimal for certain layers to have features that are not zero-mean or unit variance. To this end, the batch normalization layer includes learnable shift and scale parameters for each feature dimension.

[1] Sergey Ioffe and Christian Szegedy, "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift", ICML 2015.

[1]:
```
# As usual, a bit of setup
import time
import numpy as np
import matplotlib.pyplot as plt
from cs231n.classifiers.fc_net import *
from cs231n.data_utils import get_CIFAR10_data
```

```
from cs231n.gradient_check import eval_numerical_gradient,␣
 ↪eval_numerical_gradient_array
from cs231n.solver import Solver

%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'

# for auto-reloading external modules
# see http://stackoverflow.com/questions/1907993/
 ↪autoreload-of-modules-in-ipython
%load_ext autoreload
%autoreload 2

def rel_error(x, y):
    """ returns relative error """
    return np.max(np.abs(x - y) / (np.maximum(1e-8, np.abs(x) + np.abs(y))))

def print_mean_std(x,axis=0):
    print('  means: ', x.mean(axis=axis))
    print('  stds:  ', x.std(axis=axis))
    print()
```

[2]:
```
# Load the (preprocessed) CIFAR10 data.
data = get_CIFAR10_data()
for k, v in data.items():
  print('%s: ' % k, v.shape)
```

```
X_train:  (49000, 3, 32, 32)
y_train:  (49000,)
X_val:  (1000, 3, 32, 32)
y_val:  (1000,)
X_test:  (1000, 3, 32, 32)
y_test:  (1000,)
```

1.1 Batch normalization: forward

In the file `cs231n/layers.py`, we have provided an implementation for the batch normalization training forward pass in the function `batchnorm_forward`. Please make sure you understand the code. Then, implement the batch normalization forward pass to be used in test mode. Once you have done so, run the following to test your implementation.

Referencing the paper linked to above in [1] may be helpful!

[3]:
```
# Check the training-time forward pass by checking means and variances
# of features both before and after batch normalization
```

```python
# Simulate the forward pass for a two-layer network
np.random.seed(231)
N, D1, D2, D3 = 200, 50, 60, 3
X = np.random.randn(N, D1)
W1 = np.random.randn(D1, D2)
W2 = np.random.randn(D2, D3)
a = np.maximum(0, X.dot(W1)).dot(W2)

print('Before batch normalization:')
print_mean_std(a,axis=0)

gamma = np.ones((D3,))
beta = np.zeros((D3,))
# Means should be close to zero and stds close to one
print('After batch normalization (gamma=1, beta=0)')
a_norm, _ = batchnorm_forward(a, gamma, beta, {'mode': 'train'})
print_mean_std(a_norm,axis=0)

gamma = np.asarray([1.0, 2.0, 3.0])
beta = np.asarray([11.0, 12.0, 13.0])
# Now means should be close to beta and stds close to gamma
print('After batch normalization (gamma=', gamma, ', beta=', beta, ')')
a_norm, _ = batchnorm_forward(a, gamma, beta, {'mode': 'train'})
print_mean_std(a_norm,axis=0)
```

```
Before batch normalization:
  means:  [ -2.3814598  -13.18038246   1.91780462]
  stds:   [27.18502186 34.21455511 37.68611762]

After batch normalization (gamma=1, beta=0)
  means:  [ 6.21724894e-17  7.82707232e-17 -7.42461648e-18]
  stds:   [0.99999999 1.         1.        ]

After batch normalization (gamma= [1. 2. 3.] , beta= [11. 12. 13.] )
  means:  [11. 12. 13.]
  stds:   [0.99999999 1.99999999 2.99999999]
```

[4]:

```python
# Check the test-time forward pass by running the training-time
# forward pass many times to warm up the running averages, and then
# checking the means and variances of activations after a test-time
# forward pass.

np.random.seed(231)
N, D1, D2, D3 = 200, 50, 60, 3
W1 = np.random.randn(D1, D2)
W2 = np.random.randn(D2, D3)
```

```python
bn_param = {'mode': 'train'}
gamma = np.ones(D3)
beta = np.zeros(D3)

for t in range(50):
  X = np.random.randn(N, D1)
  a = np.maximum(0, X.dot(W1)).dot(W2)
  batchnorm_forward(a, gamma, beta, bn_param)

bn_param['mode'] = 'test'
X = np.random.randn(N, D1)
a = np.maximum(0, X.dot(W1)).dot(W2)
a_norm, _ = batchnorm_forward(a, gamma, beta, bn_param)

# Means should be close to zero and stds close to one, but will be
# noisier than training-time forward passes.
print('After batch normalization (test-time):')
print_mean_std(a_norm,axis=0)
```

```
After batch normalization (test-time):
  means:  [-0.03927354 -0.04349152 -0.10452688]
  stds:   [1.01531428 1.01238373 0.97819988]
```

1.2 Batch normalization: backward

Now make sure you understand the backward pass for batch normalization in the function `batchnorm_backward` we have provided for you.

To derive the backward pass it is always convenient to write out the computation graph for batch normalization and backprop through each of the intermediate nodes. Note some intermediates may have multiple outgoing branches; one needs to sum gradients across these branches in the backward pass.

Once you have finished, run the following to numerically check the backward pass.

[5]:
```python
# Gradient check batchnorm backward pass
np.random.seed(231)
N, D = 4, 5
x = 5 * np.random.randn(N, D) + 12
gamma = np.random.randn(D)
beta = np.random.randn(D)
dout = np.random.randn(N, D)

bn_param = {'mode': 'train'}
fx = lambda x: batchnorm_forward(x, gamma, beta, bn_param)[0]
fg = lambda a: batchnorm_forward(x, a, beta, bn_param)[0]
fb = lambda b: batchnorm_forward(x, gamma, b, bn_param)[0]
```

```
dx_num = eval_numerical_gradient_array(fx, x, dout)
da_num = eval_numerical_gradient_array(fg, gamma.copy(), dout)
db_num = eval_numerical_gradient_array(fb, beta.copy(), dout)

_, cache = batchnorm_forward(x, gamma, beta, bn_param)
dx, dgamma, dbeta = batchnorm_backward(dout, cache)
#You should expect to see relative errors between 1e-13 and 1e-8
print('dx error: ', rel_error(dx_num, dx))
print('dgamma error: ', rel_error(da_num, dgamma))
print('dbeta error: ', rel_error(db_num, dbeta))
```

```
dx error:  1.6674604875341426e-09
dgamma error:  7.417225040694815e-13
dbeta error:  2.379446949959628e-12
```

1.3 Inline Question 1

During training BN keeps an exponentially decaying running mean of the mean and variance of each feature. Why shouldn't we directly use the average mean in all iterations?

1.4 Answer:

al utilizar el "Running mean", se está considerando el momento o la historia de valores de dicha variable. Se realiza de una forma ponderada con respecto a la media calculada en la iteración actual, para poder darle el peso que querramos al valor histórico.

Si utilizáramos solamente la media calculada en cada iteración, sin tener en cuenta el histórico, estaríamos dependiendo mucho de los valores de entrada del minibatch. Los valores, por ejemplo, podrían llegar a estar ordenados y se distorsionarían mucho los resultados.

1.5 Fully Connected Nets with Batch Normalization

Now that you have a working implementation for batch normalization, go back to your `FullyConnectedNet` in the file `cs231n/classifiers/fc_net.py`. Modify your implementation to add batch normalization.

Concretely, when the `normalization` flag is set to `"batchnorm"` in the constructor, you should insert a batch normalization layer before each ReLU nonlinearity. The outputs from the last layer of the network should not be normalized. Once you are done, run the following to gradient-check your implementation.

HINT: You might find it useful to define an additional helper layer similar to those in the file `cs231n/layer_utils.py`. If you decide to do so, do it in the file `cs231n/classifiers/fc_net.py`.

[6]:
```
np.random.seed(231)
N, D, H1, H2, C = 2, 15, 20, 30, 10
X = np.random.randn(N, D)
y = np.random.randint(C, size=(N,))
```

```python
# You should expect losses between 1e-4~1e-10 for W,
# losses between 1e-08~1e-10 for b,
# and losses between 1e-08~1e-09 for beta and gammas.
for reg in [0, 3.14]:
  print('Running check with reg = ', reg)
  model = FullyConnectedNet([H1, H2], input_dim=D, num_classes=C,
                            reg=reg, weight_scale=5e-2, dtype=np.float64,
                            normalization='batchnorm')

  loss, grads = model.loss(X, y)
  print('Initial loss: ', loss)

  for name in sorted(grads):
    f = lambda _: model.loss(X, y)[0]
    grad_num = eval_numerical_gradient(f, model.params[name], verbose=False, h=1e-5)
    print('%s relative error: %.2e' % (name, rel_error(grad_num, grads[name])))
  if reg == 0: print()
```

```
Running check with reg =  0
Initial loss:  2.2611955101340957
W1 relative error: 1.10e-04
W2 relative error: 3.11e-06
W3 relative error: 4.05e-10
b1 relative error: 4.44e-08
b2 relative error: 2.22e-08
b3 relative error: 1.01e-10
beta1 relative error: 7.33e-09
beta2 relative error: 1.89e-09
gamma1 relative error: 6.96e-09
gamma2 relative error: 2.41e-09

Running check with reg =  3.14
Initial loss:  6.996533220108303
W1 relative error: 1.98e-06
W2 relative error: 2.28e-06
W3 relative error: 1.11e-08
b1 relative error: 5.55e-09
b2 relative error: 2.22e-08
b3 relative error: 2.10e-10
beta1 relative error: 6.65e-09
beta2 relative error: 3.39e-09
gamma1 relative error: 6.27e-09
gamma2 relative error: 5.28e-09
```

2 Batchnorm for deep networks

Run the following to train a six-layer network on a subset of 1000 training examples both with and without batch normalization.

[7]:
```
np.random.seed(231)
# Try training a very deep net with batchnorm
hidden_dims = [100, 100, 100, 100, 100]

num_train = 1000
small_data = {
  'X_train': data['X_train'][:num_train],
  'y_train': data['y_train'][:num_train],
  'X_val': data['X_val'],
  'y_val': data['y_val'],
}

weight_scale = 2e-2
bn_model = FullyConnectedNet(hidden_dims, weight_scale=weight_scale,␣
 ↪normalization='batchnorm')
model = FullyConnectedNet(hidden_dims, weight_scale=weight_scale,␣
 ↪normalization=None)

print('Solver with batch norm:')
bn_solver = Solver(bn_model, small_data,
                num_epochs=10, batch_size=50,
                update_rule='adam',
                optim_config={
                  'learning_rate': 1e-3,
                },
                verbose=True,print_every=20)
bn_solver.train()

print('\nSolver without batch norm:')
solver = Solver(model, small_data,
                num_epochs=10, batch_size=50,
                update_rule='adam',
                optim_config={
                  'learning_rate': 1e-3,
                },
                verbose=True, print_every=20)
solver.train()
```

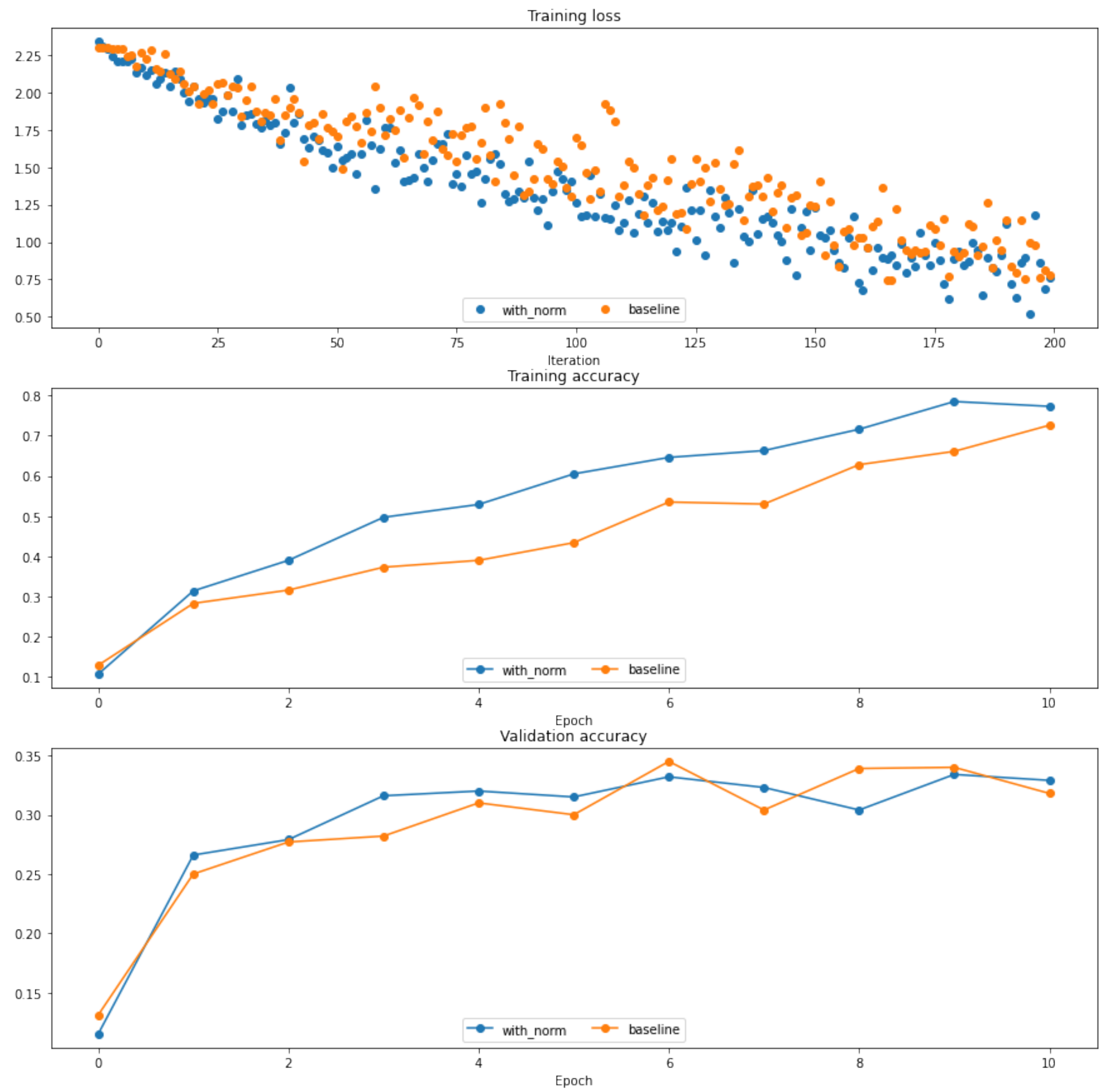
```
Solver with batch norm:
(Iteration 1 / 200) loss: 2.340974
(Epoch 0 / 10) train acc: 0.107000; val_acc: 0.115000
(Epoch 1 / 10) train acc: 0.314000; val_acc: 0.266000
(Iteration 21 / 200) loss: 2.039365
```

```
(Epoch 2 / 10) train acc: 0.390000; val_acc: 0.279000
(Iteration 41 / 200) loss: 2.036710
(Epoch 3 / 10) train acc: 0.497000; val_acc: 0.316000
(Iteration 61 / 200) loss: 1.769536
(Epoch 4 / 10) train acc: 0.529000; val_acc: 0.320000
(Iteration 81 / 200) loss: 1.268340
(Epoch 5 / 10) train acc: 0.605000; val_acc: 0.315000
(Iteration 101 / 200) loss: 1.267965
(Epoch 6 / 10) train acc: 0.646000; val_acc: 0.332000
(Iteration 121 / 200) loss: 1.130897
(Epoch 7 / 10) train acc: 0.663000; val_acc: 0.323000
(Iteration 141 / 200) loss: 1.170151
(Epoch 8 / 10) train acc: 0.716000; val_acc: 0.304000
(Iteration 161 / 200) loss: 0.679499
(Epoch 9 / 10) train acc: 0.785000; val_acc: 0.334000
(Iteration 181 / 200) loss: 0.939843
(Epoch 10 / 10) train acc: 0.773000; val_acc: 0.329000

Solver without batch norm:
(Iteration 1 / 200) loss: 2.302332
(Epoch 0 / 10) train acc: 0.129000; val_acc: 0.131000
(Epoch 1 / 10) train acc: 0.283000; val_acc: 0.250000
(Iteration 21 / 200) loss: 2.041970
(Epoch 2 / 10) train acc: 0.316000; val_acc: 0.277000
(Iteration 41 / 200) loss: 1.900473
(Epoch 3 / 10) train acc: 0.373000; val_acc: 0.282000
(Iteration 61 / 200) loss: 1.713156
(Epoch 4 / 10) train acc: 0.390000; val_acc: 0.310000
(Iteration 81 / 200) loss: 1.662209
(Epoch 5 / 10) train acc: 0.434000; val_acc: 0.300000
(Iteration 101 / 200) loss: 1.696059
(Epoch 6 / 10) train acc: 0.535000; val_acc: 0.345000
(Iteration 121 / 200) loss: 1.557987
(Epoch 7 / 10) train acc: 0.530000; val_acc: 0.304000
(Iteration 141 / 200) loss: 1.432189
(Epoch 8 / 10) train acc: 0.628000; val_acc: 0.339000
(Iteration 161 / 200) loss: 1.033932
(Epoch 9 / 10) train acc: 0.661000; val_acc: 0.340000
(Iteration 181 / 200) loss: 0.901035
(Epoch 10 / 10) train acc: 0.726000; val_acc: 0.318000
```

Run the following to visualize the results from two networks trained above. You should find that using batch normalization helps the network to converge much faster.

[8]:
```
def plot_training_history(title, label, baseline, bn_solvers, plot_fn,␣
 ↪bl_marker='.', bn_marker='.', labels=None):
    """utility function for plotting training history"""
    plt.title(title)
```

```
    plt.xlabel(label)
    bn_plots = [plot_fn(bn_solver) for bn_solver in bn_solvers]
    bl_plot = plot_fn(baseline)
    num_bn = len(bn_plots)
    for i in range(num_bn):
        label='with_norm'
        if labels is not None:
            label += str(labels[i])
        plt.plot(bn_plots[i], bn_marker, label=label)
    label='baseline'
    if labels is not None:
        label += str(labels[0])
    plt.plot(bl_plot, bl_marker, label=label)
    plt.legend(loc='lower center', ncol=num_bn+1)


plt.subplot(3, 1, 1)
plot_training_history('Training loss','Iteration', solver, [bn_solver], \
                      lambda x: x.loss_history, bl_marker='o', bn_marker='o')
plt.subplot(3, 1, 2)
plot_training_history('Training accuracy','Epoch', solver, [bn_solver], \
                      lambda x: x.train_acc_history, bl_marker='-o',␣
 ↪bn_marker='-o')
plt.subplot(3, 1, 3)
plot_training_history('Validation accuracy','Epoch', solver, [bn_solver], \
                      lambda x: x.val_acc_history, bl_marker='-o',␣
 ↪bn_marker='-o')

plt.gcf().set_size_inches(15, 15)
plt.show()
```



3 Batch normalization and initialization

We will now run a small experiment to study the interaction of batch normalization and weight initialization.

The first cell will train 8-layer networks both with and without batch normalization using different scales for weight initialization. The second layer will plot training accuracy, validation set accuracy, and training loss as a function of the weight initialization scale.

[9]:
```
np.random.seed(231)
# Try training a very deep net with batchnorm
hidden_dims = [50, 50, 50, 50, 50, 50, 50]
num_train = 1000
```

```
small_data = {
  'X_train': data['X_train'][:num_train],
  'y_train': data['y_train'][:num_train],
  'X_val': data['X_val'],
  'y_val': data['y_val'],
}

bn_solvers_ws = {}
solvers_ws = {}
weight_scales = np.logspace(-4, 0, num=20)
for i, weight_scale in enumerate(weight_scales):
    print('Running weight scale %d / %d' % (i + 1, len(weight_scales)))
    bn_model = FullyConnectedNet(hidden_dims, weight_scale=weight_scale,␣
 ↪normalization='batchnorm')
    model = FullyConnectedNet(hidden_dims, weight_scale=weight_scale,␣
 ↪normalization=None)

    bn_solver = Solver(bn_model, small_data,
                    num_epochs=10, batch_size=50,
                    update_rule='adam',
                    optim_config={
                      'learning_rate': 1e-3,
                    },
                    verbose=False, print_every=200)
    bn_solver.train()
    bn_solvers_ws[weight_scale] = bn_solver

    solver = Solver(model, small_data,
                    num_epochs=10, batch_size=50,
                    update_rule='adam',
                    optim_config={
                      'learning_rate': 1e-3,
                    },
                    verbose=False, print_every=200)
    solver.train()
    solvers_ws[weight_scale] = solver
```

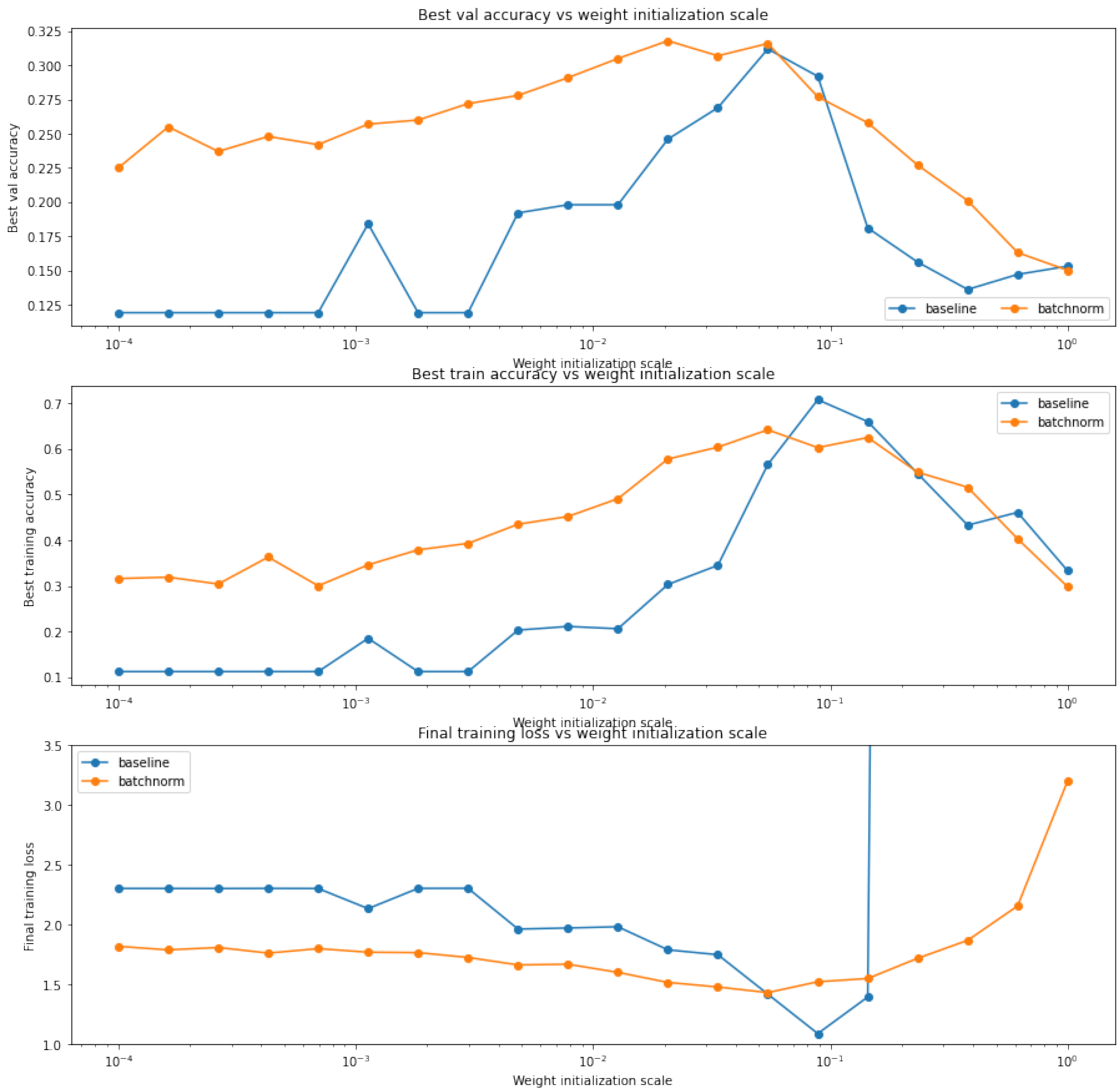
```
Running weight scale 1 / 20
Running weight scale 2 / 20
Running weight scale 3 / 20
Running weight scale 4 / 20
Running weight scale 5 / 20
Running weight scale 6 / 20
Running weight scale 7 / 20
Running weight scale 8 / 20
Running weight scale 9 / 20
Running weight scale 10 / 20
```

```
Running weight scale 11 / 20
Running weight scale 12 / 20
Running weight scale 13 / 20
Running weight scale 14 / 20
Running weight scale 15 / 20
Running weight scale 16 / 20
Running weight scale 17 / 20
Running weight scale 18 / 20
Running weight scale 19 / 20
Running weight scale 20 / 20
```

[10]:

```
# Plot results of weight scale experiment
best_train_accs, bn_best_train_accs = [], []
best_val_accs, bn_best_val_accs = [], []
final_train_loss, bn_final_train_loss = [], []

for ws in weight_scales:
  best_train_accs.append(max(solvers_ws[ws].train_acc_history))
  bn_best_train_accs.append(max(bn_solvers_ws[ws].train_acc_history))

  best_val_accs.append(max(solvers_ws[ws].val_acc_history))
  bn_best_val_accs.append(max(bn_solvers_ws[ws].val_acc_history))

  final_train_loss.append(np.mean(solvers_ws[ws].loss_history[-100:]))
  bn_final_train_loss.append(np.mean(bn_solvers_ws[ws].loss_history[-100:]))

plt.subplot(3, 1, 1)
plt.title('Best val accuracy vs weight initialization scale')
plt.xlabel('Weight initialization scale')
plt.ylabel('Best val accuracy')
plt.semilogx(weight_scales, best_val_accs, '-o', label='baseline')
plt.semilogx(weight_scales, bn_best_val_accs, '-o', label='batchnorm')
plt.legend(ncol=2, loc='lower right')

plt.subplot(3, 1, 2)
plt.title('Best train accuracy vs weight initialization scale')
plt.xlabel('Weight initialization scale')
plt.ylabel('Best training accuracy')
plt.semilogx(weight_scales, best_train_accs, '-o', label='baseline')
plt.semilogx(weight_scales, bn_best_train_accs, '-o', label='batchnorm')
plt.legend()

plt.subplot(3, 1, 3)
plt.title('Final training loss vs weight initialization scale')
plt.xlabel('Weight initialization scale')
plt.ylabel('Final training loss')
plt.semilogx(weight_scales, final_train_loss, '-o', label='baseline')
```

```
plt.semilogx(weight_scales, bn_final_train_loss, '-o', label='batchnorm')
plt.legend()
plt.gca().set_ylim(1.0, 3.5)

plt.gcf().set_size_inches(15, 15)
plt.show()
```



3.1 Inline Question 2:

Describe the results of this experiment. How does the scale of weight initialization affect models with/without batch normalization differently, and why?

3.2 Answer:

En las gráficas puede observarse que la red con Batchnorm se comporta casi siempre mejor que la que no lo tiene. También puede observarse que las gráficas de batchnorm son más suaves, mostrando que la red con este tipo de normalización es menos sensible a la inicialización de los parámetros.

En la grafica 2 se observa el problema de los gradientes que desaparecen para el caso de baseline con inicializaciones de parámetros muy bajas. Se puede concluir esto ya que la tasa de accuracy en el conjunto de train es baja, por lo que se deduce que las neuronas no lograron aprender, que pasa cuando los gradientes tienden a cero. En la tercer gráfica se observa el problema de gradientes que explotan para el caso de baselines con inicializaciones de parámetros mayores a 0.1.

Batch normalization mejora la robustez a la inicialización y no sufre de los problemas de gradientes que explotan o desaparecen, ya que al normalizar, los valores en la red no son ni muy altos ni muy bajos.

4 Batch normalization and batch size

We will now run a small experiment to study the interaction of batch normalization and batch size.

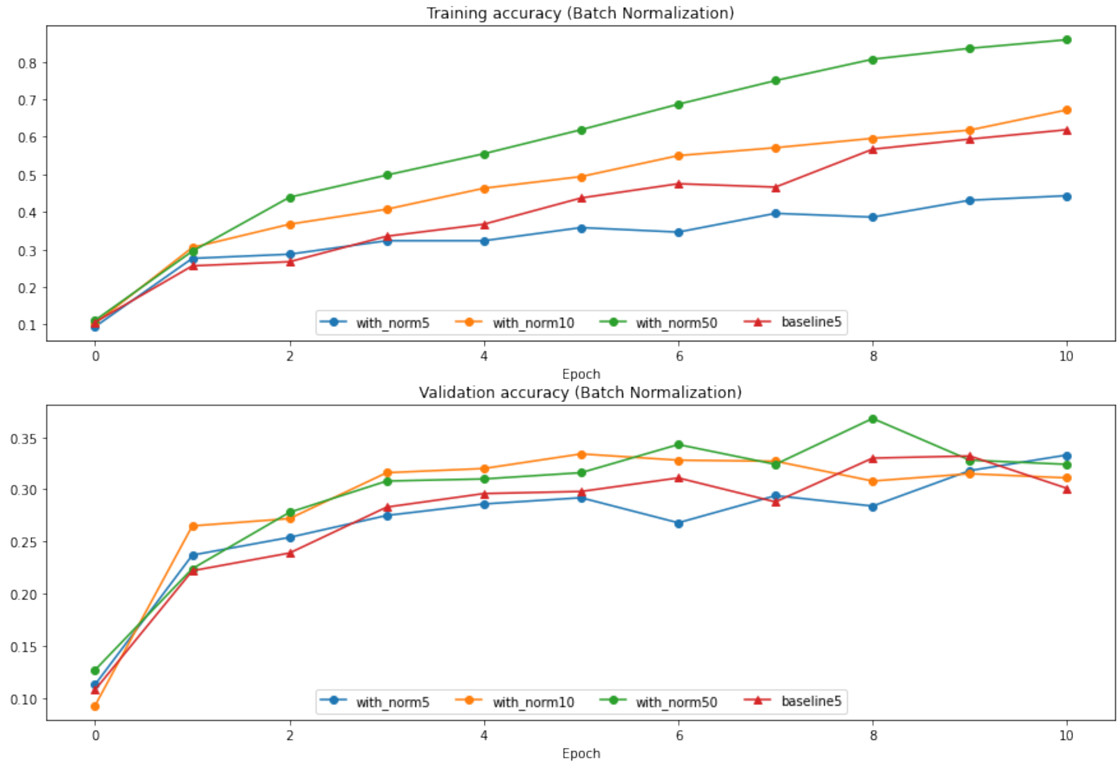
The first cell will train 6-layer networks both with and without batch normalization using different batch sizes. The second layer will plot training accuracy and validation set accuracy over time.

[11]:
```
def run_batchsize_experiments(normalization_mode):
    np.random.seed(231)
    # Try training a very deep net with batchnorm
    hidden_dims = [100, 100, 100, 100, 100]
    num_train = 1000
    small_data = {
      'X_train': data['X_train'][:num_train],
      'y_train': data['y_train'][:num_train],
      'X_val': data['X_val'],
      'y_val': data['y_val'],
    }
    n_epochs=10
    weight_scale = 2e-2
    batch_sizes = [5,10,50]
    lr = 10**(-3.5)
    solver_bsize = batch_sizes[0]

    print('No normalization: batch size = ',solver_bsize)
    model = FullyConnectedNet(hidden_dims, weight_scale=weight_scale,␣
↪normalization=None)
    solver = Solver(model, small_data,
                    num_epochs=n_epochs, batch_size=solver_bsize,
                    update_rule='adam',
                    optim_config={
                      'learning_rate': lr,
                    },
```

```
                    verbose=False)
    solver.train()

    bn_solvers = []
    for i in range(len(batch_sizes)):
        b_size=batch_sizes[i]
        print('Normalization: batch size = ',b_size)
        bn_model = FullyConnectedNet(hidden_dims, weight_scale=weight_scale,␣
↪normalization=normalization_mode)
        bn_solver = Solver(bn_model, small_data,
                        num_epochs=n_epochs, batch_size=b_size,
                        update_rule='adam',
                        optim_config={
                          'learning_rate': lr,
                        },
                        verbose=False)
        bn_solver.train()
        bn_solvers.append(bn_solver)

    return bn_solvers, solver, batch_sizes

batch_sizes = [5,10,50]
bn_solvers_bsize, solver_bsize, batch_sizes =␣
↪run_batchsize_experiments('batchnorm')
```

```
No normalization: batch size =  5
Normalization: batch size =  5
Normalization: batch size =  10
Normalization: batch size =  50
```

[12]:
```
plt.subplot(2, 1, 1)
plot_training_history('Training accuracy (Batch Normalization)','Epoch',␣
↪solver_bsize, bn_solvers_bsize, \
                      lambda x: x.train_acc_history, bl_marker='-^',␣
↪bn_marker='-o', labels=batch_sizes)
plt.subplot(2, 1, 2)
plot_training_history('Validation accuracy (Batch Normalization)','Epoch',␣
↪solver_bsize, bn_solvers_bsize, \
                      lambda x: x.val_acc_history, bl_marker='-^',␣
↪bn_marker='-o', labels=batch_sizes)

plt.gcf().set_size_inches(15, 10)
plt.show()
```



4.1 Inline Question 3:

Describe the results of this experiment. What does this imply about the relationship between batch normalization and batch size? Why is this relationship observed?

4.2 Answer:

A medida que tomamos mayores tamaños de batch, los resultados en ambos conjuntos mejoran. Esto tiene sentido ya que a más cantidad de ejemplos en una corrida, más similar será la media y varianza al del conjunto entero con todos los datos (es menos sensible a los datos del batch).

5 Layer Normalization

Batch normalization has proved to be effective in making networks easier to train, but the dependency on batch size makes it less useful in complex networks which have a cap on the input batch size due to hardware limitations.

Several alternatives to batch normalization have been proposed to mitigate this problem; one such technique is Layer Normalization [2]. Instead of normalizing over the batch, we normalize over the features. In other words, when using Layer Normalization, each feature vector corresponding to a single datapoint is normalized based on the sum of all terms within that feature vector.

[2] Ba, Jimmy Lei, Jamie Ryan Kiros, and Geoffrey E. Hinton. "Layer Normalization." stat 1050 (2016): 21.

5.1 Inline Question 4:

Which of these data preprocessing steps is analogous to batch normalization, and which is analogous to layer normalization?

1. Scaling each image in the dataset, so that the RGB channels for each row of pixels within an image sums up to 1.
2. Scaling each image in the dataset, so that the RGB channels for all pixels within an image sums up to 1.

3. Subtracting the mean image of the dataset from each image in the dataset.
4. Setting all RGB values to either 0 or 1 depending on a given threshold.

5.2 Answer:

La opción 3 es análoga a Batch Normalization tomando gamma como la desviación estándard del dataset y beta como la media del dataset. Pero estos parámetros se aprenden por la red, entonces, podemos fijarlos para que no se aprendan, o sino tomar el batch como el tamaño del dataset.

La opción 2 puede verse como Layer Normalization, viendo la suma de los canales RGB como una feature, y observando que la normalización se realiza para cada imagen, y no sobre un conjunto de éstas.

[ ]:

```

```

Dropout

November 17, 2020

1 Dropout

Dropout [1] is a technique for regularizing neural networks by randomly setting some output activations to zero during the forward pass. In this exercise you will implement a dropout layer and modify your fully-connected network to optionally use dropout.

[1] Geoffrey E. Hinton et al, "Improving neural networks by preventing co-adaptation of feature detectors", arXiv 2012

[1]:
```
# As usual, a bit of setup
from __future__ import print_function
import time
import numpy as np
import matplotlib.pyplot as plt
from cs231n.classifiers.fc_net import *
from cs231n.data_utils import get_CIFAR10_data
from cs231n.gradient_check import eval_numerical_gradient,␣
↪eval_numerical_gradient_array
from cs231n.solver import Solver

%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'

# for auto-reloading external modules
# see http://stackoverflow.com/questions/1907993/
↪autoreload-of-modules-in-ipython
%load_ext autoreload
%autoreload 2

def rel_error(x, y):
  """ returns relative error """
  return np.max(np.abs(x - y) / (np.maximum(1e-8, np.abs(x) + np.abs(y))))
```

[2]:
```
# Load the (preprocessed) CIFAR10 data.

data = get_CIFAR10_data()
```

```python
for k, v in data.items():
  print('%s: ' % k, v.shape)
```

```
X_train:  (49000, 3, 32, 32)
y_train:  (49000,)
X_val:  (1000, 3, 32, 32)
y_val:  (1000,)
X_test:  (1000, 3, 32, 32)
y_test:  (1000,)
```

2 Dropout forward pass

In the file `cs231n/layers.py`, implement the forward pass for dropout. Since dropout behaves differently during training and testing, make sure to implement the operation for both modes.

Once you have done so, run the cell below to test your implementation.

[3]:

```python
np.random.seed(231)
x = np.random.randn(500, 500) + 10

for p in [0.25, 0.4, 0.7]:
  out, _ = dropout_forward(x, {'mode': 'train', 'p': p})
  out_test, _ = dropout_forward(x, {'mode': 'test', 'p': p})

  print('Running tests with p = ', p)
  print('Mean of input: ', x.mean())
  print('Mean of train-time output: ', out.mean())
  print('Mean of test-time output: ', out_test.mean())
  print('Fraction of train-time output set to zero: ', (out == 0).mean())
  print('Fraction of test-time output set to zero: ', (out_test == 0).mean())
  print()
```

```
Running tests with p =  0.25
Mean of input:  10.000207878477502
Mean of train-time output:  10.014059116977283
Mean of test-time output:  10.000207878477502
Fraction of train-time output set to zero:  0.749784
Fraction of test-time output set to zero:  0.0

Running tests with p =  0.4
Mean of input:  10.000207878477502
Mean of train-time output:  9.977917658761159
Mean of test-time output:  10.000207878477502
Fraction of train-time output set to zero:  0.600796
Fraction of test-time output set to zero:  0.0

Running tests with p =  0.7
Mean of input:  10.000207878477502
```

```
Mean of train-time output:  9.987811912159426
Mean of test-time output:  10.000207878477502
Fraction of train-time output set to zero:  0.30074
Fraction of test-time output set to zero:  0.0
```

3 Dropout backward pass

In the file `cs231n/layers.py`, implement the backward pass for dropout. After doing so, run the following cell to numerically gradient-check your implementation.

[4]:
```python
np.random.seed(231)
x = np.random.randn(10, 10) + 10
dout = np.random.randn(*x.shape)

dropout_param = {'mode': 'train', 'p': 0.2, 'seed': 123}
out, cache = dropout_forward(x, dropout_param)
dx = dropout_backward(dout, cache)
dx_num = eval_numerical_gradient_array(lambda xx: dropout_forward(xx,␣
 ↪dropout_param)[0], x, dout)

# Error should be around e-10 or less
print('dx relative error: ', rel_error(dx, dx_num))
```

```
dx relative error:  5.44560814873387e-11
```

3.1 Inline Question 1:

Why do the training and testing phases of Dropout need to be implemented differently? What is the difference between the two phases?

3.2 Answer:

En el caso de Train, la capa de dropout ayuda a disminuir el sobreajuste, al no tener en cuenta la salida de un porcentaje de neuronas. Tiene un efecto similar al entrenamiento de diferentes modelos. En el caso de Test, se necesita contar con todos los pesos aprendidos en la etapa de train para poder predecir, por lo que debo tener en cuenta las salidas de todas las neuronas, no debo hacer dropout. Se podría interpretar como una combinación de los modelos aprendidos en la etapa de test.

Es por eso que la implementación es diferente. En Train se realiza el Dropout de algunas salidas, y en test no.

3.3 Inline Question 2:

What happens if we do not divide the values being passed through inverse dropout by `p` in the dropout layer? Why does that happen?

3.4 Answer:

Si no se hace el re-escalamiento en la etapa de entrenamiento, dividiendo por `p`, entonces dicho re-escalamiento debería hacerse en la etapa de test.

El re-escalamiento es necesario para asegurarnos tener en test la salida esperada.

Consideremos Dropout original: Sea x la salida esperada de la nuerona sin Dropout. Con Dropout la salida esperada será p.x. por lo que en test se debería multiplicar la salida de la neurona por p (x.p) para que sea la misma salida que en train.

Ahora bien, consideremos ahora el caso de Inverse-Dropout: Si en entrenamiento dividimos por p, la salida esperada será (p.x.(1/p) = x). Por lo que en test no debo modificar la salida para que sea la misma que en train).

Inverse Dropout re-escala en la etapa de entrenamiento, para no enlentecer la etapa de test, agregandole la tarea de re-escalamiento.

4 Fully-connected nets with Dropout

In the file `cs231n/classifiers/fc_net.py`, modify your implementation to use dropout. Specifically, if the constructor of the network receives a value that is not 1 for the `dropout` parameter, then the net should add a dropout layer immediately after every ReLU nonlinearity. After doing so, run the following to numerically gradient-check your implementation.

[5]:
```
np.random.seed(231)
N, D, H1, H2, C = 2, 15, 20, 30, 10
X = np.random.randn(N, D)
y = np.random.randint(C, size=(N,))

for dropout in [1, 0.75, 0.5]:
  print('Running check with dropout = ', dropout)
  model = FullyConnectedNet([H1, H2], input_dim=D, num_classes=C,
                            weight_scale=5e-2, dtype=np.float64,
                            dropout=dropout, seed=123)

  loss, grads = model.loss(X, y)
  print('Initial loss: ', loss)

  # Relative errors should be around e-6 or less; Note that it's fine
  # if for dropout=1 you have W2 error be on the order of e-5.
  for name in sorted(grads):
    f = lambda _: model.loss(X, y)[0]
    grad_num = eval_numerical_gradient(f, model.params[name], verbose=False,␣
↪h=1e-5)
    print('%s relative error: %.2e' % (name, rel_error(grad_num, grads[name])))
  print()
```

```
Running check with dropout =  1
Initial loss:  2.3004790897684924
```

```
W1 relative error: 1.48e-07
W2 relative error: 2.21e-05
W3 relative error: 3.53e-07
b1 relative error: 5.38e-09
b2 relative error: 2.09e-09
b3 relative error: 5.80e-11

Running check with dropout =  0.75
Initial loss:  2.302371489704412
W1 relative error: 1.90e-07
W2 relative error: 4.76e-06
W3 relative error: 2.60e-08
b1 relative error: 4.73e-09
b2 relative error: 1.82e-09
b3 relative error: 1.70e-10

Running check with dropout =  0.5
Initial loss:  2.3042759220785896
W1 relative error: 3.11e-07
W2 relative error: 1.84e-08
W3 relative error: 5.35e-08
b1 relative error: 5.37e-09
b2 relative error: 2.99e-09
b3 relative error: 1.13e-10
```

5 Regularization experiment

As an experiment, we will train a pair of two-layer networks on 500 training examples: one will use no dropout, and one will use a keep probability of 0.25. We will then visualize the training and validation accuracies of the two networks over time.

[6]:
```
# Train two identical nets, one with dropout and one without
np.random.seed(231)
num_train = 500
small_data = {
  'X_train': data['X_train'][:num_train],
  'y_train': data['y_train'][:num_train],
  'X_val': data['X_val'],
  'y_val': data['y_val'],
}

solvers = {}
dropout_choices = [1, 0.25]
for dropout in dropout_choices:
  model = FullyConnectedNet([500], dropout=dropout)
  print(dropout)
```

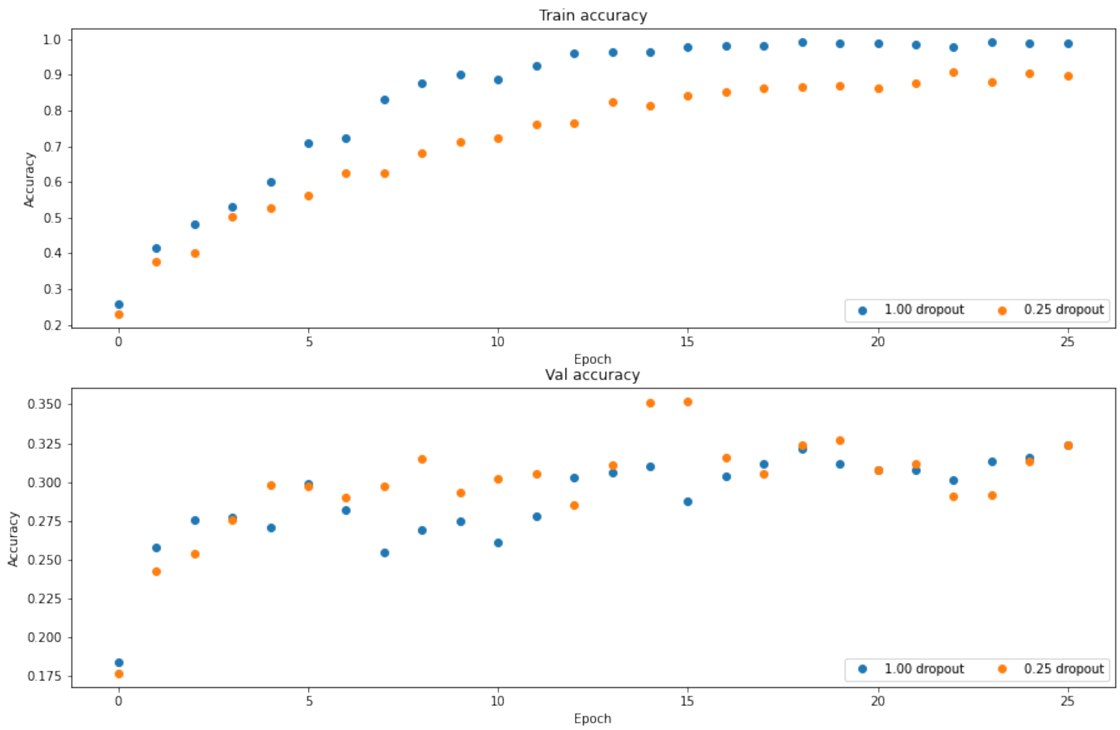
```
solver = Solver(model, small_data,
                num_epochs=25, batch_size=100,
                update_rule='adam',
                optim_config={
                  'learning_rate': 5e-4,
                },
                verbose=True, print_every=100)
solver.train()
solvers[dropout] = solver
print()
```

```
1
(Iteration 1 / 125) loss: 7.856643
(Epoch 0 / 25) train acc: 0.260000; val_acc: 0.184000
(Epoch 1 / 25) train acc: 0.416000; val_acc: 0.258000
(Epoch 2 / 25) train acc: 0.482000; val_acc: 0.276000
(Epoch 3 / 25) train acc: 0.532000; val_acc: 0.277000
(Epoch 4 / 25) train acc: 0.600000; val_acc: 0.271000
(Epoch 5 / 25) train acc: 0.708000; val_acc: 0.299000
(Epoch 6 / 25) train acc: 0.722000; val_acc: 0.282000
(Epoch 7 / 25) train acc: 0.832000; val_acc: 0.255000
(Epoch 8 / 25) train acc: 0.878000; val_acc: 0.269000
(Epoch 9 / 25) train acc: 0.902000; val_acc: 0.275000
(Epoch 10 / 25) train acc: 0.888000; val_acc: 0.261000
(Epoch 11 / 25) train acc: 0.926000; val_acc: 0.278000
(Epoch 12 / 25) train acc: 0.960000; val_acc: 0.303000
(Epoch 13 / 25) train acc: 0.964000; val_acc: 0.306000
(Epoch 14 / 25) train acc: 0.966000; val_acc: 0.310000
(Epoch 15 / 25) train acc: 0.978000; val_acc: 0.288000
(Epoch 16 / 25) train acc: 0.982000; val_acc: 0.304000
(Epoch 17 / 25) train acc: 0.982000; val_acc: 0.312000
(Epoch 18 / 25) train acc: 0.992000; val_acc: 0.321000
(Epoch 19 / 25) train acc: 0.988000; val_acc: 0.312000
(Epoch 20 / 25) train acc: 0.988000; val_acc: 0.308000
(Iteration 101 / 125) loss: 0.034214
(Epoch 21 / 25) train acc: 0.986000; val_acc: 0.308000
(Epoch 22 / 25) train acc: 0.980000; val_acc: 0.301000
(Epoch 23 / 25) train acc: 0.992000; val_acc: 0.313000
(Epoch 24 / 25) train acc: 0.990000; val_acc: 0.316000
(Epoch 25 / 25) train acc: 0.990000; val_acc: 0.324000

0.25
(Iteration 1 / 125) loss: 17.318478
(Epoch 0 / 25) train acc: 0.230000; val_acc: 0.177000
(Epoch 1 / 25) train acc: 0.378000; val_acc: 0.243000
(Epoch 2 / 25) train acc: 0.402000; val_acc: 0.254000
(Epoch 3 / 25) train acc: 0.502000; val_acc: 0.276000
```

```
(Epoch 4 / 25) train acc: 0.528000; val_acc: 0.298000
(Epoch 5 / 25) train acc: 0.562000; val_acc: 0.297000
(Epoch 6 / 25) train acc: 0.626000; val_acc: 0.290000
(Epoch 7 / 25) train acc: 0.626000; val_acc: 0.297000
(Epoch 8 / 25) train acc: 0.682000; val_acc: 0.315000
(Epoch 9 / 25) train acc: 0.714000; val_acc: 0.293000
(Epoch 10 / 25) train acc: 0.724000; val_acc: 0.302000
(Epoch 11 / 25) train acc: 0.762000; val_acc: 0.305000
(Epoch 12 / 25) train acc: 0.766000; val_acc: 0.285000
(Epoch 13 / 25) train acc: 0.824000; val_acc: 0.311000
(Epoch 14 / 25) train acc: 0.814000; val_acc: 0.351000
(Epoch 15 / 25) train acc: 0.842000; val_acc: 0.352000
(Epoch 16 / 25) train acc: 0.852000; val_acc: 0.316000
(Epoch 17 / 25) train acc: 0.862000; val_acc: 0.305000
(Epoch 18 / 25) train acc: 0.868000; val_acc: 0.324000
(Epoch 19 / 25) train acc: 0.870000; val_acc: 0.327000
(Epoch 20 / 25) train acc: 0.862000; val_acc: 0.308000
(Iteration 101 / 125) loss: 4.256361
(Epoch 21 / 25) train acc: 0.876000; val_acc: 0.312000
(Epoch 22 / 25) train acc: 0.910000; val_acc: 0.291000
(Epoch 23 / 25) train acc: 0.880000; val_acc: 0.292000
(Epoch 24 / 25) train acc: 0.906000; val_acc: 0.313000
(Epoch 25 / 25) train acc: 0.898000; val_acc: 0.324000
```

[7]:
```
# Plot train and validation accuracies of the two models

train_accs = []
val_accs = []
for dropout in dropout_choices:
  solver = solvers[dropout]
  train_accs.append(solver.train_acc_history[-1])
  val_accs.append(solver.val_acc_history[-1])

plt.subplot(3, 1, 1)
for dropout in dropout_choices:
  plt.plot(solvers[dropout].train_acc_history, 'o', label='%.2f dropout' %␣
 ↪dropout)
plt.title('Train accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(ncol=2, loc='lower right')

plt.subplot(3, 1, 2)
for dropout in dropout_choices:
  plt.plot(solvers[dropout].val_acc_history, 'o', label='%.2f dropout' %␣
 ↪dropout)
```

```
plt.title('Val accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(ncol=2, loc='lower right')

plt.gcf().set_size_inches(15, 15)
plt.show()
```



5.1 Inline Question 3:

Compare the validation and training accuracies with and without dropout – what do your results suggest about dropout as a regularizer?

5.2 Answer:

En entrenamiento, cuando no hago Dropout, se ajusta más a los datos de entrenamiento. En test, para algunas épocas se comporta mejor la red con Dropout, y en otros casos tiene mejor performance sin Dropout. Mayoritariamente tiene mejor performance la red con Dropout, por lo que este método, como método de regularización parecería ser efectivo, al reducir el sobreajuste.

```
[ ]:
```

ConvolutionalNetworks

November 17, 2020

1 Convolutional Networks

So far we have worked with deep fully-connected networks, using them to explore different optimization strategies and network architectures. Fully-connected networks are a good testbed for experimentation because they are very computationally efficient, but in practice all state-of-the-art results use convolutional networks instead.

First you will implement several layer types that are used in convolutional networks. You will then use these layers to train a convolutional network on the CIFAR-10 dataset.

[ ]:
```python
# As usual, a bit of setup
import numpy as np
import matplotlib.pyplot as plt
from cs231n.classifiers.cnn import *
from cs231n.data_utils import get_CIFAR10_data
from cs231n.gradient_check import eval_numerical_gradient_array,␣
↪eval_numerical_gradient
from cs231n.layers import *
from cs231n.fast_layers import *
from cs231n.solver import Solver

%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'

# for auto-reloading external modules
# see http://stackoverflow.com/questions/1907993/
↪autoreload-of-modules-in-ipython
%load_ext autoreload
%autoreload 2

def rel_error(x, y):
  """ returns relative error """
  return np.max(np.abs(x - y) / (np.maximum(1e-8, np.abs(x) + np.abs(y))))
```

[ ]:
```python
# Load the (preprocessed) CIFAR10 data.
```

```python
data = get_CIFAR10_data()
for k, v in data.items():
  print('%s: ' % k, v.shape)
```

2 Convolution: Naive forward pass

The core of a convolutional network is the convolution operation. In the file `cs231n/layers.py`, implement the forward pass for the convolution layer in the function `conv_forward_naive`.

You don't have to worry too much about efficiency at this point; just write the code in whatever way you find most clear.

You can test your implementation by running the following:

[ ]:
```python
x_shape = (2, 3, 4, 4)
w_shape = (3, 3, 4, 4)
x = np.linspace(-0.1, 0.5, num=np.prod(x_shape)).reshape(x_shape)
w = np.linspace(-0.2, 0.3, num=np.prod(w_shape)).reshape(w_shape)
b = np.linspace(-0.1, 0.2, num=3)

conv_param = {'stride': 2, 'pad': 1}
out, _ = conv_forward_naive(x, w, b, conv_param)
correct_out = np.array([[[[-0.08759809, -0.10987781],
                           [-0.18387192, -0.2109216 ]],
                          [[ 0.21027089,  0.21661097],
                           [ 0.22847626,  0.23004637]],
                          [[ 0.50813986,  0.54309974],
                           [ 0.64082444,  0.67101435]]],
                         [[[-0.98053589, -1.03143541],
                           [-1.19128892, -1.24695841]],
                          [[ 0.69108355,  0.66880383],
                           [ 0.59480972,  0.56776003]],
                          [[ 2.36270298,  2.36904306],
                           [ 2.38090835,  2.38247847]]]])

# Compare your output to ours; difference should be around e-8
print('Testing conv_forward_naive')
print('difference: ', rel_error(out, correct_out))
```

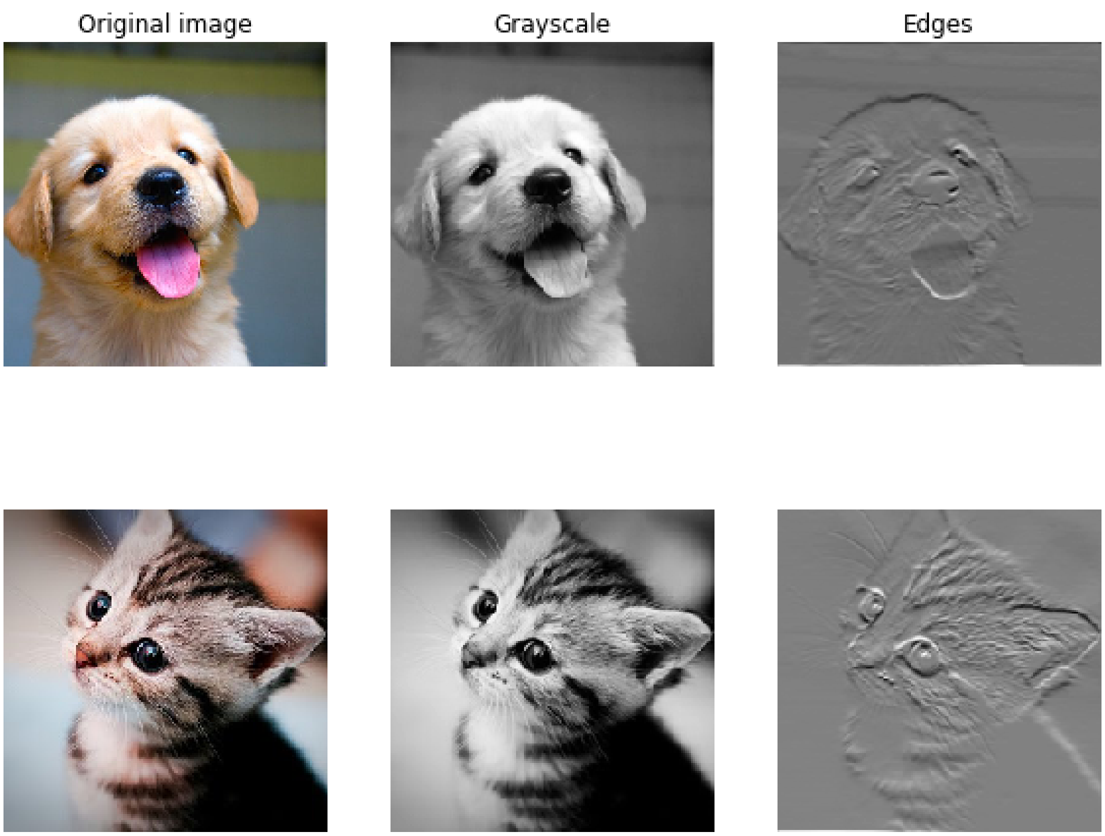
3 Aside: Image processing via convolutions

As fun way to both check your implementation and gain a better understanding of the type of operation that convolutional layers can perform, we will set up an input containing two images and manually set up filters that perform common image processing operations (grayscale conversion and edge detection). The convolution forward pass will apply these operations to each of the input images. We can then visualize the results as a sanity check.

[4]:

```
from imageio import imread
from PIL import Image

kitten = imread('cs231n/notebook_images/kitten.jpg')
puppy = imread('cs231n/notebook_images/puppy.jpg')
# kitten is wide, and puppy is already square
d = kitten.shape[1] - kitten.shape[0]
kitten_cropped = kitten[:, d//2:-d//2, :]

img_size = 200   # Make this smaller if it runs too slow
resized_puppy = np.array(Image.fromarray(puppy).resize((img_size, img_size)))
resized_kitten = np.array(Image.fromarray(kitten_cropped).resize((img_size,␣
 ↪img_size)))
x = np.zeros((2, 3, img_size, img_size))
x[0, :, :, :] = resized_puppy.transpose((2, 0, 1))
x[1, :, :, :] = resized_kitten.transpose((2, 0, 1))

# Set up a convolutional weights holding 2 filters, each 3x3
w = np.zeros((2, 3, 3, 3))

# The first filter converts the image to grayscale.
# Set up the red, green, and blue channels of the filter.
w[0, 0, :, :] = [[0, 0, 0], [0, 0.3, 0], [0, 0, 0]]
w[0, 1, :, :] = [[0, 0, 0], [0, 0.6, 0], [0, 0, 0]]
w[0, 2, :, :] = [[0, 0, 0], [0, 0.1, 0], [0, 0, 0]]

# Second filter detects horizontal edges in the blue channel.
w[1, 2, :, :] = [[1, 2, 1], [0, 0, 0], [-1, -2, -1]]

# Vector of biases. We don't need any bias for the grayscale
# filter, but for the edge detection filter we want to add 128
# to each output so that nothing is negative.
b = np.array([0, 128])

# Compute the result of convolving each input in x with each filter in w,
# offsetting by b, and storing the results in out.
out, _ = conv_forward_naive(x, w, b, {'stride': 1, 'pad': 1})

def imshow_no_ax(img, normalize=True):
    """ Tiny helper to show images as uint8 and remove axis labels """
    if normalize:
        img_max, img_min = np.max(img), np.min(img)
        img = 255.0 * (img - img_min) / (img_max - img_min)
    plt.imshow(img.astype('uint8'))
    plt.gca().axis('off')

# Show the original images and the results of the conv operation
```

```
plt.subplot(2, 3, 1)
imshow_no_ax(puppy, normalize=False)
plt.title('Original image')
plt.subplot(2, 3, 2)
imshow_no_ax(out[0, 0])
plt.title('Grayscale')
plt.subplot(2, 3, 3)
imshow_no_ax(out[0, 1])
plt.title('Edges')
plt.subplot(2, 3, 4)
imshow_no_ax(kitten_cropped, normalize=False)
plt.subplot(2, 3, 5)
imshow_no_ax(out[1, 0])
plt.subplot(2, 3, 6)
imshow_no_ax(out[1, 1])
plt.show()
```



4 Convolution: Naive backward pass

Implement the backward pass for the convolution operation in the function `conv_backward_naive` in the file `cs231n/layers.py`. Again, you don't need to worry too much about computational efficiency.

When you are done, run the following to check your backward pass with a numeric gradient check.

[5]:
```
np.random.seed(231)
x = np.random.randn(4, 3, 5, 5)
w = np.random.randn(2, 3, 3, 3)
b = np.random.randn(2,)
dout = np.random.randn(4, 2, 5, 5)
conv_param = {'stride': 1, 'pad': 1}

dx_num = eval_numerical_gradient_array(lambda x: conv_forward_naive(x, w, b,␣
 ↪conv_param)[0], x, dout)
dw_num = eval_numerical_gradient_array(lambda w: conv_forward_naive(x, w, b,␣
 ↪conv_param)[0], w, dout)
db_num = eval_numerical_gradient_array(lambda b: conv_forward_naive(x, w, b,␣
 ↪conv_param)[0], b, dout)

out, cache = conv_forward_naive(x, w, b, conv_param)
dx, dw, db = conv_backward_naive(dout, cache)

# Your errors should be around e-8 or less.
print('Testing conv_backward_naive function')
print('dx error: ', rel_error(dx, dx_num))
print('dw error: ', rel_error(dw, dw_num))
print('db error: ', rel_error(db, db_num))
```

```
Testing conv_backward_naive function
dx error:  1.159803161159293e-08
dw error:  2.2471264748452487e-10
db error:  3.37264006649648e-11
```

5 Max-Pooling: Naive forward

Implement the forward pass for the max-pooling operation in the function `max_pool_forward_naive` in the file `cs231n/layers.py`. Again, don't worry too much about computational efficiency.

Check your implementation by running the following:

[6]:
```
x_shape = (2, 3, 4, 4)
x = np.linspace(-0.3, 0.4, num=np.prod(x_shape)).reshape(x_shape)
pool_param = {'pool_width': 2, 'pool_height': 2, 'stride': 2}

out, _ = max_pool_forward_naive(x, pool_param)
```

```
correct_out = np.array([[[[-0.26315789, -0.24842105],
                          [-0.20421053, -0.18947368]],
                         [[-0.14526316, -0.13052632],
                          [-0.08631579, -0.07157895]],
                         [[-0.02736842, -0.01263158],
                          [ 0.03157895,  0.04631579]]],
                        [[[ 0.09052632,  0.10526316],
                          [ 0.14947368,  0.16421053]],
                         [[ 0.20842105,  0.22315789],
                          [ 0.26736842,  0.28210526]],
                         [[ 0.32631579,  0.34105263],
                          [ 0.38526316,  0.4       ]]]])

# Compare your output with ours. Difference should be on the order of e-8.
print('Testing max_pool_forward_naive function:')
print('difference: ', rel_error(out, correct_out))
```

```
Testing max_pool_forward_naive function:
difference:  4.1666665157267834e-08
```

6 Max-Pooling: Naive backward

Implement the backward pass for the max-pooling operation in the function `max_pool_backward_naive` in the file `cs231n/layers.py`. You don't need to worry about computational efficiency.

Check your implementation with numeric gradient checking by running the following:

[7]:
```
np.random.seed(231)
x = np.random.randn(3, 2, 8, 8)
dout = np.random.randn(3, 2, 4, 4)
pool_param = {'pool_height': 2, 'pool_width': 2, 'stride': 2}

dx_num = eval_numerical_gradient_array(lambda x: max_pool_forward_naive(x,␣
 ↪pool_param)[0], x, dout)

out, cache = max_pool_forward_naive(x, pool_param)
dx = max_pool_backward_naive(dout, cache)

# Your error should be on the order of e-12
print('Testing max_pool_backward_naive function:')
print('dx error: ', rel_error(dx, dx_num))
```

```
Testing max_pool_backward_naive function:
dx error:  3.27562514223145e-12
```

7 Fast layers

Making convolution and pooling layers fast can be challenging. To spare you the pain, we've provided fast implementations of the forward and backward passes for convolution and pooling layers in the file `cs231n/fast_layers.py`.

The fast convolution implementation depends on a Cython extension; to compile it either execute the local development cell (option A) if you are developing locally, or the Colab cell (option B) if you are running this assignment in Colab.

Very Important, Please Read. For **both** option A and B, you have to **restart** the notebook after compiling the cython extension. In Colab, please save the notebook `File -> Save`, then click `Runtime -> Restart Runtime -> Yes`. This will restart the kernel which means local variables will be lost. Just re-execute the cells from top to bottom and skip the cell below as you only need to run it once for the compilation step.

7.1 Option A: Local Development

Go to the cs231n directory and execute the following in your terminal:

`python setup.py build_ext --inplace`

7.2 Option B: Colab

Execute the cell below only only **ONCE**.

[8]:
```
%cd drive/My\ Drive/$FOLDERNAME/cs231n/
!python setup.py build_ext --inplace
```

```
[Errno 2] No such file or directory: 'drive/My Drive/$FOLDERNAME/cs231n/'
/Users/luciabouza/FING/DLVis/assignment2_jupyter LUCIA
/System/Library/Frameworks/Python.framework/Versions/2.7/Resources/Python.app/Co
ntents/MacOS/Python: can't open file 'setup.py': [Errno 2] No such file or
directory
```

The API for the fast versions of the convolution and pooling layers is exactly the same as the naive versions that you implemented above: the forward pass receives data, weights, and parameters and produces outputs and a cache object; the backward pass recieves upstream derivatives and the cache object and produces gradients with respect to the data and weights.

NOTE: The fast implementation for pooling will only perform optimally if the pooling regions are non-overlapping and tile the input. If these conditions are not met then the fast pooling implementation will not be much faster than the naive implementation.

You can compare the performance of the naive and fast versions of these layers by running the following:

[9]:
```
# Rel errors should be around e-9 or less
from cs231n.fast_layers import conv_forward_fast, conv_backward_fast
```

```python
from time import time
np.random.seed(231)
x = np.random.randn(100, 3, 31, 31)
w = np.random.randn(25, 3, 3, 3)
b = np.random.randn(25,)
dout = np.random.randn(100, 25, 16, 16)
conv_param = {'stride': 2, 'pad': 1}

t0 = time()
out_naive, cache_naive = conv_forward_naive(x, w, b, conv_param)
t1 = time()
out_fast, cache_fast = conv_forward_fast(x, w, b, conv_param)
t2 = time()

print('Testing conv_forward_fast:')
print('Naive: %fs' % (t1 - t0))
print('Fast: %fs' % (t2 - t1))
print('Speedup: %fx' % ((t1 - t0) / (t2 - t1)))
print('Difference: ', rel_error(out_naive, out_fast))

t0 = time()
dx_naive, dw_naive, db_naive = conv_backward_naive(dout, cache_naive)
t1 = time()
dx_fast, dw_fast, db_fast = conv_backward_fast(dout, cache_fast)
t2 = time()

print('\nTesting conv_backward_fast:')
print('Naive: %fs' % (t1 - t0))
print('Fast: %fs' % (t2 - t1))
print('Speedup: %fx' % ((t1 - t0) / (t2 - t1)))
print('dx difference: ', rel_error(dx_naive, dx_fast))
print('dw difference: ', rel_error(dw_naive, dw_fast))
print('db difference: ', rel_error(db_naive, db_fast))
```

```
Testing conv_forward_fast:
Naive: 12.990649s
Fast: 0.020889s
Speedup: 621.888158x
Difference:  4.926407851494105e-11

Testing conv_backward_fast:
Naive: 20.460379s
Fast: 0.023294s
Speedup: 878.355100x
dx difference:  1.949764775345631e-11
dw difference:  4.075435603295637e-13
db difference:  3.481354613192702e-14
```

[10]:

```python
# Relative errors should be close to 0.0
from cs231n.fast_layers import max_pool_forward_fast, max_pool_backward_fast
np.random.seed(231)
x = np.random.randn(100, 3, 32, 32)
dout = np.random.randn(100, 3, 16, 16)
pool_param = {'pool_height': 2, 'pool_width': 2, 'stride': 2}

t0 = time()
out_naive, cache_naive = max_pool_forward_naive(x, pool_param)
t1 = time()
out_fast, cache_fast = max_pool_forward_fast(x, pool_param)
t2 = time()

print('Testing pool_forward_fast:')
print('Naive: %fs' % (t1 - t0))
print('fast: %fs' % (t2 - t1))
print('speedup: %fx' % ((t1 - t0) / (t2 - t1)))
print('difference: ', rel_error(out_naive, out_fast))

t0 = time()
dx_naive = max_pool_backward_naive(dout, cache_naive)
t1 = time()
dx_fast = max_pool_backward_fast(dout, cache_fast)
t2 = time()

print('\nTesting pool_backward_fast:')
print('Naive: %fs' % (t1 - t0))
print('fast: %fs' % (t2 - t1))
print('speedup: %fx' % ((t1 - t0) / (t2 - t1)))
print('dx difference: ', rel_error(dx_naive, dx_fast))
```

```
Testing pool_forward_fast:
Naive: 0.996089s
fast: 0.005261s
speedup: 189.345162x
difference:  0.0

Testing pool_backward_fast:
Naive: 1.529023s
fast: 0.032701s
speedup: 46.757666x
dx difference:  0.0
```

8 Convolutional "sandwich" layers

Previously we introduced the concept of "sandwich" layers that combine multiple operations into commonly used patterns. In the file `cs231n/layer_utils.py` you will find sandwich layers that implement a few commonly used patterns for convolutional networks. Run the cells below to sanity check they're working.

[11]:
```
from cs231n.layer_utils import conv_relu_pool_forward, conv_relu_pool_backward
np.random.seed(231)
x = np.random.randn(2, 3, 16, 16)
w = np.random.randn(3, 3, 3, 3)
b = np.random.randn(3,)
dout = np.random.randn(2, 3, 8, 8)
conv_param = {'stride': 1, 'pad': 1}
pool_param = {'pool_height': 2, 'pool_width': 2, 'stride': 2}

out, cache = conv_relu_pool_forward(x, w, b, conv_param, pool_param)
dx, dw, db = conv_relu_pool_backward(dout, cache)

dx_num = eval_numerical_gradient_array(lambda x: conv_relu_pool_forward(x, w,␣
 ↪b, conv_param, pool_param)[0], x, dout)
dw_num = eval_numerical_gradient_array(lambda w: conv_relu_pool_forward(x, w,␣
 ↪b, conv_param, pool_param)[0], w, dout)
db_num = eval_numerical_gradient_array(lambda b: conv_relu_pool_forward(x, w,␣
 ↪b, conv_param, pool_param)[0], b, dout)

# Relative errors should be around e-8 or less
print('Testing conv_relu_pool')
print('dx error: ', rel_error(dx_num, dx))
print('dw error: ', rel_error(dw_num, dw))
print('db error: ', rel_error(db_num, db))
```

```
Testing conv_relu_pool
dx error:  9.591132621921372e-09
dw error:  5.802391137330214e-09
db error:  1.0146343411762047e-09
```

[12]:
```
from cs231n.layer_utils import conv_relu_forward, conv_relu_backward
np.random.seed(231)
x = np.random.randn(2, 3, 8, 8)
w = np.random.randn(3, 3, 3, 3)
b = np.random.randn(3,)
dout = np.random.randn(2, 3, 8, 8)
conv_param = {'stride': 1, 'pad': 1}

out, cache = conv_relu_forward(x, w, b, conv_param)
dx, dw, db = conv_relu_backward(dout, cache)

dx_num = eval_numerical_gradient_array(lambda x: conv_relu_forward(x, w, b,␣
 ↪conv_param)[0], x, dout)
dw_num = eval_numerical_gradient_array(lambda w: conv_relu_forward(x, w, b,␣
 ↪conv_param)[0], w, dout)
```

```
db_num = eval_numerical_gradient_array(lambda b: conv_relu_forward(x, w, b,␣
 ↪conv_param)[0], b, dout)

# Relative errors should be around e-8 or less
print('Testing conv_relu:')
print('dx error: ', rel_error(dx_num, dx))
print('dw error: ', rel_error(dw_num, dw))
print('db error: ', rel_error(db_num, db))
```

```
Testing conv_relu:
dx error:  1.5218619980349303e-09
dw error:  2.702022646099404e-10
db error:  1.451272393591721e-10
```

9 Three-layer ConvNet

Now that you have implemented all the necessary layers, we can put them together into a simple convolutional network.

Open the file `cs231n/classifiers/cnn.py` and complete the implementation of the `ThreeLayerConvNet` class. Remember you can use the fast/sandwich layers (already imported for you) in your implementation. Run the following cells to help you debug:

9.1 Sanity check loss

After you build a new network, one of the first things you should do is sanity check the loss. When we use the softmax loss, we expect the loss for random weights (and no regularization) to be about `log(C)` for `C` classes. When we add regularization the loss should go up slightly.

[13]:
```
model = ThreeLayerConvNet()

N = 50
X = np.random.randn(N, 3, 32, 32)
y = np.random.randint(10, size=N)

loss, grads = model.loss(X, y)
print('Initial loss (no regularization): ', loss)

model.reg = 0.5
loss, grads = model.loss(X, y)
print('Initial loss (with regularization): ', loss)
```

```
Initial loss (no regularization):  2.302586071243987
Initial loss (with regularization):  2.5080059990794514
```

9.2 Gradient check

After the loss looks reasonable, use numeric gradient checking to make sure that your backward pass is correct. When you use numeric gradient checking you should use a small amount of artifical data and a small number of neurons at each layer. Note: correct implementations may still have relative errors up to the order of e-2.

[14]:
```
num_inputs = 2
input_dim = (3, 16, 16)
reg = 0.0
num_classes = 10
np.random.seed(231)
X = np.random.randn(num_inputs, *input_dim)
y = np.random.randint(num_classes, size=num_inputs)

model = ThreeLayerConvNet(num_filters=3, filter_size=3,
                          input_dim=input_dim, hidden_dim=7,
                          dtype=np.float64)
loss, grads = model.loss(X, y)
# Errors should be small, but correct implementations may have
# relative errors up to the order of e-2
for param_name in sorted(grads):
    f = lambda _: model.loss(X, y)[0]
    param_grad_num = eval_numerical_gradient(f, model.params[param_name],␣
 ↪verbose=False, h=1e-6)
    e = rel_error(param_grad_num, grads[param_name])
    print('%s max relative error: %e' % (param_name, rel_error(param_grad_num,␣
 ↪grads[param_name])))
```

```
W1 max relative error: 1.380104e-04
W2 max relative error: 1.822723e-02
W3 max relative error: 3.064049e-04
b1 max relative error: 3.477652e-05
b2 max relative error: 2.516375e-03
b3 max relative error: 7.945660e-10
```

9.3 Overfit small data

A nice trick is to train your model with just a few training samples. You should be able to overfit small datasets, which will result in very high training accuracy and comparatively low validation accuracy.

[15]:
```
np.random.seed(231)

num_train = 100
small_data = {
  'X_train': data['X_train'][:num_train],
  'y_train': data['y_train'][:num_train],
  'X_val': data['X_val'],
  'y_val': data['y_val'],
}
```

```python
model = ThreeLayerConvNet(weight_scale=1e-2)

solver = Solver(model, small_data,
                num_epochs=15, batch_size=50,
                update_rule='adam',
                optim_config={
                  'learning_rate': 1e-3,
                },
                verbose=True, print_every=1)
solver.train()
```

```
(Iteration 1 / 30) loss: 2.414060
(Epoch 0 / 15) train acc: 0.200000; val_acc: 0.137000
(Iteration 2 / 30) loss: 3.102925
(Epoch 1 / 15) train acc: 0.140000; val_acc: 0.087000
(Iteration 3 / 30) loss: 2.270330
(Iteration 4 / 30) loss: 2.096705
(Epoch 2 / 15) train acc: 0.240000; val_acc: 0.094000
(Iteration 5 / 30) loss: 1.838880
(Iteration 6 / 30) loss: 1.934188
(Epoch 3 / 15) train acc: 0.510000; val_acc: 0.173000
(Iteration 7 / 30) loss: 1.827912
(Iteration 8 / 30) loss: 1.639574
(Epoch 4 / 15) train acc: 0.520000; val_acc: 0.188000
(Iteration 9 / 30) loss: 1.330082
(Iteration 10 / 30) loss: 1.756115
(Epoch 5 / 15) train acc: 0.630000; val_acc: 0.167000
(Iteration 11 / 30) loss: 1.024162
(Iteration 12 / 30) loss: 1.041826
(Epoch 6 / 15) train acc: 0.750000; val_acc: 0.229000
(Iteration 13 / 30) loss: 1.142777
(Iteration 14 / 30) loss: 0.835706
(Epoch 7 / 15) train acc: 0.790000; val_acc: 0.247000
(Iteration 15 / 30) loss: 0.587786
(Iteration 16 / 30) loss: 0.645509
(Epoch 8 / 15) train acc: 0.820000; val_acc: 0.252000
(Iteration 17 / 30) loss: 0.786844
(Iteration 18 / 30) loss: 0.467054
(Epoch 9 / 15) train acc: 0.820000; val_acc: 0.178000
(Iteration 19 / 30) loss: 0.429880
(Iteration 20 / 30) loss: 0.635498
(Epoch 10 / 15) train acc: 0.900000; val_acc: 0.206000
(Iteration 21 / 30) loss: 0.365807
(Iteration 22 / 30) loss: 0.284220
(Epoch 11 / 15) train acc: 0.820000; val_acc: 0.201000
(Iteration 23 / 30) loss: 0.469343
(Iteration 24 / 30) loss: 0.509369
(Epoch 12 / 15) train acc: 0.920000; val_acc: 0.211000
```

```
(Iteration 25 / 30) loss: 0.111638
(Iteration 26 / 30) loss: 0.145388
(Epoch 13 / 15) train acc: 0.930000; val_acc: 0.213000
(Iteration 27 / 30) loss: 0.155575
(Iteration 28 / 30) loss: 0.143398
(Epoch 14 / 15) train acc: 0.960000; val_acc: 0.212000
(Iteration 29 / 30) loss: 0.158160
(Iteration 30 / 30) loss: 0.118934
(Epoch 15 / 15) train acc: 0.990000; val_acc: 0.220000
```

[16]:
```
# Print final training accuracy
print(
    "Small data training accuracy:",
    solver.check_accuracy(small_data['X_train'], small_data['y_train'])
)
```

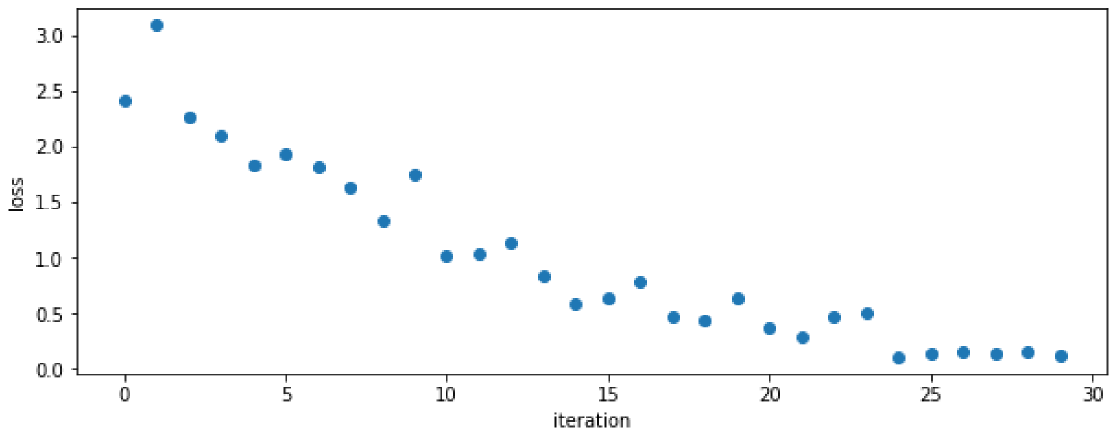
```
Small data training accuracy: 0.82
```

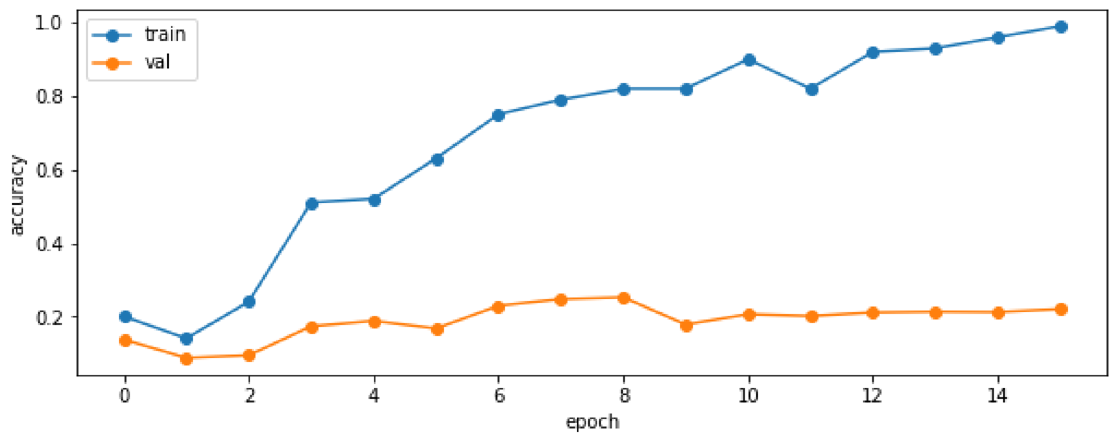
[17]:
```
# Print final validation accuracy
print(
    "Small data validation accuracy:",
    solver.check_accuracy(small_data['X_val'], small_data['y_val'])
)
```

```
Small data validation accuracy: 0.252
```

Plotting the loss, training accuracy, and validation accuracy should show clear overfitting:

[18]:
```
plt.subplot(2, 1, 1)
plt.plot(solver.loss_history, 'o')
plt.xlabel('iteration')
plt.ylabel('loss')

plt.subplot(2, 1, 2)
plt.plot(solver.train_acc_history, '-o')
plt.plot(solver.val_acc_history, '-o')
plt.legend(['train', 'val'], loc='upper left')
plt.xlabel('epoch')
plt.ylabel('accuracy')
plt.show()
```





9.4 Train the net

By training the three-layer convolutional network for one epoch, you should achieve greater than 40% accuracy on the training set:

[19]:
```
model = ThreeLayerConvNet(weight_scale=0.001, hidden_dim=500, reg=0.001)

solver = Solver(model, data,
                num_epochs=1, batch_size=50,
                update_rule='adam',
                optim_config={
                  'learning_rate': 1e-3,
                },
                verbose=True, print_every=20)
solver.train()
```

```
(Iteration 1 / 980) loss: 2.304737
(Epoch 0 / 1) train acc: 0.103000; val_acc: 0.107000
(Iteration 21 / 980) loss: 2.098183
(Iteration 41 / 980) loss: 1.949728
```

```
(Iteration 61 / 980) loss: 1.888330
(Iteration 81 / 980) loss: 1.877023
(Iteration 101 / 980) loss: 1.851805
(Iteration 121 / 980) loss: 1.859282
(Iteration 141 / 980) loss: 1.800109
(Iteration 161 / 980) loss: 2.143221
(Iteration 181 / 980) loss: 1.830502
(Iteration 201 / 980) loss: 2.037209
(Iteration 221 / 980) loss: 2.020234
(Iteration 241 / 980) loss: 1.823658
(Iteration 261 / 980) loss: 1.692611
(Iteration 281 / 980) loss: 1.882525
(Iteration 301 / 980) loss: 1.798192
(Iteration 321 / 980) loss: 1.851890
(Iteration 341 / 980) loss: 1.716254
(Iteration 361 / 980) loss: 1.897586
(Iteration 381 / 980) loss: 1.319675
(Iteration 401 / 980) loss: 1.738721
(Iteration 421 / 980) loss: 1.488797
(Iteration 441 / 980) loss: 1.718340
(Iteration 461 / 980) loss: 1.744368
(Iteration 481 / 980) loss: 1.605387
(Iteration 501 / 980) loss: 1.494771
(Iteration 521 / 980) loss: 1.835102
(Iteration 541 / 980) loss: 1.483846
(Iteration 561 / 980) loss: 1.676794
(Iteration 581 / 980) loss: 1.438248
(Iteration 601 / 980) loss: 1.443393
(Iteration 621 / 980) loss: 1.529293
(Iteration 641 / 980) loss: 1.763398
(Iteration 661 / 980) loss: 1.790253
(Iteration 681 / 980) loss: 1.693265
(Iteration 701 / 980) loss: 1.636999
(Iteration 721 / 980) loss: 1.644484
(Iteration 741 / 980) loss: 1.708837
(Iteration 761 / 980) loss: 1.494169
(Iteration 781 / 980) loss: 1.901667
(Iteration 801 / 980) loss: 1.898906
(Iteration 821 / 980) loss: 1.489902
(Iteration 841 / 980) loss: 1.377528
(Iteration 861 / 980) loss: 1.763665
(Iteration 881 / 980) loss: 1.540198
(Iteration 901 / 980) loss: 1.525496
(Iteration 921 / 980) loss: 1.674080
(Iteration 941 / 980) loss: 1.714226
(Iteration 961 / 980) loss: 1.534575
(Epoch 1 / 1) train acc: 0.504000; val_acc: 0.499000
```

[20]:
```
# Print final training accuracy
print(
    "Full data training accuracy:",
    solver.check_accuracy(small_data['X_train'], small_data['y_train'])
)
```

```
Full data training accuracy: 0.4
```

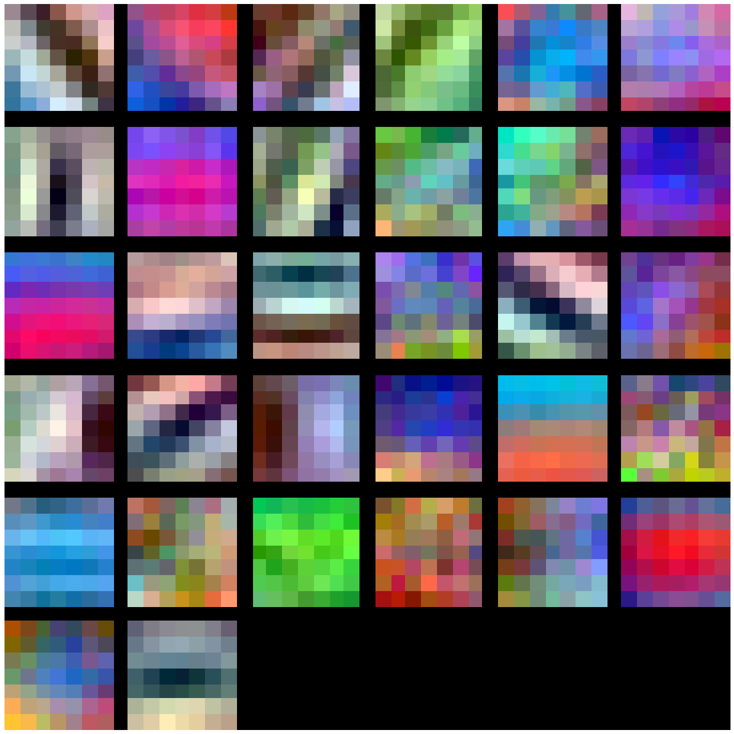
[21]:
```
# Print final validation accuracy
print(
    "Full data validation accuracy:",
    solver.check_accuracy(data['X_val'], data['y_val'])
)
```

```
Full data validation accuracy: 0.499
```

9.5 Visualize Filters

You can visualize the first-layer convolutional filters from the trained network by running the following:

[22]:
```
from cs231n.vis_utils import visualize_grid

grid = visualize_grid(model.params['W1'].transpose(0, 2, 3, 1))
plt.imshow(grid.astype('uint8'))
plt.axis('off')
plt.gcf().set_size_inches(5, 5)
plt.show()
```



10 Spatial Batch Normalization

We already saw that batch normalization is a very useful technique for training deep fully-connected networks. As proposed in the original paper (link in `BatchNormalization.ipynb`), batch normalization can also be used for convolutional networks, but we need to tweak it a bit; the modification will be called "spatial batch normalization."

Normally batch-normalization accepts inputs of shape `(N, D)` and produces outputs of shape `(N, D)`, where we normalize across the minibatch dimension `N`. For data coming from convolutional layers, batch normalization needs to accept inputs of shape `(N, C, H, W)` and produce outputs of shape `(N, C, H, W)` where the `N` dimension gives the minibatch size and the `(H, W)` dimensions give the spatial size of the feature map.

If the feature map was produced using convolutions, then we expect every feature channel's statistics e.g. mean, variance to be relatively consistent both between different images, and different locations within the same image – after all, every feature channel is produced by the same convolutional filter! Therefore spatial batch normalization computes a mean and variance for each of the `C` feature channels by computing statistics over the minibatch dimension `N` as well the spatial dimensions `H` and `W`.

[1] Sergey Ioffe and Christian Szegedy, "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift", ICML 2015.

10.1 Spatial batch normalization: forward

In the file `cs231n/layers.py`, implement the forward pass for spatial batch normalization in the function `spatial_batchnorm_forward`. Check your implementation by running the following:

[23]:
```
np.random.seed(231)
# Check the training-time forward pass by checking means and variances
# of features both before and after spatial batch normalization

N, C, H, W = 2, 3, 4, 5
x = 4 * np.random.randn(N, C, H, W) + 10

print('Before spatial batch normalization:')
print('  Shape: ', x.shape)
print('  Means: ', x.mean(axis=(0, 2, 3)))
print('  Stds: ', x.std(axis=(0, 2, 3)))

# Means should be close to zero and stds close to one
gamma, beta = np.ones(C), np.zeros(C)
bn_param = {'mode': 'train'}
out, _ = spatial_batchnorm_forward(x, gamma, beta, bn_param)
print('After spatial batch normalization:')
print('  Shape: ', out.shape)
print('  Means: ', out.mean(axis=(0, 2, 3)))
print('  Stds: ', out.std(axis=(0, 2, 3)))

# Means should be close to beta and stds close to gamma
gamma, beta = np.asarray([3, 4, 5]), np.asarray([6, 7, 8])
out, _ = spatial_batchnorm_forward(x, gamma, beta, bn_param)
print('After spatial batch normalization (nontrivial gamma, beta):')
print('  Shape: ', out.shape)
print('  Means: ', out.mean(axis=(0, 2, 3)))
print('  Stds: ', out.std(axis=(0, 2, 3)))
```

```
Before spatial batch normalization:
  Shape:  (2, 3, 4, 5)
  Means:  [9.33463814 8.90909116 9.11056338]
  Stds:  [3.61447857 3.19347686 3.5168142 ]
After spatial batch normalization:
  Shape:  (2, 3, 4, 5)
  Means:  [ 5.85642645e-16  5.93969318e-16 -8.88178420e-17]
  Stds:  [0.99999962 0.99999951 0.9999996 ]
After spatial batch normalization (nontrivial gamma, beta):
  Shape:  (2, 3, 4, 5)
  Means:  [6. 7. 8.]
  Stds:  [2.99999885 3.99999804 4.99999798]
```

[24]:
```
np.random.seed(231)
# Check the test-time forward pass by running the training-time
# forward pass many times to warm up the running averages, and then
# checking the means and variances of activations after a test-time
# forward pass.
N, C, H, W = 10, 4, 11, 12

bn_param = {'mode': 'train'}
gamma = np.ones(C)
beta = np.zeros(C)
for t in range(50):
  x = 2.3 * np.random.randn(N, C, H, W) + 13
  spatial_batchnorm_forward(x, gamma, beta, bn_param)
bn_param['mode'] = 'test'
x = 2.3 * np.random.randn(N, C, H, W) + 13
a_norm, _ = spatial_batchnorm_forward(x, gamma, beta, bn_param)

# Means should be close to zero and stds close to one, but will be
# noisier than training-time forward passes.
print('After spatial batch normalization (test-time):')
print('  means: ', a_norm.mean(axis=(0, 2, 3)))
print('  stds: ', a_norm.std(axis=(0, 2, 3)))
```

```
After spatial batch normalization (test-time):
  means:  [-0.08034406  0.07562881  0.05716371  0.04378383]
  stds:  [0.96718744 1.0299714  1.02887624 1.00585577]
```

10.2 Spatial batch normalization: backward

In the file `cs231n/layers.py`, implement the backward pass for spatial batch normalization in the function `spatial_batchnorm_backward`. Run the following to check your implementation using a numeric gradient check:

[26]:
```
np.random.seed(231)
N, C, H, W = 2, 3, 4, 5
x = 5 * np.random.randn(N, C, H, W) + 12
gamma = np.random.randn(C)
beta = np.random.randn(C)
dout = np.random.randn(N, C, H, W)

bn_param = {'mode': 'train'}
fx = lambda x: spatial_batchnorm_forward(x, gamma, beta, bn_param)[0]
fg = lambda a: spatial_batchnorm_forward(x, gamma, beta, bn_param)[0]
fb = lambda b: spatial_batchnorm_forward(x, gamma, beta, bn_param)[0]

dx_num = eval_numerical_gradient_array(fx, x, dout)
da_num = eval_numerical_gradient_array(fg, gamma, dout)
db_num = eval_numerical_gradient_array(fb, beta, dout)
```

```python
#You should expect errors of magnitudes between 1e-12~1e-06
_, cache = spatial_batchnorm_forward(x, gamma, beta, bn_param)
dx, dgamma, dbeta = spatial_batchnorm_backward(dout, cache)
print('dx error: ', rel_error(dx_num, dx))
print('dgamma error: ', rel_error(da_num, dgamma))
print('dbeta error: ', rel_error(db_num, dbeta))
```

```
dx error:  3.0838468285639314e-07
dgamma error:  7.09738489671469e-12
dbeta error:  3.275608725278405e-12
```

10.3 Inline Question 1

Consider an input color image (3 channels) of size 200×200 pixels. A convolutional block is applied to it, consisting of: 10 5×5 filters with zero padding of 2, followed by a spatial batch normalization layer, and finally a 2×2 max-pooling layer. How many parameters does this convolutional block have? Justify.

10.4 Answer:

Tamaño imagen: - H = 200 - W = 200 - C = 3

Parámetros de la primer capa Conv:

- HH = 5
- WW = 5
- F = 10

Tamaño W = (F, C, filter_size, filter_size) = (10, 3, 5, 5) = 750

Tamaño bias = F = 10

Parámetros de la capa spatial batch normalization: debe aprender beta y gamma. el tamaño de la entrada es (F, H’, W’) donde H’ = 1 + (H + 2 * pad - HH) / stride = 1 + (200 + 2*2 -5)/1 = 200 (asumo stride = 1) W’ = 1 + (W + 2* pad - WW) / stride = 1 + (200 + 2*2 -5)/1 = 200 (asumo stride = 1) F = 10

entonces: Tamaño vector Beta = tamaño vector Gamma = F = 10

Parámetros de la capa max-pooling: No tiene parámetros a aprender.

En total de parámetros son: 750 +10 + 2*10 = 780

11 Inline Question 2

Compare the number of parameters of the convolutional block of the previous question with those of a fully connected layer with the same input and output size.

11.1 Answer:

Tamaño imagen (entrada): - H = 200 - W = 200 - C = 3

200x200x3 = 120.000

Tamaño salida = Tamaño entrada / tamaño pooling (2x2 = 4) = 200*200*10 /4 = 100.000

Tamaño entrada = H'*W'*F donde: H' = 1 + (H + 2 * pad - HH) / stride = 1 + (200 + 2*2 -5)/1 = 200 (asumo stride = 1)

W' = 1 + (W + 2 * pad - WW) / stride = 1 + (200 + 2*2 -5)/1 = 200 (asumo stride = 1)

tamaño matriz W = Tamaño entrada * Tamaño salida = 120.000 * 100.000 = 1,2 x 10^10

Tamaño bias = 100.0000

El total de parámetros son = 1,20001 x 10^10 La cantidad de parámetros a aprender con las redes Conv son notoriamente muchísimos menos, en órdenes de magnitud menor.

12 Group Normalization (Optional: 10 points)

In the previous notebook, we mentioned that Layer Normalization is an alternative normalization technique that mitigates the batch size limitations of Batch Normalization. However, as the authors of [2] observed, Layer Normalization does not perform as well as Batch Normalization when used with Convolutional Layers:

> With fully connected layers, all the hidden units in a layer tend to make similar contributions to the final prediction, and re-centering and rescaling the summed inputs to a layer works well. However, the assumption of similar contributions is no longer true for convolutional neural networks. The large number of the hidden units whose receptive fields lie near the boundary of the image are rarely turned on and thus have very different statistics from the rest of the hidden units within the same layer.

The authors of [3] propose an intermediary technique. In contrast to Layer Normalization, where you normalize over the entire feature per-datapoint, they suggest a consistent splitting of each per-datapoint feature into G groups, and a per-group per-datapoint normalization instead.

Visual comparison of the normalization techniques discussed so far (image edited from [3])

Even though an assumption of equal contribution is still being made within each group, the authors hypothesize that this is not as problematic, as innate grouping arises within features for visual recognition. One example they use to illustrate this is that many high-performance handcrafted features in traditional Computer Vision have terms that are explicitly grouped together. Take for example Histogram of Oriented Gradients [4]– after computing histograms per spatially local block, each per-block histogram is normalized before being concatenated together to form the final feature vector.

You will now implement Group Normalization. Note that this normalization technique that you are to implement in the following cells was introduced and published to ECCV just in 2018 – this truly is still an ongoing and excitingly active field of research!

[2] Ba, Jimmy Lei, Jamie Ryan Kiros, and Geoffrey E. Hinton. "Layer Normalization." stat 1050 (2016): 21.

[3] Wu, Yuxin, and Kaiming He. "Group Normalization." arXiv preprint arXiv:1803.08494 (2018).

[4] N. Dalal and B. Triggs. Histograms of oriented gradients for human detection. In Computer Vision and Pattern Recognition (CVPR), 2005.

12.1 Group normalization: forward (Optional)

In the file `cs231n/layers.py`, implement the forward pass for group normalization in the function `spatial_groupnorm_forward`. Check your implementation by running the following:

[27]:
```
np.random.seed(231)
# Check the training-time forward pass by checking means and variances
# of features both before and after spatial batch normalization

N, C, H, W = 2, 6, 4, 5
G = 2
x = 4 * np.random.randn(N, C, H, W) + 10
x_g = x.reshape((N*G,-1))
print('Before spatial group normalization:')
print('  Shape: ', x.shape)
print('  Means: ', x_g.mean(axis=1))
print('  Stds: ', x_g.std(axis=1))

# Means should be close to zero and stds close to one
gamma, beta = np.ones((1,C,1,1)), np.zeros((1,C,1,1))
bn_param = {'mode': 'train'}

out, _ = spatial_groupnorm_forward(x, gamma, beta, G, bn_param)
out_g = out.reshape((N*G,-1))
print('After spatial group normalization:')
print('  Shape: ', out.shape)
print('  Means: ', out_g.mean(axis=1))
print('  Stds: ', out_g.std(axis=1))
```

```
Before spatial group normalization:
  Shape:  (2, 6, 4, 5)
  Means:  [9.72505327 8.51114185 8.9147544  9.43448077]
  Stds:  [3.67070958 3.09892597 4.27043622 3.97521327]
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
<ipython-input-27-f5737e63d501> in <module>
     17
     18 out, _ = spatial_groupnorm_forward(x, gamma, beta, G, bn_param)
---> 19 out_g = out.reshape((N*G,-1))
     20 print('After spatial group normalization:')
     21 print('  Shape: ', out.shape)
```

```
AttributeError: 'NoneType' object has no attribute 'reshape'
```

12.2 Spatial group normalization: backward (Optional)

In the file `cs231n/layers.py`, implement the backward pass for spatial batch normalization in the function `spatial_groupnorm_backward`. Run the following to check your implementation using a numeric gradient check:

[ ]:
```
np.random.seed(231)
N, C, H, W = 2, 6, 4, 5
G = 2
x = 5 * np.random.randn(N, C, H, W) + 12
gamma = np.random.randn(1,C,1,1)
beta = np.random.randn(1,C,1,1)
dout = np.random.randn(N, C, H, W)

gn_param = {}
fx = lambda x: spatial_groupnorm_forward(x, gamma, beta, G, gn_param)[0]
fg = lambda a: spatial_groupnorm_forward(x, gamma, beta, G, gn_param)[0]
fb = lambda b: spatial_groupnorm_forward(x, gamma, beta, G, gn_param)[0]

dx_num = eval_numerical_gradient_array(fx, x, dout)
da_num = eval_numerical_gradient_array(fg, gamma, dout)
db_num = eval_numerical_gradient_array(fb, beta, dout)

_, cache = spatial_groupnorm_forward(x, gamma, beta, G, gn_param)
dx, dgamma, dbeta = spatial_groupnorm_backward(dout, cache)
#You should expect errors of magnitudes between 1e-12~1e-07
print('dx error: ', rel_error(dx_num, dx))
print('dgamma error: ', rel_error(da_num, dgamma))
print('dbeta error: ', rel_error(db_num, dbeta))
```

PyTorch

November 17, 2020

1 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).

1.0.1 What is PyTorch?

PyTorch is a system for executing dynamic computational graphs over Tensor objects that behave similarly as numpy ndarray. It comes with a powerful automatic differentiation engine that removes the need for manual back-propagation.

1.0.2 Why?

- Our code will now run on GPUs! Much faster training. When using a framework like PyTorch or TensorFlow you can harness the power of the GPU for your own custom neural network architectures without having to write CUDA code directly (which is beyond the scope of this class).
- We want you to be ready to use one of these frameworks for your project so you can experiment more efficiently than if you were writing every feature you want to use by hand.
- We want you to stand on the shoulders of giants! TensorFlow and PyTorch are both excellent frameworks that will make your lives a lot easier, and now that you understand their guts, you are free to use them :)
- We want you to be exposed to the sort of deep learning code you might run into in academia or industry.

1.0.3 PyTorch versions

This notebook assumes that you are using **PyTorch version 1.4**. In some of the previous versions (e.g. before 0.4), Tensors had to be wrapped in Variable objects to be used in autograd; however Variables have now been deprecated. In addition 1.0+ versions separate a Tensor's datatype from its device, and use numpy-style factories for constructing Tensors rather than directly invoking Tensor constructors.

1.1 How will I learn PyTorch?

Justin Johnson has made an excellent tutorial for PyTorch.

You can also find the detailed API doc here. If you have other questions that are not addressed by the API docs, the PyTorch forum is a much better place to ask than StackOverflow.

1.2 Install PyTorch 1.4 (ONLY IF YOU ARE WORKING LOCALLY)

1. Have the latest version of Anaconda installed on your machine.
2. Create a new conda environment starting from Python 3.7. In this setup example, we'll call it `torch_env`.
3. Run the command: `conda activate torch_env`
4. Run the command: `pip install torch==1.4 torchvision==0.5.0`

2 Table of Contents

This assignment has 5 parts. You will learn PyTorch on **three different levels of abstraction**, which will help you understand it better and prepare you for the final project.

1. Part I, Preparation: we will use CIFAR-10 dataset.
2. Part II, Barebones PyTorch: **Abstraction level 1**, we will work directly with the lowest-level PyTorch Tensors.
3. Part III, PyTorch Module API: **Abstraction level 2**, we will use `nn.Module` to define arbitrary neural network architecture.
4. Part IV, PyTorch Sequential API: **Abstraction level 3**, we will use `nn.Sequential` to define a linear feed-forward network very conveniently.
5. Part V, CIFAR-10 open-ended challenge: please implement your own network to get as high accuracy as possible on CIFAR-10. You can experiment with any layer, optimizer, hyperparameters or other advanced features.

Here is a table of comparison:

API	Flexibility	Convenience
Barebone	High	Low
`nn.Module`	High	Medium
`nn.Sequential`	Low	High

3 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.

```
[ ]: import torch
assert '.'.join(torch.__version__.split('.')[:2]) == '1.4'
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader
from torch.utils.data import sampler

import torchvision.datasets as dset
import torchvision.transforms as T

import numpy as np
```

```
[ ]: NUM_TRAIN = 49000

# The torchvision.transforms package provides tools for preprocessing data
# and for performing data augmentation; here we set up a transform to
# preprocess the data by subtracting the mean RGB value and dividing by the
# standard deviation of each RGB value; we've hardcoded the mean and std.
transform = T.Compose([
                T.ToTensor(),
                T.Normalize((0.4914, 0.4822, 0.4465), (0.2023, 0.1994, 0.2010))
            ])

# We set up a Dataset object for each split (train / val / test); Datasets load
# training examples one at a time, so we wrap each Dataset in a DataLoader which
# iterates through the Dataset and forms minibatches. We divide the CIFAR-10
# training set into train and val sets by passing a Sampler object to the
# DataLoader telling how it should sample from the underlying Dataset.
cifar10_train = dset.CIFAR10('./cs231n/datasets', train=True, download=True,
                             transform=transform)
loader_train = DataLoader(cifar10_train, batch_size=64,
                          sampler=sampler.SubsetRandomSampler(range(NUM_TRAIN)))

cifar10_val = dset.CIFAR10('./cs231n/datasets', train=True, download=True,
                           transform=transform)
loader_val = DataLoader(cifar10_val, batch_size=64,
                        sampler=sampler.SubsetRandomSampler(range(NUM_TRAIN,
 ↪50000)))

cifar10_test = dset.CIFAR10('./cs231n/datasets', train=False, download=True,
                            transform=transform)
loader_test = DataLoader(cifar10_test, batch_size=64)
```

You have an option to **use GPU by setting the flag to True below**. It is not necessary to use GPU for this assignment. Note that if your computer does not have CUDA enabled, `torch.cuda.is_available()` will return False and this notebook will fallback to CPU mode.

The global variables `dtype` and `device` will control the data types throughout this assignment.

3.1 Colab Users

If you are using Colab, you need to manually switch to a GPU device. You can do this by clicking `Runtime -> Change runtime type` and selecting `GPU` under `Hardware Accelerator`. Note that you have to rerun the cells from the top since the kernel gets restarted upon switching runtimes.

[ ]:
```
USE_GPU = True

dtype = torch.float32 # we will be using float throughout this tutorial

if USE_GPU and torch.cuda.is_available():
    device = torch.device('cuda')
else:
    device = torch.device('cpu')

# Constant to control how frequently we print train loss
print_every = 100

print('using device:', device)
```

4 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.

4.0.1 PyTorch Tensors: Flatten Function

A PyTorch Tensor is conceptionally similar to a numpy array: it is an n-dimensional grid of numbers, and like numpy PyTorch provides many functions to efficiently operate on Tensors. As a simple example, we provide a `flatten` function below which reshapes image data for use in a fully-connected neural network.

Recall that image data is typically stored in a Tensor of shape N x C x H x W, where:

- N is the number of datapoints
- C is the number of channels

- H is the height of the intermediate feature map in pixels
- W is the height of the intermediate feature map in pixels

This is the right way to represent the data when we are doing something like a 2D convolution, that needs spatial understanding of where the intermediate features are relative to each other. When we use fully connected affine layers to process the image, however, we want each datapoint to be represented by a single vector – it's no longer useful to segregate the different channels, rows, and columns of the data. So, we use a "flatten" operation to collapse the `C x H x W` values per representation into a single long vector. The flatten function below first reads in the N, C, H, and W values from a given batch of data, and then returns a "view" of that data. "View" is analogous to numpy's "reshape" method: it reshapes x's dimensions to be N x ??, where ?? is allowed to be anything (in this case, it will be C x H x W, but we don't need to specify that explicitly).

[ ]:
```
def flatten(x):
    N = x.shape[0] # read in N, C, H, W
    return x.view(N, -1)  # "flatten" the C * H * W values into a single vector␣
 ↪per image

def test_flatten():
    x = torch.arange(12).view(2, 1, 3, 2)
    print('Before flattening: ', x)
    print('After flattening: ', flatten(x))

test_flatten()
```

4.0.2 Barebones PyTorch: Two-Layer Network

Here we define a function `two_layer_fc` which performs the forward pass of a two-layer fully-connected ReLU network on a batch of image data. After defining the forward pass we check that it doesn't crash and that it produces outputs of the right shape by running zeros through the network.

You don't have to write any code here, but it's important that you read and understand the implementation.

[ ]:
```
import torch.nn.functional as F  # useful stateless functions

def two_layer_fc(x, params):
    """
    A fully-connected neural networks; the architecture is:
    NN is fully connected -> ReLU -> fully connected layer.
    Note that this function only defines the forward pass;
    PyTorch will take care of the backward pass for us.

    The input to the network will be a minibatch of data, of shape
    (N, d1, ..., dM) where d1 * ... * dM = D. The hidden layer will have H␣
 ↪units,
    and the output layer will produce scores for C classes.
```

```
    Inputs:
    - x: A PyTorch Tensor of shape (N, d1, ..., dM) giving a minibatch of
      input data.
    - params: A list [w1, w2] of PyTorch Tensors giving weights for the network;
      w1 has shape (D, H) and w2 has shape (H, C).

    Returns:
    - scores: A PyTorch Tensor of shape (N, C) giving classification scores for
      the input data x.
    """
    # first we flatten the image
    x = flatten(x)  # shape: [batch_size, C x H x W]

    w1, w2 = params

    # Forward pass: compute predicted y using operations on Tensors. Since w1␣
 ↪and
    # w2 have requires_grad=True, operations involving these Tensors will cause
    # PyTorch to build a computational graph, allowing automatic computation of
    # gradients. Since we are no longer implementing the backward pass by hand␣
 ↪we
    # don't need to keep references to intermediate values.
    # you can also use `.clamp(min=0)`, equivalent to F.relu()
    x = F.relu(x.mm(w1))
    x = x.mm(w2)
    return x


def two_layer_fc_test():
    hidden_layer_size = 42
    x = torch.zeros((64, 50), dtype=dtype)  # minibatch size 64, feature␣
 ↪dimension 50
    w1 = torch.zeros((50, hidden_layer_size), dtype=dtype)
    w2 = torch.zeros((hidden_layer_size, 10), dtype=dtype)
    scores = two_layer_fc(x, [w1, w2])
    print(scores.size())  # you should see [64, 10]

two_layer_fc_test()
```

4.0.3 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.

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

[ ]:
```python
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)*****

    pass

    # *****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).

```
[ ]: def three_layer_convnet_test():
    x = torch.zeros((64, 3, 32, 32), dtype=dtype)  # minibatch size 64, image size [3, 32, 32]

    conv_w1 = torch.zeros((6, 3, 5, 5), dtype=dtype)  # [out_channel, in_channel, kernel_H, kernel_W]
    conv_b1 = torch.zeros((6,))  # out_channel
    conv_w2 = torch.zeros((9, 6, 3, 3), dtype=dtype)  # [out_channel, in_channel, kernel_H, kernel_W]
    conv_b2 = torch.zeros((9,))  # out_channel

    # you must calculate the shape of the tensor after two conv layers, before the fully-connected layer
    fc_w = torch.zeros((9 * 32 * 32, 10))
    fc_b = torch.zeros(10)

    scores = three_layer_convnet(x, [conv_w1, conv_b1, conv_w2, conv_b2, fc_w, fc_b])
    print(scores.size())  # you should see [64, 10]
three_layer_convnet_test()
```

4.0.4 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

[ ]:
```python
def random_weight(shape):
    """
    Create random Tensors for weights; setting requires_grad=True means that we
    want to compute gradients for these Tensors during the backward pass.
    We use Kaiming normalization: sqrt(2 / fan_in)
    """
    if len(shape) == 2:  # FC weight
        fan_in = shape[0]
    else:
        fan_in = np.prod(shape[1:]) # conv weight [out_channel, in_channel, kH,␣
↪kW]
    # randn is standard normal distribution generator.
    w = torch.randn(shape, device=device, dtype=dtype) * np.sqrt(2. / fan_in)
    w.requires_grad = True
    return w

def zero_weight(shape):
    return torch.zeros(shape, device=device, dtype=dtype, requires_grad=True)

# create a weight of shape [3 x 5]
# you should see the type `torch.cuda.FloatTensor` if you use GPU.
# Otherwise it should be `torch.FloatTensor`
random_weight((3, 5))
```

4.0.5 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.

[ ]:
```python
def check_accuracy_part2(loader, model_fn, params):
    """
    Check the accuracy of a classification model.

    Inputs:
    - loader: A DataLoader for the data split we want to check
    - model_fn: A function that performs the forward pass of the model,
      with the signature scores = model_fn(x, params)
    - params: List of PyTorch Tensors giving parameters of the model

    Returns: Nothing, but prints the accuracy of the model
```

```
    """
    split = 'val' if loader.dataset.train else 'test'
    print('Checking accuracy on the %s set' % split)
    num_correct, num_samples = 0, 0
    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.int64)
            scores = model_fn(x, params)
            _, 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))
```

4.0.6 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.

[ ]:
```
def train_part2(model_fn, params, learning_rate):
    """
    Train a model on CIFAR-10.

    Inputs:
    - model_fn: A Python function that performs the forward pass of the model.
      It should have the signature scores = model_fn(x, params) where x is a
      PyTorch Tensor of image data, params is a list of PyTorch Tensors giving
      model weights, and scores is a PyTorch Tensor of shape (N, C) giving
      scores for the elements in x.
    - params: List of PyTorch Tensors giving weights for the model
    - learning_rate: Python scalar giving the learning rate to use for SGD

    Returns: Nothing
    """
    for t, (x, y) in enumerate(loader_train):
        # Move the data to the proper device (GPU or CPU)
        x = x.to(device=device, dtype=dtype)
        y = y.to(device=device, dtype=torch.long)

        # Forward pass: compute scores and loss
        scores = model_fn(x, params)
        loss = F.cross_entropy(scores, y)
```

```
        # Backward pass: PyTorch figures out which Tensors in the computational
        # graph has requires_grad=True and uses backpropagation to compute the
        # gradient of the loss with respect to these Tensors, and stores the
        # gradients in the .grad attribute of each Tensor.
        loss.backward()

        # Update parameters. We don't want to backpropagate through the
        # parameter updates, so we scope the updates under a torch.no_grad()
        # context manager to prevent a computational graph from being built.
        with torch.no_grad():
            for w in params:
                w -= learning_rate * w.grad

                # Manually zero the gradients after running the backward pass
                w.grad.zero_()

        if t % print_every == 0:
            print('Iteration %d, loss = %.4f' % (t, loss.item()))
            check_accuracy_part2(loader_val, model_fn, params)
            print()
```

4.0.7 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.

[ ]:
```
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)
```

4.0.8 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.

[ ]:
```
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)*****

pass

# *****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)
```

5 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.

5.0.1 Module API: Two-Layer Network

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

[ ]:
```
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()
```

5.0.2 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.

[ ]:
```
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)*****

        pass

        # *****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)*****
```

```
        pass

        # *****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()
```

5.0.3 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.

[ ]:
```
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))
```

5.0.4 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.

```
[ ]: 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.
            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()
```

5.0.5 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.

[ ]:
```
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)
```

5.0.6 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.

[ ]:
```
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)*****

pass

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

train_part34(model, optimizer)
```

6 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.

6.0.1 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.

[ ]:
```
# 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)
```

6.0.2 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.

[ ]:
```
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)*****

pass

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

train_part34(model, optimizer)
```

7 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

7.0.1 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.

7.0.2 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.

7.0.3 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

7.0.4 Have fun and happy training!

```
[ ]: ################################################################################
     # 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)*****

     pass

     # *****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)
```

7.1 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: Describe what you did

7.2 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.

```
[ ]: best_model = model
     check_accuracy_part34(loader_test, best_model)
```

TensorFlow

November 17, 2020

1 What's this TensorFlow 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, TensorFlow (or PyTorch, if you choose to work with that notebook).

What is it? TensorFlow is a system for executing computational graphs over Tensor objects, with native support for performing backpropogation for its Variables. In it, we work with Tensors which are n-dimensional arrays analogous to the numpy ndarray.

Why?

- Our code will now run on GPUs! Much faster training. Writing your own modules to run on GPUs is beyond the scope of this class, unfortunately.
- We want you to be ready to use one of these frameworks for your project so you can experiment more efficiently than if you were writing every feature you want to use by hand.
- We want you to stand on the shoulders of giants! TensorFlow and PyTorch are both excellent frameworks that will make your lives a lot easier, and now that you understand their guts, you are free to use them :)
- We want you to be exposed to the sort of deep learning code you might run into in academia or industry.

1.1 How will I learn TensorFlow?

TensorFlow has many excellent tutorials available, including those from Google themselves.

Otherwise, this notebook will walk you through much of what you need to do to train models in TensorFlow. See the end of the notebook for some links to helpful tutorials if you want to learn more or need further clarification on topics that aren't fully explained here.

NOTE: This notebook is meant to teach you the latest version of Tensorflow which is as of this homework version `2.2.0-rc3`. Most examples on the web today are still in 1.x, so be careful not to confuse the two when looking up documentation.

1.2 Install Tensorflow 2.0 (ONLY IF YOU ARE WORKING LOCALLY)

1. Have the latest version of Anaconda installed on your machine.

2. Create a new conda environment starting from Python 3.7. In this setup example, we'll call it `tf_20_env`.
3. Run the command: `source activate tf_20_env`
4. Then pip install TF 2.0 as described here: https://www.tensorflow.org/install

2 Table of Contents

This notebook has 5 parts. We will walk through TensorFlow at **three different levels of abstraction**, which should help you better understand it and prepare you for working on your project.

1. Part I, Preparation: load the CIFAR-10 dataset.
2. Part II, Barebone TensorFlow: **Abstraction Level 1**, we will work directly with low-level TensorFlow graphs.
3. Part III, Keras Model API: **Abstraction Level 2**, we will use `tf.keras.Model` to define arbitrary neural network architecture.
4. Part IV, Keras Sequential + Functional API: **Abstraction Level 3**, we will use `tf.keras.Sequential` to define a linear feed-forward network very conveniently, and then explore the functional libraries for building unique and uncommon models that require more flexibility.
5. Part V, CIFAR-10 open-ended challenge: please implement your own network to get as high accuracy as possible on CIFAR-10. You can experiment with any layer, optimizer, hyperparameters or other advanced features.

We will discuss Keras in more detail later in the notebook.

Here is a table of comparison:

API	Flexibility	Convenience
Barebone	High	Low
`tf.keras.Model`	High	Medium
`tf.keras.Sequential`	Low	High

3 Part I: Preparation

First, we load the CIFAR-10 dataset. This might take a few minutes to download the first time you run it, but after that the files should be cached on disk and loading should be faster.

In previous parts of the assignment we used CS231N-specific code to download and read the CIFAR-10 dataset; however the `tf.keras.datasets` package in TensorFlow provides prebuilt utility functions for loading many common datasets.

For the purposes of this assignment we will still write our own code to preprocess the data and iterate through it in minibatches. The `tf.data` package in TensorFlow provides tools for automating this process, but working with this package adds extra complication and is beyond the scope of this notebook. However using `tf.data` can be much more efficient than the simple approach used in this notebook, so you should consider using it for your project.

```
[ ]: import os
     import tensorflow as tf
     import numpy as np
     import math
     import timeit
     import matplotlib.pyplot as plt

     %matplotlib inline
```

```
[ ]: def load_cifar10(num_training=49000, num_validation=1000, num_test=10000):
         """
         Fetch the CIFAR-10 dataset from the web and perform preprocessing to prepare
         it for the two-layer neural net classifier. These are the same steps as
         we used for the SVM, but condensed to a single function.
         """
         # Load the raw CIFAR-10 dataset and use appropriate data types and shapes
         cifar10 = tf.keras.datasets.cifar10.load_data()
         (X_train, y_train), (X_test, y_test) = cifar10
         X_train = np.asarray(X_train, dtype=np.float32)
         y_train = np.asarray(y_train, dtype=np.int32).flatten()
         X_test = np.asarray(X_test, dtype=np.float32)
         y_test = np.asarray(y_test, dtype=np.int32).flatten()

         # Subsample the data
         mask = range(num_training, num_training + num_validation)
         X_val = X_train[mask]
         y_val = y_train[mask]
         mask = range(num_training)
         X_train = X_train[mask]
         y_train = y_train[mask]
         mask = range(num_test)
         X_test = X_test[mask]
         y_test = y_test[mask]

         # Normalize the data: subtract the mean pixel and divide by std
         mean_pixel = X_train.mean(axis=(0, 1, 2), keepdims=True)
         std_pixel = X_train.std(axis=(0, 1, 2), keepdims=True)
         X_train = (X_train - mean_pixel) / std_pixel
         X_val = (X_val - mean_pixel) / std_pixel
         X_test = (X_test - mean_pixel) / std_pixel

         return X_train, y_train, X_val, y_val, X_test, y_test

     # If there are errors with SSL downloading involving self-signed certificates,
     # it may be that your Python version was recently installed on the current␣
      ↪machine.
     # See: https://github.com/tensorflow/tensorflow/issues/10779
```

```
# To fix, run the command: /Applications/Python\ 3.7/Install\ Certificates.
↪command
#   ...replacing paths as necessary.

# Invoke the above function to get our data.
NHW = (0, 1, 2)
X_train, y_train, X_val, y_val, X_test, y_test = load_cifar10()
print('Train data shape: ', X_train.shape)
print('Train labels shape: ', y_train.shape, y_train.dtype)
print('Validation data shape: ', X_val.shape)
print('Validation labels shape: ', y_val.shape)
print('Test data shape: ', X_test.shape)
print('Test labels shape: ', y_test.shape)
```

[ ]:
```
class Dataset(object):
    def __init__(self, X, y, batch_size, shuffle=False):
        """
        Construct a Dataset object to iterate over data X and labels y

        Inputs:
        - X: Numpy array of data, of any shape
        - y: Numpy array of labels, of any shape but with y.shape[0] == X.
↪shape[0]
        - batch_size: Integer giving number of elements per minibatch
        - shuffle: (optional) Boolean, whether to shuffle the data on each epoch
        """
        assert X.shape[0] == y.shape[0], 'Got different numbers of data and␣
↪labels'
        self.X, self.y = X, y
        self.batch_size, self.shuffle = batch_size, shuffle

    def __iter__(self):
        N, B = self.X.shape[0], self.batch_size
        idxs = np.arange(N)
        if self.shuffle:
            np.random.shuffle(idxs)
        return iter((self.X[i:i+B], self.y[i:i+B]) for i in range(0, N, B))


train_dset = Dataset(X_train, y_train, batch_size=64, shuffle=True)
val_dset = Dataset(X_val, y_val, batch_size=64, shuffle=False)
test_dset = Dataset(X_test, y_test, batch_size=64)
```

[ ]:
```
# We can iterate through a dataset like this:
for t, (x, y) in enumerate(train_dset):
    print(t, x.shape, y.shape)
    if t > 5: break
```

You can optionally **use GPU by setting the flag to True below**.

3.1 Colab Users

If you are using Colab, you need to manually switch to a GPU device. You can do this by clicking `Runtime -> Change runtime type` and selecting `GPU` under `Hardware Accelerator`. Note that you have to rerun the cells from the top since the kernel gets restarted upon switching runtimes.

[ ]:
```
# Set up some global variables
USE_GPU = True

if USE_GPU:
    device = '/device:GPU:0'
else:
    device = '/cpu:0'

# Constant to control how often we print when training models
print_every = 100

print('Using device: ', device)
```

4 Part II: Barebones TensorFlow

TensorFlow ships with various high-level APIs which make it very convenient to define and train neural networks; we will cover some of these constructs in Part III and Part IV of this notebook. In this section we will start by building a model with basic TensorFlow constructs to help you better understand what's going on under the hood of the higher-level APIs.

"Barebones Tensorflow" is important to understanding the building blocks of TensorFlow, but much of it involves concepts from TensorFlow 1.x. We will be working with legacy modules such as `tf.Variable`.

Therefore, please read and understand the differences between legacy (1.x) TF and the new (2.0) TF.

4.0.1 Historical background on TensorFlow 1.x

TensorFlow 1.x is primarily a framework for working with **static computational graphs**. Nodes in the computational graph are Tensors which will hold n-dimensional arrays when the graph is run; edges in the graph represent functions that will operate on Tensors when the graph is run to actually perform useful computation.

Before Tensorflow 2.0, we had to configure the graph into two phases. There are plenty of tutorials online that explain this two-step process. The process generally looks like the following for TF 1.x: 1. **Build a computational graph that describes the computation that you want to perform**. This stage doesn't actually perform any computation; it just builds up a symbolic representation of your computation. This stage will typically define one or more `placeholder` objects that represent inputs to the computational graph. 2. **Run the computational graph many times.** Each time the graph is run (e.g. for one gradient descent step) you will specify which parts of the graph you want to compute, and pass a `feed_dict` dictionary that will give concrete values to any `placeholders` in the graph.

4.0.2 The new paradigm in Tensorflow 2.0

Now, with Tensorflow 2.0, we can simply adopt a functional form that is more Pythonic and similar in spirit to PyTorch and direct Numpy operation. Instead of the 2-step paradigm with computation graphs, making it (among other things) easier to debug TF code. You can read more details at https://www.tensorflow.org/guide/eager.

The main difference between the TF 1.x and 2.0 approach is that the 2.0 approach doesn't make use of `tf.Session`, `tf.run`, `placeholder`, `feed_dict`. To get more details of what's different between the two version and how to convert between the two, check out the official migration guide: https://www.tensorflow.org/alpha/guide/migration_guide

Later, in the rest of this notebook we'll focus on this new, simpler approach.

4.0.3 TensorFlow warmup: Flatten Function

We can see this in action by defining a simple `flatten` function that will reshape image data for use in a fully-connected network.

In TensorFlow, data for convolutional feature maps is typically stored in a Tensor of shape N x H x W x C where:

- N is the number of datapoints (minibatch size)
- H is the height of the feature map
- W is the width of the feature map
- C is the number of channels in the feature map

This is the right way to represent the data when we are doing something like a 2D convolution, that needs spatial understanding of where the intermediate features are relative to each other. When we use fully connected affine layers to process the image, however, we want each datapoint to be represented by a single vector – it's no longer useful to segregate the different channels, rows, and columns of the data. So, we use a "flatten" operation to collapse the `H x W x C` values per representation into a single long vector.

Notice the `tf.reshape` call has the target shape as `(N, -1)`, meaning it will reshape/keep the first dimension to be N, and then infer as necessary what the second dimension is in the output, so we can collapse the remaining dimensions from the input properly.

NOTE: TensorFlow and PyTorch differ on the default Tensor layout; TensorFlow uses N x H x W x C but PyTorch uses N x C x H x W.

[ ]:
```
def flatten(x):
    """
    Input:
    - TensorFlow Tensor of shape (N, D1, ..., DM)

    Output:
    - TensorFlow Tensor of shape (N, D1 * ... * DM)
    """
```

```
    N = tf.shape(x)[0]
    return tf.reshape(x, (N, -1))
```

[ ]:
```
def test_flatten():
    # Construct concrete values of the input data x using numpy
    x_np = np.arange(24).reshape((2, 3, 4))
    print('x_np:\n', x_np, '\n')
    # Compute a concrete output value.
    x_flat_np = flatten(x_np)
    print('x_flat_np:\n', x_flat_np, '\n')

test_flatten()
```

4.0.4 Barebones TensorFlow: Define a Two-Layer Network

We will now implement our first neural network with TensorFlow: a fully-connected ReLU network with two hidden layers and no biases on the CIFAR10 dataset. For now we will use only low-level TensorFlow operators to define the network; later we will see how to use the higher-level abstractions provided by `tf.keras` to simplify the process.

We will define the forward pass of the network in the function `two_layer_fc`; this will accept TensorFlow Tensors for the inputs and weights of the network, and return a TensorFlow Tensor for the scores.

After defining the network architecture in the `two_layer_fc` function, we will test the implementation by checking the shape of the output.

It's important that you read and understand this implementation.

[ ]:
```
def two_layer_fc(x, params):
    """
    A fully-connected neural network; the architecture is:
    fully-connected layer -> ReLU -> fully connected layer.
    Note that we only need to define the forward pass here; TensorFlow will take
    care of computing the gradients for us.

    The input to the network will be a minibatch of data, of shape
    (N, d1, ..., dM) where d1 * ... * dM = D. The hidden layer will have H␣
 ↪units,
    and the output layer will produce scores for C classes.

    Inputs:
    - x: A TensorFlow Tensor of shape (N, d1, ..., dM) giving a minibatch of
      input data.
    - params: A list [w1, w2] of TensorFlow Tensors giving weights for the
      network, where w1 has shape (D, H) and w2 has shape (H, C).

    Returns:
    - scores: A TensorFlow Tensor of shape (N, C) giving classification scores
```

```
      for the input data x.
    """
    w1, w2 = params                   # Unpack the parameters
    x = flatten(x)                    # Flatten the input; now x has shape (N,␣
↪D)
    h = tf.nn.relu(tf.matmul(x, w1))  # Hidden layer: h has shape (N, H)
    scores = tf.matmul(h, w2)         # Compute scores of shape (N, C)
    return scores
```

[ ]:
```
def two_layer_fc_test():
    hidden_layer_size = 42

    # Scoping our TF operations under a tf.device context manager
    # lets us tell TensorFlow where we want these Tensors to be
    # multiplied and/or operated on, e.g. on a CPU or a GPU.
    with tf.device(device):
        x = tf.zeros((64, 32, 32, 3))
        w1 = tf.zeros((32 * 32 * 3, hidden_layer_size))
        w2 = tf.zeros((hidden_layer_size, 10))

        # Call our two_layer_fc function for the forward pass of the network.
        scores = two_layer_fc(x, [w1, w2])

    print(scores.shape)

two_layer_fc_test()
```

4.0.5 Barebones TensorFlow: 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. 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.

HINT: For convolutions: https://www.tensorflow.org/versions/r2.0/api_docs/python/tf/nn/conv2d; be careful with padding!

HINT: For biases: https://www.tensorflow.org/performance/xla/broadcasting

[ ]:
```
def three_layer_convnet(x, params):
    """
    A three-layer convolutional network with the architecture described above.
```

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

    pass

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

After defing the forward pass of the three-layer ConvNet above, run the following cell to test your implementation. Like the two-layer network, we run the graph on a batch of zeros just to make sure the function doesn't crash, and produces outputs of the correct shape.

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

[ ]:
```
def three_layer_convnet_test():

    with tf.device(device):
        x = tf.zeros((64, 32, 32, 3))
        conv_w1 = tf.zeros((5, 5, 3, 6))
        conv_b1 = tf.zeros((6,))
        conv_w2 = tf.zeros((3, 3, 6, 9))
        conv_b2 = tf.zeros((9,))
        fc_w = tf.zeros((32 * 32 * 9, 10))
```

```
        fc_b = tf.zeros((10,))
        params = [conv_w1, conv_b1, conv_w2, conv_b2, fc_w, fc_b]
        scores = three_layer_convnet(x, params)

    # Inputs to convolutional layers are 4-dimensional arrays with shape
    # [batch_size, height, width, channels]
    print('scores_np has shape: ', scores.shape)

three_layer_convnet_test()
```

4.0.6 Barebones TensorFlow: Training Step

We now define the `training_step` function performs a single training step. This will take three basic steps:

1. Compute the loss
2. Compute the gradient of the loss with respect to all network weights
3. Make a weight update step using (stochastic) gradient descent.

We need to use a few new TensorFlow functions to do all of this: - For computing the cross-entropy loss we'll use `tf.nn.sparse_softmax_cross_entropy_with_logits`: https://www.tensorflow.org/versions/r2.0/api_docs/python/tf/nn/sparse_softmax_cross_entropy_with_logits

- For averaging the loss across a minibatch of data we'll use `tf.reduce_mean`: https://www.tensorflow.org/versions/r2.0/api_docs/python/tf/reduce_mean
- For computing gradients of the loss with respect to the weights we'll use `tf.GradientTape` (useful for Eager execution): https://www.tensorflow.org/versions/r2.0/api_docs/python/tf/GradientTape
- We'll mutate the weight values stored in a TensorFlow Tensor using `tf.assign_sub` ("sub" is for subtraction): https://www.tensorflow.org/api_docs/python/tf/assign_sub

[ ]:
```
def training_step(model_fn, x, y, params, learning_rate):
    with tf.GradientTape() as tape:
        scores = model_fn(x, params) # Forward pass of the model
        loss = tf.nn.sparse_softmax_cross_entropy_with_logits(labels=y,␣
↪logits=scores)
        total_loss = tf.reduce_mean(loss)
        grad_params = tape.gradient(total_loss, params)

        # Make a vanilla gradient descent step on all of the model parameters
        # Manually update the weights using assign_sub()
        for w, grad_w in zip(params, grad_params):
            w.assign_sub(learning_rate * grad_w)

        return total_loss
```

[ ]:
```
def train_part2(model_fn, init_fn, learning_rate):
    """
```

```
    Train a model on CIFAR-10.

    Inputs:
    - model_fn: A Python function that performs the forward pass of the model
      using TensorFlow; it should have the following signature:
      scores = model_fn(x, params) where x is a TensorFlow Tensor giving a
      minibatch of image data, params is a list of TensorFlow Tensors holding
      the model weights, and scores is a TensorFlow Tensor of shape (N, C)
      giving scores for all elements of x.
    - init_fn: A Python function that initializes the parameters of the model.
      It should have the signature params = init_fn() where params is a list
      of TensorFlow Tensors holding the (randomly initialized) weights of the
      model.
    - learning_rate: Python float giving the learning rate to use for SGD.
    """


    params = init_fn()  # Initialize the model parameters

    for t, (x_np, y_np) in enumerate(train_dset):
        # Run the graph on a batch of training data.
        loss = training_step(model_fn, x_np, y_np, params, learning_rate)

        # Periodically print the loss and check accuracy on the val set.
        if t % print_every == 0:
            print('Iteration %d, loss = %.4f' % (t, loss))
            check_accuracy(val_dset, x_np, model_fn, params)
```

[ ]:
```
def check_accuracy(dset, x, model_fn, params):
    """
    Check accuracy on a classification model, e.g. for validation.

    Inputs:
    - dset: A Dataset object against which to check accuracy
    - x: A TensorFlow placeholder Tensor where input images should be fed
    - model_fn: the Model we will be calling to make predictions on x
    - params: parameters for the model_fn to work with

    Returns: Nothing, but prints the accuracy of the model
    """
    num_correct, num_samples = 0, 0
    for x_batch, y_batch in dset:
        scores_np = model_fn(x_batch, params).numpy()
        y_pred = scores_np.argmax(axis=1)
        num_samples += x_batch.shape[0]
        num_correct += (y_pred == y_batch).sum()
    acc = float(num_correct) / num_samples
```

```
    print('Got %d / %d correct (%.2f%%)' % (num_correct, num_samples, 100 *␣
↪acc))
```

4.0.7 Barebones TensorFlow: Initialization

We'll use the following utility method to initialize the weight matrices for our models using Kaiming's normalization method.

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

[ ]:
```
def create_matrix_with_kaiming_normal(shape):
    if len(shape) == 2:
        fan_in, fan_out = shape[0], shape[1]
    elif len(shape) == 4:
        fan_in, fan_out = np.prod(shape[:3]), shape[3]
    return tf.keras.backend.random_normal(shape) * np.sqrt(2.0 / fan_in)
```

4.0.8 Barebones TensorFlow: Train a Two-Layer Network

We are finally ready to use all of the pieces defined above to train a two-layer fully-connected network on CIFAR-10.

We just need to define a function to initialize the weights of the model, and call `train_part2`.

Defining the weights of the network introduces another important piece of TensorFlow API: `tf.Variable`. A TensorFlow Variable is a Tensor whose value is stored in the graph and persists across runs of the computational graph; however unlike constants defined with `tf.zeros` or `tf.random_normal`, the values of a Variable can be mutated as the graph runs; these mutations will persist across graph runs. Learnable parameters of the network are usually stored in Variables.

You don't need to tune any hyperparameters, but you should achieve validation accuracies above 40% after one epoch of training.

[ ]:
```
def two_layer_fc_init():
    """
    Initialize the weights of a two-layer network, for use with the
    two_layer_network function defined above.
    You can use the `create_matrix_with_kaiming_normal` helper!

    Inputs: None

    Returns: A list of:
    - w1: TensorFlow tf.Variable giving the weights for the first layer
    - w2: TensorFlow tf.Variable giving the weights for the second layer
    """
    hidden_layer_size = 4000
    w1 = tf.Variable(create_matrix_with_kaiming_normal((3 * 32 * 32, 4000)))
    w2 = tf.Variable(create_matrix_with_kaiming_normal((4000, 10)))
    return [w1, w2]
```

```
learning_rate = 1e-2
train_part2(two_layer_fc, two_layer_fc_init, learning_rate)
```

4.0.9 Barebones TensorFlow: Train a three-layer ConvNet

We will now use TensorFlow to train a three-layer ConvNet on CIFAR-10.

You need to implement the `three_layer_convnet_init` function. Recall that the architecture of the network is:

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

You don't need to do any hyperparameter tuning, but you should see validation accuracies above 43% after one epoch of training.

[ ]:
```
def three_layer_convnet_init():
    """
    Initialize the weights of a Three-Layer ConvNet, for use with the
    three_layer_convnet function defined above.
    You can use the `create_matrix_with_kaiming_normal` helper!

    Inputs: None

    Returns a list containing:
    - conv_w1: TensorFlow tf.Variable giving weights for the first conv layer
    - conv_b1: TensorFlow tf.Variable giving biases for the first conv layer
    - conv_w2: TensorFlow tf.Variable giving weights for the second conv layer
    - conv_b2: TensorFlow tf.Variable giving biases for the second conv layer
    - fc_w: TensorFlow tf.Variable giving weights for the fully-connected layer
    - fc_b: TensorFlow tf.Variable giving biases for the fully-connected layer
    """
    params = None
    ############################################################################
    # TODO: Initialize the parameters of the three-layer network.              #
    ############################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

    pass

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

```
learning_rate = 3e-3
train_part2(three_layer_convnet, three_layer_convnet_init, learning_rate)
```

5 Part III: Keras Model Subclassing API

Implementing a neural network using the low-level TensorFlow API is a good way to understand how TensorFlow works, but it's a little inconvenient - we had to manually keep track of all Tensors holding learnable parameters. This was fine for a small network, but could quickly become unweildy for a large complex model.

Fortunately TensorFlow 2.0 provides higher-level APIs such as `tf.keras` which make it easy to build models out of modular, object-oriented layers. Further, TensorFlow 2.0 uses eager execution that evaluates operations immediately, without explicitly constructing any computational graphs. This makes it easy to write and debug models, and reduces the boilerplate code.

In this part of the notebook we will define neural network models using the `tf.keras.Model` API. To implement your own model, you need to do the following:

1. Define a new class which subclasses `tf.keras.Model`. Give your class an intuitive name that describes it, like `TwoLayerFC` or `ThreeLayerConvNet`.
2. In the initializer `__init__()` for your new class, define all the layers you need as class attributes. The `tf.keras.layers` package provides many common neural-network layers, like `tf.keras.layers.Dense` for fully-connected layers and `tf.keras.layers.Conv2D` for convolutional layers. Under the hood, these layers will construct `Variable` Tensors for any learnable parameters. **Warning**: Don't forget to call `super(YourModelName, self).__init__()` as the first line in your initializer!
3. Implement the `call()` method for your class; this implements the forward pass of your model, and defines the *connectivity* of your network. Layers defined in `__init__()` implement `__call__()` so they can be used as function objects that transform input Tensors into output Tensors. Don't define any new layers in `call()`; any layers you want to use in the forward pass should be defined in `__init__()`.

After you define your `tf.keras.Model` subclass, you can instantiate it and use it like the model functions from Part II.

5.0.1 Keras Model Subclassing API: Two-Layer Network

Here is a concrete example of using the `tf.keras.Model` API to define a two-layer network. There are a few new bits of API to be aware of here:

We use an `Initializer` object to set up the initial values of the learnable parameters of the layers; in particular `tf.initializers.VarianceScaling` gives behavior similar to the Kaiming initialization method we used in Part II. You can read more about it here: https://www.tensorflow.org/versions/r2.0/api_docs/python/tf/initializers/VarianceScaling

We construct `tf.keras.layers.Dense` objects to represent the two fully-connected layers of the model. In addition to multiplying their input by a weight matrix and adding a bias vector, these layer can also apply a nonlinearity for you. For the first layer we specify a ReLU activation function by passing `activation='relu'` to the constructor; the second layer uses softmax activation function. Finally, we use `tf.keras.layers.Flatten` to flatten the output from the previous fully-connected layer.

[ ]:
```
class TwoLayerFC(tf.keras.Model):
    def __init__(self, hidden_size, num_classes):
        super(TwoLayerFC, self).__init__()
        initializer = tf.initializers.VarianceScaling(scale=2.0)
        self.fc1 = tf.keras.layers.Dense(hidden_size, activation='relu',
                                   kernel_initializer=initializer)
        self.fc2 = tf.keras.layers.Dense(num_classes, activation='softmax',
                                   kernel_initializer=initializer)
        self.flatten = tf.keras.layers.Flatten()

    def call(self, x, training=False):
        x = self.flatten(x)
        x = self.fc1(x)
        x = self.fc2(x)
        return x


def test_TwoLayerFC():
    """ A small unit test to exercise the TwoLayerFC model above. """
    input_size, hidden_size, num_classes = 50, 42, 10
    x = tf.zeros((64, input_size))
    model = TwoLayerFC(hidden_size, num_classes)
    with tf.device(device):
        scores = model(x)
        print(scores.shape)

test_TwoLayerFC()
```

5.0.2 Keras Model Subclassing API: Three-Layer ConvNet

Now it's your turn to implement a three-layer ConvNet using the `tf.keras.Model` API. Your model should have the same architecture used in Part II:

1. Convolutional layer with 5 x 5 kernels, with zero-padding of 2
2. ReLU nonlinearity
3. Convolutional layer with 3 x 3 kernels, with zero-padding of 1
4. ReLU nonlinearity
5. Fully-connected layer to give class scores
6. Softmax nonlinearity

You should initialize the weights of your network using the same initialization method as was used in the two-layer network above.

Hint: Refer to the documentation for `tf.keras.layers.Conv2D` and `tf.keras.layers.Dense`:

https://www.tensorflow.org/versions/r2.0/api_docs/python/tf/keras/layers/Conv2D https://www.tensorflow.org/versions/r2.0/api_docs/python/tf/keras/layers/Dense

```
[ ]: class ThreeLayerConvNet(tf.keras.Model):
         def __init__(self, channel_1, channel_2, num_classes):
             super(ThreeLayerConvNet, self).__init__()
             ########################################################################
             # TODO: Implement the __init__ method for a three-layer ConvNet. You   #
             # should instantiate layer objects to be used in the forward pass.     #
             ########################################################################
             # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

             pass

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

         def call(self, x, training=False):
             scores = None
             ########################################################################
             # TODO: Implement the forward pass for a three-layer ConvNet. You      #
             # should use the layer objects defined in the __init__ method.         #
             ########################################################################
             # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

             pass

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

Once you complete the implementation of the `ThreeLayerConvNet` above you can run the following to ensure that your implementation does not crash and produces outputs of the expected shape.

```
[ ]: def test_ThreeLayerConvNet():
         channel_1, channel_2, num_classes = 12, 8, 10
         model = ThreeLayerConvNet(channel_1, channel_2, num_classes)
         with tf.device(device):
             x = tf.zeros((64, 3, 32, 32))
             scores = model(x)
             print(scores.shape)

     test_ThreeLayerConvNet()
```

5.0.3 Keras Model Subclassing API: Eager Training

While keras models have a builtin training loop (using the `model.fit`), sometimes you need more customization. Here's an example, of a training loop implemented with eager execution.

In particular, notice `tf.GradientTape`. Automatic differentiation is used in the backend for implementing backpropagation in frameworks like TensorFlow. During eager execution, `tf.GradientTape` is used to trace operations for computing gradients later. A particular `tf.GradientTape` can only compute one gradient; subsequent calls to tape will throw a runtime error.

TensorFlow 2.0 ships with easy-to-use built-in metrics under `tf.keras.metrics` module. Each metric is an object, and we can use `update_state()` to add observations and `reset_state()` to clear all observations. We can get the current result of a metric by calling `result()` on the metric object.

[ ]:
```
def train_part34(model_init_fn, optimizer_init_fn, num_epochs=1,␣
↪is_training=False):
    """
    Simple training loop for use with models defined using tf.keras. It trains
    a model for one epoch on the CIFAR-10 training set and periodically checks
    accuracy on the CIFAR-10 validation set.

    Inputs:
    - model_init_fn: A function that takes no parameters; when called it
      constructs the model we want to train: model = model_init_fn()
    - optimizer_init_fn: A function which takes no parameters; when called it
      constructs the Optimizer object we will use to optimize the model:
      optimizer = optimizer_init_fn()
    - num_epochs: The number of epochs to train for

    Returns: Nothing, but prints progress during trainingn
    """
    with tf.device(device):

        # Compute the loss like we did in Part II
        loss_fn = tf.keras.losses.SparseCategoricalCrossentropy()

        model = model_init_fn()
        optimizer = optimizer_init_fn()

        train_loss = tf.keras.metrics.Mean(name='train_loss')
        train_accuracy = tf.keras.metrics.
↪SparseCategoricalAccuracy(name='train_accuracy')

        val_loss = tf.keras.metrics.Mean(name='val_loss')
        val_accuracy = tf.keras.metrics.
↪SparseCategoricalAccuracy(name='val_accuracy')
```

```
        t = 0
        for epoch in range(num_epochs):

            # Reset the metrics - https://www.tensorflow.org/alpha/guide/
↪migration_guide#new-style_metrics
            train_loss.reset_states()
            train_accuracy.reset_states()

            for x_np, y_np in train_dset:
                with tf.GradientTape() as tape:

                    # Use the model function to build the forward pass.
                    scores = model(x_np, training=is_training)
                    loss = loss_fn(y_np, scores)

                    gradients = tape.gradient(loss, model.trainable_variables)
                    optimizer.apply_gradients(zip(gradients, model.
↪trainable_variables))

                    # Update the metrics
                    train_loss.update_state(loss)
                    train_accuracy.update_state(y_np, scores)

                    if t % print_every == 0:
                        val_loss.reset_states()
                        val_accuracy.reset_states()
                        for test_x, test_y in val_dset:
                            # During validation at end of epoch, training set␣
↪to False
                            prediction = model(test_x, training=False)
                            t_loss = loss_fn(test_y, prediction)

                            val_loss.update_state(t_loss)
                            val_accuracy.update_state(test_y, prediction)

                        template = 'Iteration {}, Epoch {}, Loss: {}, Accuracy:␣
↪{}, Val Loss: {}, Val Accuracy: {}'
                        print (template.format(t, epoch+1,
                                               train_loss.result(),
                                               train_accuracy.result()*100,
                                               val_loss.result(),
                                               val_accuracy.result()*100))
                    t += 1
```

5.0.4 Keras Model Subclassing API: Train a Two-Layer Network

We can now use the tools defined above to train a two-layer network on CIFAR-10. We define the `model_init_fn` and `optimizer_init_fn` that construct the model and optimizer respectively when called. Here we want to train the model using stochastic gradient descent with no momentum, so we construct a `tf.keras.optimizers.SGD` function; you can read about it here.

You don't need to tune any hyperparameters here, but you should achieve validation accuracies above 40% after one epoch of training.

[ ]:
```
hidden_size, num_classes = 4000, 10
learning_rate = 1e-2

def model_init_fn():
    return TwoLayerFC(hidden_size, num_classes)

def optimizer_init_fn():
    return tf.keras.optimizers.SGD(learning_rate=learning_rate)

train_part34(model_init_fn, optimizer_init_fn)
```

5.0.5 Keras Model Subclassing API: Train a Three-Layer ConvNet

Here you should use the tools we've defined above to train a three-layer ConvNet on CIFAR-10. Your ConvNet should use 32 filters in the first convolutional layer and 16 filters in the second layer.

To train the model you should use gradient descent with Nesterov momentum 0.9.

HINT: https://www.tensorflow.org/versions/r2.0/api_docs/python/tf/optimizers/SGD

You don't need to perform any hyperparameter tuning, but you should achieve validation accuracies above 50% after training for one epoch.

[ ]:
```
learning_rate = 3e-3
channel_1, channel_2, num_classes = 32, 16, 10

def model_init_fn():
    model = None
    ############################################################################
    # TODO: Complete the implementation of model_fn.                           #
    ############################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

    pass

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

```
def optimizer_init_fn():
    optimizer = None
    ############################################################################
    # TODO: Complete the implementation of model_fn.                           #
    ############################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

    pass

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

train_part34(model_init_fn, optimizer_init_fn)
```

6 Part IV: Keras Sequential API

In Part III we introduced the `tf.keras.Model` API, which allows you to define models with any number of learnable layers and with arbitrary connectivity between layers.

However for many models you don't need such flexibility - a lot of models can be expressed as a sequential stack of layers, with the output of each layer fed to the next layer as input. If your model fits this pattern, then there is an even easier way to define your model: using `tf.keras.Sequential`. You don't need to write any custom classes; you simply call the `tf.keras.Sequential` constructor with a list containing a sequence of layer objects.

One complication with `tf.keras.Sequential` is that you must define the shape of the input to the model by passing a value to the `input_shape` of the first layer in your model.

6.0.1 Keras Sequential API: Two-Layer Network

In this subsection, we will rewrite the two-layer fully-connected network using `tf.keras.Sequential`, and train it using the training loop defined above.

You don't need to perform any hyperparameter tuning here, but you should see validation accuracies above 40% after training for one epoch.

[ ]:
```
learning_rate = 1e-2

def model_init_fn():
    input_shape = (32, 32, 3)
    hidden_layer_size, num_classes = 4000, 10
    initializer = tf.initializers.VarianceScaling(scale=2.0)
    layers = [
        tf.keras.layers.Flatten(input_shape=input_shape),
        tf.keras.layers.Dense(hidden_layer_size, activation='relu',
```

```
                              kernel_initializer=initializer),
        tf.keras.layers.Dense(num_classes, activation='softmax',
                              kernel_initializer=initializer),
    ]
    model = tf.keras.Sequential(layers)
    return model

def optimizer_init_fn():
    return tf.keras.optimizers.SGD(learning_rate=learning_rate)

train_part34(model_init_fn, optimizer_init_fn)
```

6.0.2 Abstracting Away the Training Loop

In the previous examples, we used a customised training loop to train models (e.g. `train_part34`). Writing your own training loop is only required if you need more flexibility and control during training your model. Alternately, you can also use built-in APIs like `tf.keras.Model.fit()` and `tf.keras.Model.evaluate` to train and evaluate a model. Also remember to configure your model for training by calling 'tf.keras.Model.compile.

You don't need to perform any hyperparameter tuning here, but you should see validation and test accuracies above 42% after training for one epoch.

[ ]:
```
model = model_init_fn()
model.compile(optimizer=tf.keras.optimizers.SGD(learning_rate=learning_rate),
              loss='sparse_categorical_crossentropy',
              metrics=[tf.keras.metrics.sparse_categorical_accuracy])
model.fit(X_train, y_train, batch_size=64, epochs=1, validation_data=(X_val,␣
 ↪y_val))
model.evaluate(X_test, y_test)
```

6.0.3 Keras Sequential API: Three-Layer ConvNet

Here you should use `tf.keras.Sequential` to reimplement the same three-layer ConvNet architecture used in Part II and Part III. As a reminder, your model should have the following architecture:

1. Convolutional layer with 32 5x5 kernels, using zero padding of 2
2. ReLU nonlinearity
3. Convolutional layer with 16 3x3 kernels, using zero padding of 1
4. ReLU nonlinearity
5. Fully-connected layer giving class scores
6. Softmax nonlinearity

You should initialize the weights of the model using a `tf.initializers.VarianceScaling` as above.

You should train the model using Nesterov momentum 0.9.

You don't need to perform any hyperparameter search, but you should achieve accuracy above 45% after training for one epoch.

[ ]:
```
def model_init_fn():
    model = None
    ############################################################################
    # TODO: Construct a three-layer ConvNet using tf.keras.Sequential.         #
    ############################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

    pass

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

learning_rate = 5e-4
def optimizer_init_fn():
    optimizer = None
    ############################################################################
    # TODO: Complete the implementation of model_fn.                           #
    ############################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

    pass

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

train_part34(model_init_fn, optimizer_init_fn)
```

We will also train this model with the built-in training loop APIs provided by TensorFlow.

[ ]:
```
model = model_init_fn()
model.compile(optimizer='sgd',
              loss='sparse_categorical_crossentropy',
              metrics=[tf.keras.metrics.sparse_categorical_accuracy])
model.fit(X_train, y_train, batch_size=64, epochs=1, validation_data=(X_val,␣
 ↪y_val))
model.evaluate(X_test, y_test)
```

6.1 Part IV: Functional API

6.1.1 Demonstration with a Two-Layer Network

In the previous section, we saw how we can use `tf.keras.Sequential` to stack layers to quickly build simple models. But this comes at the cost of losing flexibility.

Often we will have to write complex models that have non-sequential data flows: a layer can have **multiple inputs and/or outputs**, such as stacking the output of 2 previous layers together to feed as input to a third! (Some examples are residual connections and dense blocks.)

In such cases, we can use Keras functional API to write models with complex topologies such as:

1. Multi-input models
2. Multi-output models
3. Models with shared layers (the same layer called several times)
4. Models with non-sequential data flows (e.g. residual connections)

Writing a model with Functional API requires us to create a `tf.keras.Model` instance and explicitly write input tensors and output tensors for this model.

[ ]:
```
def two_layer_fc_functional(input_shape, hidden_size, num_classes):
    initializer = tf.initializers.VarianceScaling(scale=2.0)
    inputs = tf.keras.Input(shape=input_shape)
    flattened_inputs = tf.keras.layers.Flatten()(inputs)
    fc1_output = tf.keras.layers.Dense(hidden_size, activation='relu',
                                                              ␣
 ↪kernel_initializer=initializer)(flattened_inputs)
    scores = tf.keras.layers.Dense(num_classes, activation='softmax',
                                 kernel_initializer=initializer)(fc1_output)

    # Instantiate the model given inputs and outputs.
    model = tf.keras.Model(inputs=inputs, outputs=scores)
    return model

def test_two_layer_fc_functional():
    """ A small unit test to exercise the TwoLayerFC model above. """
    input_size, hidden_size, num_classes = 50, 42, 10
    input_shape = (50,)

    x = tf.zeros((64, input_size))
    model = two_layer_fc_functional(input_shape, hidden_size, num_classes)

    with tf.device(device):
        scores = model(x)
        print(scores.shape)

test_two_layer_fc_functional()
```

6.1.2 Keras Functional API: Train a Two-Layer Network

You can now train this two-layer network constructed using the functional API.

You don't need to perform any hyperparameter tuning here, but you should see validation accuracies above 40% after training for one epoch.

[ ]:
```
input_shape = (32, 32, 3)
hidden_size, num_classes = 4000, 10
learning_rate = 1e-2

def model_init_fn():
    return two_layer_fc_functional(input_shape, hidden_size, num_classes)

def optimizer_init_fn():
    return tf.keras.optimizers.SGD(learning_rate=learning_rate)

train_part34(model_init_fn, optimizer_init_fn)
```

7 Part V: CIFAR-10 open-ended challenge

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

You should experiment with architectures, hyperparameters, loss functions, regularization, or anything else you can think of to train a model that achieves **at least 70%** accuracy on the **validation** set within 10 epochs. You can use the built-in train function, the `train_part34` function from above, or implement your own training loop.

Describe what you did at the end of the notebook.

7.0.1 Some things you can try:

- **Filter size**: Above we used 5x5 and 3x3; is this optimal?
- **Number of filters**: Above we used 16 and 32 filters. Would more or fewer do better?
- **Pooling**: We didn't use any pooling above. Would this improve the model?
- **Normalization**: Would your model be improved with batch normalization, layer normalization, group normalization, or some other normalization strategy?
- **Network architecture**: The ConvNet above has only three layers of trainable parameters. Would a deeper model do better?
- **Global average pooling**: Instead of flattening after the final convolutional layer, would global average pooling do better? This strategy is used for example in Google's Inception network and in Residual Networks.
- **Regularization**: Would some kind of regularization improve performance? Maybe weight decay or dropout?

7.0.2 NOTE: Batch Normalization / Dropout

If you are using Batch Normalization and Dropout, remember to pass `is_training=True` if you use the `train_part34()` function. BatchNorm and Dropout layers have different behaviors at training and inference time. `training` is a specific keyword argument reserved for this purpose in any `tf.keras.Model`'s `call()` function. Read more about this here : https://www.tensorflow.org/versions/r2.0/api_docs/python/tf/keras/layers/BatchNormalization#methods https://www.tensorflow.org/versions/r2.0/api_docs/python/tf/keras/layers/Dropout#methods

7.0.3 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.

7.0.4 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

7.0.5 Have fun and happy training!

[ ]:
```
class CustomConvNet(tf.keras.Model):
    def __init__(self):
        super(CustomConvNet, self).__init__()
        ␣
↪##############################################################################
        # TODO: Construct a model that performs well on CIFAR-10                ␣
↪    #
        ␣
↪##############################################################################
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

        pass

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

```
        #                               END OF YOUR CODE                          ␣
 ↪   #
        ␣
 ↪###########################################################################

    def call(self, input_tensor, training=False):
        ␣
 ↪###########################################################################
        # TODO: Construct a model that performs well on CIFAR-10                  ␣
 ↪   #
        ␣
 ↪###########################################################################
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

        pass

        # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
        ␣
 ↪###########################################################################
        #                               END OF YOUR CODE                          ␣
 ↪   #
        ␣
 ↪###########################################################################
        return x


print_every = 700
num_epochs = 10

model = CustomConvNet()

def model_init_fn():
    return CustomConvNet()

def optimizer_init_fn():
    learning_rate = 1e-3
    return tf.keras.optimizers.Adam(learning_rate)

train_part34(model_init_fn, optimizer_init_fn, num_epochs=num_epochs,␣
 ↪is_training=True)
```

7.1 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: Tell us what you did