FullyConnectedNets

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[1]:
```
# this mounts your Google Drive to the Colab VM.
from google.colab import drive
drive.mount('/content/drive', force_remount=True)

# enter the foldername in your Drive where you have saved the unzipped
# assignment folder, e.g. 'CV7062610/assignments/assignment2/'
FOLDERNAME = 'CV7062610/assignments/assignment2/'
assert FOLDERNAME is not None, "[!] Enter the foldername."

# now that we've mounted your Drive, this ensures that
# the Python interpreter of the Colab VM can load
# python files from within it.
import sys
sys.path.append('/content/drive/My Drive/{}'.format(FOLDERNAME))

# this downloads the CIFAR-10 dataset to your Drive
# if it doesn't already exist.
%cd drive/MyDrive/$FOLDERNAME/CV7062610/datasets/
!bash get_datasets.sh
%cd /content
```

```
Mounted at /content/drive
/content/drive/MyDrive/CV7062610/assignments/assignment2/CV7062610/datasets
/content
```

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:

```
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:

```
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,(in the second part of the assingment) we will 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.

[17]:
```
# As usual, a bit of setup
from __future__ import print_function
import time
import numpy as np
import matplotlib.pyplot as plt
from CV7062610.classifiers.fc_net import *
from CV7062610.data_utils import get_CIFAR10_data
from CV7062610.gradient_check import eval_numerical_gradient,␣
 ↪eval_numerical_gradient_array
from CV7062610.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))))
```

```
The autoreload extension is already loaded. To reload it, use:
  %reload_ext autoreload
```

[18]:
```
# 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 (fully-conected): forward

Open the file `CV7062610/layers.py` and implement the `affine_forward` function.

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

[19]:
```
# 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.

[20]:
```
# 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:

[21]:
```
# 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:

[22]:
```
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

5.2 Answer:

The sigmoid activation function has a problem with getting zero (or close to zero) gradient flow during backpropagation, particularly for input values that are very large or very small. This is because the sigmoid function saturates when its input is far away from zero, causing the gradient to become close to zero, which can lead to vanishing gradients.

In the one dimensional case, the types of input that can lead to the zero gradient problem in the sigmoid activation function are inputs that are very large (positive or negative) or very close to zero. This is because the sigmoid function approaches zero or one as its input becomes more extreme, which causes the derivative to become very small, leading to the vanishing gradient problem.

On the other hand, ReLU and Leaky ReLU do not have this problem. Threfore, there are no specific types of input that lead to the zero gradient problem since they have a non-zero gradient for positive inputs, and thus they can avoid the vanishing gradient problem. However, ReLU can suffer from the "dying ReLU" problem, where neurons that output zero will never activate again, causing the gradient to be zero and the weights to never get updated during training. Leaky ReLU solves this problem by allowing a small positive gradient for negative inputs, preventing the neuron from dying completely.

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 `CV7062610/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:

[23]:
```
from CV7062610.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

You implemented this loss functions in the last assignment, so we'll give it to you for free here. You should still make sure you understand how it work by looking at the implementations in `CV7062610/layers.py`.

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

[24]:
```
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: 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 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 `CV7062610 /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.

[25]:
```
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 `CV7062610/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 `45%` accuracy on the validation set. If you are doing it corectly this shouldn't take more than 5 epochs of training and more than 5 minuts using vanilla sgd.

[26]:
```
model = TwoLayerNet()
solver = None
best_val = -1
################################################################################
# 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)*****
```

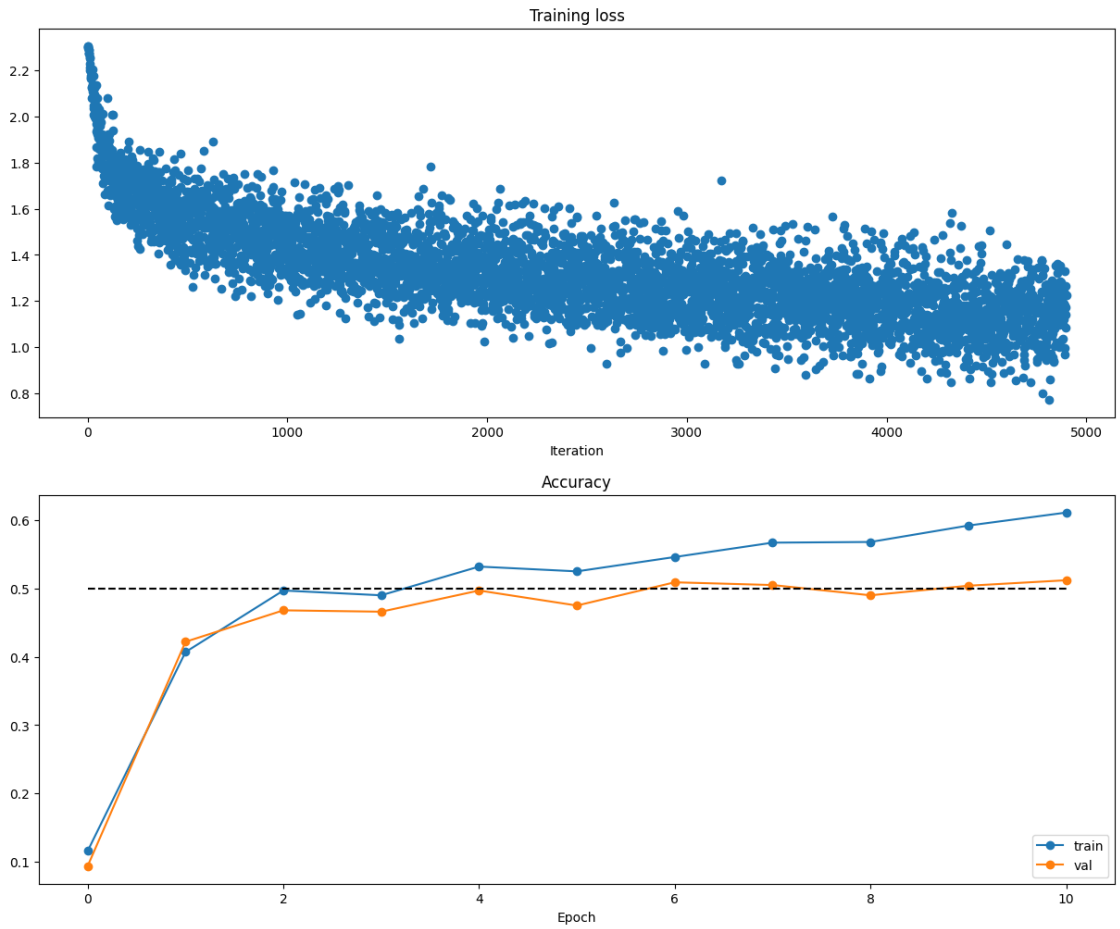
```
solver = Solver(model, data,
                update_rule='sgd',
                optim_config={
                    'learning_rate': 1e-3,
                },
                lr_decay=0.95,
                num_epochs=10, batch_size=100,
                print_every=100)
solver.train()

best_val = solver.best_val_acc
print('Best validation accuracy:', best_val)

# *****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
Best validation accuracy: 0.512
```

[27]:
```
# 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 `CV7062610/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.

[28]:
```
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: 6.86e-09
W2 relative error: 3.52e-08
W3 relative error: 1.32e-08
b1 relative error: 1.48e-08
b2 relative error: 1.72e-09
b3 relative error: 1.80e-10
```

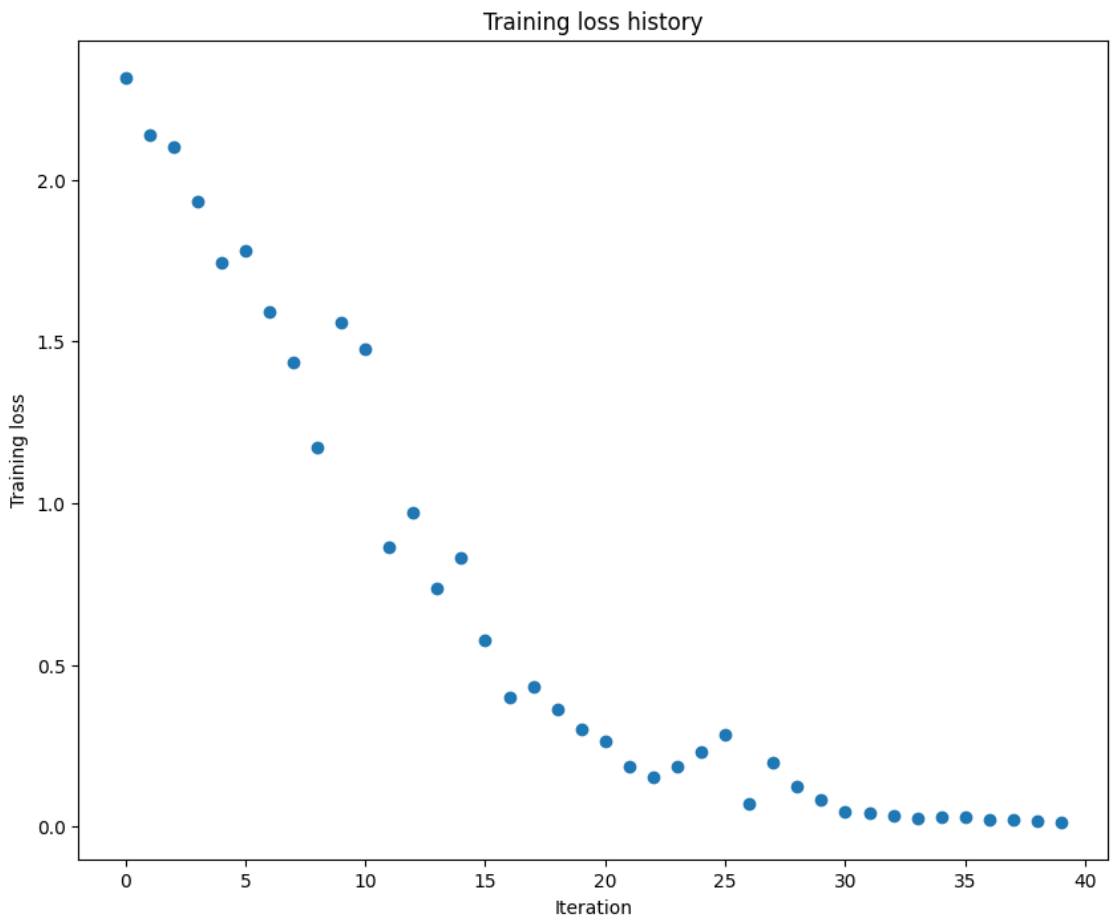
As another sanity check, make sure you can overfit a small dataset of 50 images. First we will try a three-layer network with 100 units in each hidden layer. In the following cell, tweak the **learning rate** and **weight initialization scale** to overfit and achieve 100% training accuracy within 20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

[50]:
```
# 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'],
}

##### TODO: find the best lr and wight scale ##########
weight_scale = 1e-2   # 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: 2.316449
(Epoch 0 / 20) train acc: 0.180000; val_acc: 0.100000
(Epoch 1 / 20) train acc: 0.360000; val_acc: 0.102000
(Epoch 2 / 20) train acc: 0.520000; val_acc: 0.134000
(Epoch 3 / 20) train acc: 0.500000; val_acc: 0.150000
(Epoch 4 / 20) train acc: 0.540000; val_acc: 0.145000
(Epoch 5 / 20) train acc: 0.600000; val_acc: 0.133000
(Iteration 11 / 40) loss: 1.475598
(Epoch 6 / 20) train acc: 0.820000; val_acc: 0.201000
(Epoch 7 / 20) train acc: 0.860000; val_acc: 0.178000
(Epoch 8 / 20) train acc: 0.920000; val_acc: 0.182000
(Epoch 9 / 20) train acc: 0.960000; val_acc: 0.211000
(Epoch 10 / 20) train acc: 0.960000; val_acc: 0.219000
(Iteration 21 / 40) loss: 0.265581
(Epoch 11 / 20) train acc: 1.000000; val_acc: 0.222000
(Epoch 12 / 20) train acc: 0.980000; val_acc: 0.198000
(Epoch 13 / 20) train acc: 0.960000; val_acc: 0.198000
(Epoch 14 / 20) train acc: 0.980000; val_acc: 0.228000
(Epoch 15 / 20) train acc: 0.980000; val_acc: 0.207000
```

```
(Iteration 31 / 40) loss: 0.046989
(Epoch 16 / 20) train acc: 0.980000; val_acc: 0.203000
(Epoch 17 / 20) train acc: 0.980000; val_acc: 0.202000
(Epoch 18 / 20) train acc: 0.980000; val_acc: 0.200000
(Epoch 19 / 20) train acc: 0.980000; val_acc: 0.202000
(Epoch 20 / 20) train acc: 0.980000; val_acc: 0.205000
```



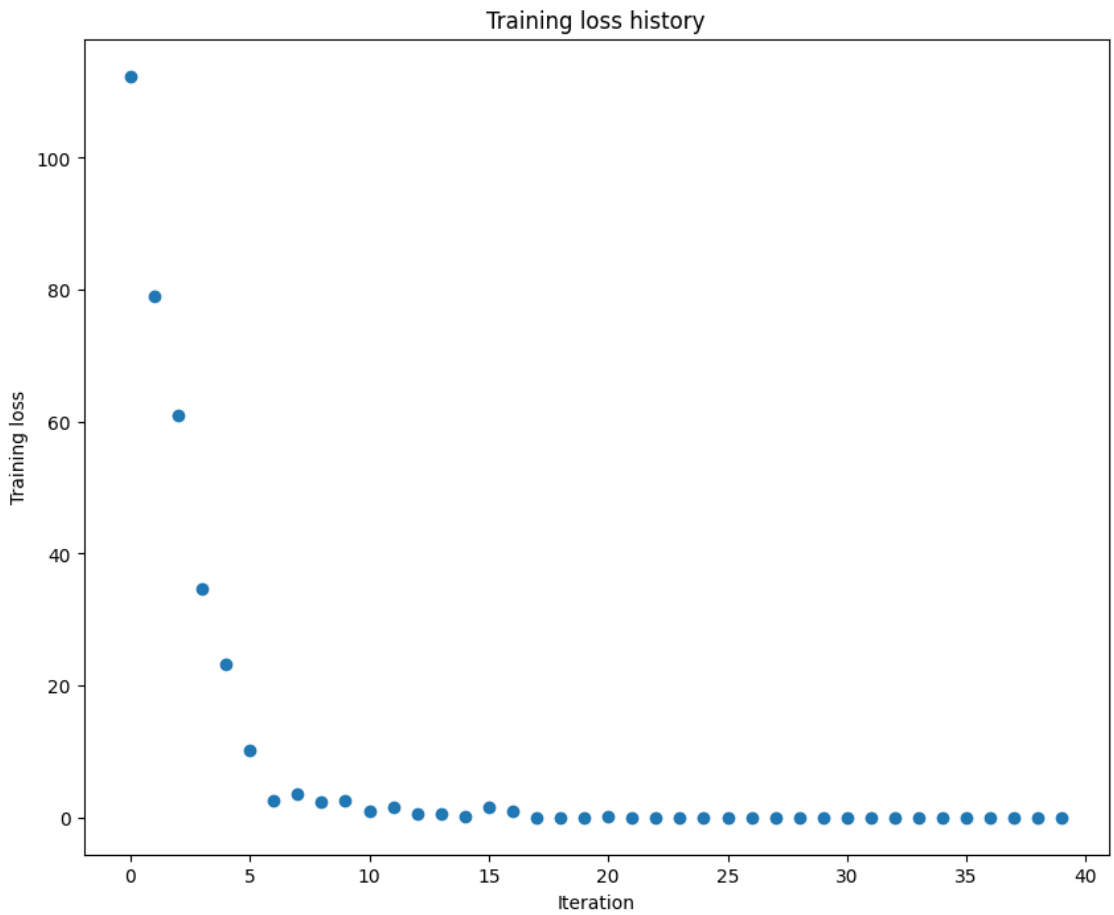
Now try to use a five-layer network with 100 units on each layer to overfit 50 training examples. Again, you will have to adjust the learning rate and weight initialization scale, but you should be able to achieve 100% training accuracy within 20 epochs.

[51]:
```
# 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'],
}

##### TODO: find the best lr and wight scale ##########
learning_rate = 2e-3  # Experiment with this!
weight_scale = 9e-2  # 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: 112.390275
(Epoch 0 / 20) train acc: 0.140000; val_acc: 0.090000
(Epoch 1 / 20) train acc: 0.200000; val_acc: 0.098000
(Epoch 2 / 20) train acc: 0.360000; val_acc: 0.125000
(Epoch 3 / 20) train acc: 0.480000; val_acc: 0.137000
(Epoch 4 / 20) train acc: 0.660000; val_acc: 0.131000
(Epoch 5 / 20) train acc: 0.840000; val_acc: 0.152000
(Iteration 11 / 40) loss: 0.881846
(Epoch 6 / 20) train acc: 0.840000; val_acc: 0.147000
(Epoch 7 / 20) train acc: 0.940000; val_acc: 0.146000
(Epoch 8 / 20) train acc: 0.900000; val_acc: 0.139000
(Epoch 9 / 20) train acc: 0.980000; val_acc: 0.135000
(Epoch 10 / 20) train acc: 0.980000; val_acc: 0.137000
(Iteration 21 / 40) loss: 0.102517
(Epoch 11 / 20) train acc: 1.000000; val_acc: 0.134000
(Epoch 12 / 20) train acc: 1.000000; val_acc: 0.133000
(Epoch 13 / 20) train acc: 1.000000; val_acc: 0.133000
(Epoch 14 / 20) train acc: 1.000000; val_acc: 0.133000
(Epoch 15 / 20) train acc: 1.000000; val_acc: 0.133000
(Iteration 31 / 40) loss: 0.001751
(Epoch 16 / 20) train acc: 1.000000; val_acc: 0.134000
(Epoch 17 / 20) train acc: 1.000000; val_acc: 0.134000
(Epoch 18 / 20) train acc: 1.000000; val_acc: 0.134000
```

```
(Epoch 19 / 20) train acc: 1.000000; val_acc: 0.134000
(Epoch 20 / 20) train acc: 1.000000; val_acc: 0.134000
```



10.2 Inline Question 2:

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:

The five-layer net seemed more sensitive to the initialization scale. This is likely because deeper networks are more sensitive to initialization compared to shallower networks. In deeper networks, gradients can vanish or explode, making it difficult to optimize the network. If the initialization scale is too small, the gradients can vanish as they propagate through the layers, and if it is too large, the gradients can explode. This can cause the network to fail to converge or converge very slowly, leading to poor performance. Therefore, it is important to choose an appropriate initialization scale, especially when training deep neural networks.

11 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 40% accuracy on the validation set using a fully-connected net. Using sgd this shouldn't take more than 5 minuts per traing over 10 epochs.

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.

[ ]:
```
best_model = None
best_val = 0.0
################################################################################
# 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)*****

# # Hyperparameter search space
# weight_scales = np.logspace(-2, -1, num=5)
# learning_rates = np.logspace(-5, -2, num=5)
# regularization_strengths = np.logspace(-3, 3, num=7)

# Define the hyperparameters to be searched over
hidden_sizes = [100, 100]
num_epochs = 10
batch_size = 200
learning_rates = [1e-2, 5e-3, 1e-3, 5e-4, 1e-4]
weight_scales = [1e-2, 5e-3, 1e-3, 5e-4, 1e-4]
reg_strengths = [1e-3, 5e-3, 1e-4, 5e-4, 1e-5, 5e-5]
num_iter = 20

# Perform random search over hyperparameters
for i in range(num_iter):
    # Choose hyperparameters at random
    hs = hidden_sizes
    lr = learning_rates[np.random.randint(len(learning_rates))]
    ws = weight_scales[np.random.randint(len(weight_scales))]
    reg = reg_strengths[np.random.randint(len(reg_strengths))]

    # Create a new FullyConnectedNet with the chosen hyperparameters
    model = FullyConnectedNet(hs, weight_scale=ws, reg=reg)

    # Train the model
    solver = Solver(model, data,
                    num_epochs=num_epochs, batch_size=batch_size,
```

```
                    update_rule='sgd',
                    optim_config={
                      'learning_rate': lr
                    },
                    verbose=False)
    solver.train()
    val_accuracy = solver.best_val_acc

    # Update the best validation accuracy and best model if necessary
    if best_val < val_accuracy:
        best_val = val_accuracy
        best_model = model

    # Print results
    print('combination %d/%d - hs %s lr %e ws %e reg %e val accuracy: %f' % (
                i+1, num_iter, hs, lr, ws, reg, val_accuracy))

print('best validation accuracy achieved: %f' % best_val)

################################################################################
#                                END OF YOUR CODE                              #
################################################################################
```

```
combination 1/20 - hs [100, 100] lr 1.000000e-02 ws 5.000000e-03 reg
1.000000e-04 val accuracy: 0.532000
combination 2/20 - hs [100, 100] lr 5.000000e-03 ws 1.000000e-03 reg
1.000000e-03 val accuracy: 0.527000
combination 3/20 - hs [100, 100] lr 1.000000e-03 ws 1.000000e-02 reg
5.000000e-04 val accuracy: 0.462000
combination 4/20 - hs [100, 100] lr 1.000000e-02 ws 1.000000e-02 reg
5.000000e-03 val accuracy: 0.530000
combination 5/20 - hs [100, 100] lr 5.000000e-04 ws 1.000000e-03 reg
5.000000e-04 val accuracy: 0.195000
combination 6/20 - hs [100, 100] lr 5.000000e-03 ws 1.000000e-03 reg
1.000000e-05 val accuracy: 0.508000
combination 7/20 - hs [100, 100] lr 1.000000e-04 ws 1.000000e-03 reg
5.000000e-03 val accuracy: 0.162000
combination 8/20 - hs [100, 100] lr 1.000000e-04 ws 5.000000e-03 reg
5.000000e-04 val accuracy: 0.241000
combination 9/20 - hs [100, 100] lr 1.000000e-02 ws 1.000000e-03 reg
5.000000e-05 val accuracy: 0.516000
combination 10/20 - hs [100, 100] lr 1.000000e-03 ws 1.000000e-04 reg
1.000000e-04 val accuracy: 0.112000
combination 11/20 - hs [100, 100] lr 1.000000e-02 ws 5.000000e-03 reg
5.000000e-03 val accuracy: 0.532000
combination 12/20 - hs [100, 100] lr 5.000000e-03 ws 5.000000e-03 reg
5.000000e-05 val accuracy: 0.517000
```

```
combination 13/20 - hs [100, 100] lr 1.000000e-03 ws 5.000000e-04 reg
5.000000e-03 val accuracy: 0.161000
combination 14/20 - hs [100, 100] lr 1.000000e-04 ws 5.000000e-03 reg
1.000000e-05 val accuracy: 0.250000
combination 15/20 - hs [100, 100] lr 5.000000e-03 ws 1.000000e-04 reg
1.000000e-03 val accuracy: 0.166000
combination 16/20 - hs [100, 100] lr 1.000000e-02 ws 5.000000e-03 reg
5.000000e-03 val accuracy: 0.529000
combination 17/20 - hs [100, 100] lr 5.000000e-03 ws 1.000000e-02 reg
1.000000e-03 val accuracy: 0.526000
combination 18/20 - hs [100, 100] lr 1.000000e-03 ws 1.000000e-04 reg
5.000000e-04 val accuracy: 0.102000
combination 19/20 - hs [100, 100] lr 1.000000e-02 ws 1.000000e-04 reg
5.000000e-04 val accuracy: 0.495000
combination 20/20 - hs [100, 100] lr 5.000000e-03 ws 1.000000e-03 reg
1.000000e-04 val accuracy: 0.506000
best validation accuracy achieved: 0.532000
```

12 Test your model!

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

[ ]:
```
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)
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:  0.532
Test set accuracy:  0.507
```

ConvolutionalNetworks

May 5, 2023

[1]:
```
# this mounts your Google Drive to the Colab VM.
from google.colab import drive
drive.mount('/content/drive', force_remount=True)

# enter the foldername in your Drive where you have saved the unzipped
# assignment folder, e.g. 'CV7062610/assignments/assignment3/'
FOLDERNAME = 'CV7062610/assignments/assignment2/'
assert FOLDERNAME is not None, "[!] Enter the foldername."

# now that we've mounted your Drive, this ensures that
# the Python interpreter of the Colab VM can load
# python files from within it.
import sys
sys.path.append('/content/drive/My Drive/{}'.format(FOLDERNAME))

# this downloads the CIFAR-10 dataset to your Drive
# if it doesn't already exist.
%cd drive/My\ Drive/$FOLDERNAME/CV7062610/datasets/
!bash get_datasets.sh
%cd /content
```

```
Mounted at /content/drive
/content/drive/My Drive/CV7062610/assignments/assignment2/CV7062610/datasets
/content
```

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.

[2]:
```
# As usual, a bit of setup
import numpy as np
import matplotlib.pyplot as plt
```

```
from CV7062610.classifiers.cnn import *
from CV7062610.data_utils import get_CIFAR10_data
from CV7062610.gradient_check import eval_numerical_gradient_array,␣
↪eval_numerical_gradient
from CV7062610.layers import *
from CV7062610.fast_layers import *
from CV7062610.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))))
```

[3]:
```
# 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,)
```

2 Convolution: Naive forward pass

The core of a convolutional network is the convolution operation. In the file `CV7062610/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:

[4]:
```
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))
```

```
Testing conv_forward_naive
difference:  2.2121476417505994e-08
```

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.

3.1 Colab Users Only

Please execute the below cell to copy two cat images to the Colab VM.

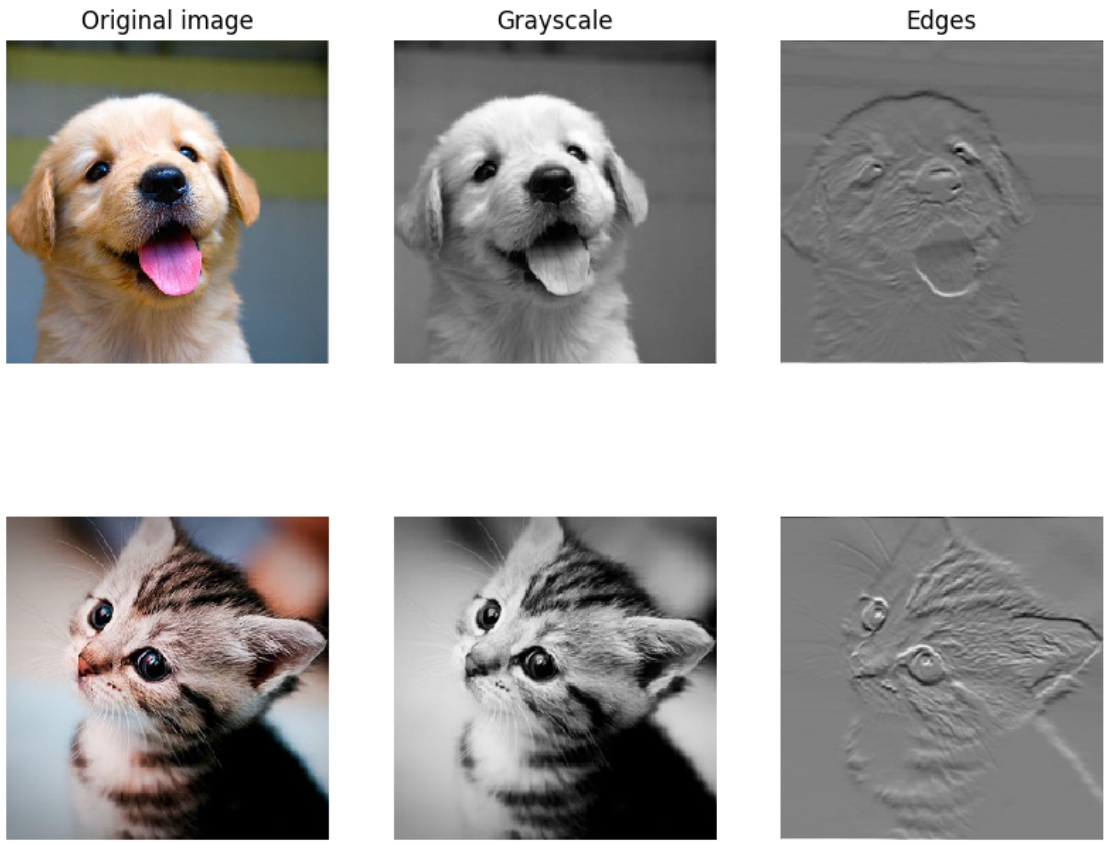
[5]:
```
# Colab users only!
%mkdir -p CV7062610/notebook_images
%cd drive/My\ Drive/$FOLDERNAME/CV7062610
%cp -r notebook_images/ /content/CV7062610/
%cd /content/
```

```
/content/drive/My Drive/CV7062610/assignments/assignment2/CV7062610
/content
```

[6]:
```
from imageio import imread
from PIL import Image

kitten = imread('CV7062610/notebook_images/kitten.jpg')
puppy = imread('CV7062610/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()
```

```
<ipython-input-6-416c27cee0c1>:4: DeprecationWarning: Starting with ImageIO v3
the behavior of this function will switch to that of iio.v3.imread. To keep the
current behavior (and make this warning disappear) use `import imageio.v2 as
imageio` or call `imageio.v2.imread` directly.
  kitten = imread('CV7062610/notebook_images/kitten.jpg')
<ipython-input-6-416c27cee0c1>:5: DeprecationWarning: Starting with ImageIO v3
the behavior of this function will switch to that of iio.v3.imread. To keep the
current behavior (and make this warning disappear) use `import imageio.v2 as
imageio` or call `imageio.v2.imread` directly.
  puppy = imread('CV7062610/notebook_images/puppy.jpg')
```



4 Convolution: Naive backward pass

Implement the backward pass for the convolution operation in the function `conv_backward_naive` in the file `CV7062610/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.

[7]:
```
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:  2.2471230668641297e-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 `CV7062610/layers.py`. Again, don't worry too much about computational efficiency.

Check your implementation by running the following:

[8]:
```
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 `CV7062610/layers.py`. You don't need to worry about computational efficiency.

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

[9]:
```
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 `CV7062610/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: Colab

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

[18]:
```
%cd /content/drive/MyDrive/$FOLDERNAME/CV7062610
!python setup.py build_ext --inplace
```

```
/content/drive/MyDrive/CV7062610/assignments/assignment2/CV7062610
/content/drive/MyDrive/CV7062610/assignments/assignment2/CV7062610/setup.py:1:
DeprecationWarning: The distutils package is deprecated and slated for removal
in Python 3.12. Use setuptools or check PEP 632 for potential alternatives
  from distutils.core import setup
Compiling im2col_cython.pyx because it changed.
[1/1] Cythonizing im2col_cython.pyx
/usr/local/lib/python3.10/dist-packages/Cython/Compiler/Main.py:369:
FutureWarning: Cython directive 'language_level' not set, using 2 for now (Py2).
This will change in a later release! File: /content/drive/MyDrive/CV7062610/assi
gnments/assignment2/CV7062610/im2col_cython.pyx
  tree = Parsing.p_module(s, pxd, full_module_name)
running build_ext
building 'im2col_cython' extension
creating build
creating build/temp.linux-x86_64-3.10
x86_64-linux-gnu-gcc -pthread -Wno-unused-result -Wsign-compare -DNDEBUG -g
-fwrapv -O2 -Wall -g -fstack-protector-strong -Wformat -Werror=format-security
-g -fwrapv -O2 -g -fstack-protector-strong -Wformat -Werror=format-security
-Wdate-time -D_FORTIFY_SOURCE=2 -fPIC -I/usr/local/lib/python3.10/dist-
packages/numpy/core/include -I/usr/include/python3.10 -c im2col_cython.c -o
build/temp.linux-x86_64-3.10/im2col_cython.o
In file included from /usr/local/lib/python3.10/dist-

packages/numpy/core/include/numpy/ndarraytypes.h:1960,
                 from /usr/local/lib/python3.10/dist-

packages/numpy/core/include/numpy/ndarrayobject.h:12,
                 from /usr/local/lib/python3.10/dist-

packages/numpy/core/include/numpy/arrayobject.h:5,
                 from im2col_cython.c:768:
/usr/local/lib/python3.10/dist-

packages/numpy/core/include/numpy/npy_1_7_deprecated_api.h:17:2:
warning: #warning "Using deprecated NumPy API, disable it with
" "#define NPY_NO_DEPRECATED_API NPY_1_7_API_VERSION" [-Wcpp]
   17 | #warning "Using deprecated NumPy API, disable it with "
\
      |  ^~~~~~~
x86_64-linux-gnu-gcc -pthread -shared -Wl,-O1 -Wl,-Bsymbolic-functions
-Wl,-Bsymbolic-functions -g -fwrapv -O2 -Wl,-Bsymbolic-functions -g -fwrapv -O2
-g -fstack-protector-strong -Wformat -Werror=format-security -Wdate-time
```

```
-D_FORTIFY_SOURCE=2 -fPIC build/temp.linux-x86_64-3.10/im2col_cython.o -o /conte
nt/drive/MyDrive/CV7062610/assignments/assignment2/CV7062610/im2col_cython.cpyth
on-310-x86_64-linux-gnu.so
```

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:

[10]:
```
# Rel errors should be around e-9 or less
from CV7062610.fast_layers import conv_forward_fast, conv_backward_fast
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: 4.223448s
Fast: 0.012321s
Speedup: 342.797875x
Difference:  4.926407851494105e-11

Testing conv_backward_fast:
Naive: 0.248359s
Fast: 0.012681s
Speedup: 19.584764x
dx difference:  1.0970337635846495e-11
dw difference:  1.8002984340569035e-14
db difference:  0.0
```

[11]:
```
# Relative errors should be close to 0.0
from CV7062610.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: 0.009089s
fast: 0.005642s
speedup: 1.610886x
difference:  0.0

Testing pool_backward_fast:
Naive: 0.659133s
fast: 0.013158s
speedup: 50.095222x
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 `CV7062610/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.

[12]:
```
from CV7062610.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
```

[13]:
```
from CV7062610.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 `CV7062610/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.

[14]:
```
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):  2.508255635671795
```

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.

[15]:
```
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.

[30]:
```
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'],
}

model = ThreeLayerConvNet(weight_scale=1e-2)

# We were not asked to implement the Adam algorithm
# solver = Solver(model, small_data,
#                 num_epochs=35, batch_size=50,
#                 update_rule='adam',
#                 optim_config={
#                   'learning_rate': 1e-3,
#                 },
#                 verbose=True, print_every=1)

solver = Solver(model, small_data,
                num_epochs=35, batch_size=50,
                update_rule='sgd',
                optim_config={
                  'learning_rate': 1e-3,
                },
                verbose=True, print_every=1)
solver.train()
```

```
(Iteration 1 / 70) loss: 2.414060
(Epoch 0 / 35) train acc: 0.140000; val_acc: 0.076000
(Iteration 2 / 70) loss: 2.388208
(Epoch 1 / 35) train acc: 0.130000; val_acc: 0.075000
(Iteration 3 / 70) loss: 2.286111
(Iteration 4 / 70) loss: 2.280937
(Epoch 2 / 35) train acc: 0.190000; val_acc: 0.095000
(Iteration 5 / 70) loss: 2.156452
```

```
(Iteration 6 / 70) loss: 2.121301
(Epoch 3 / 35) train acc: 0.220000; val_acc: 0.102000
(Iteration 7 / 70) loss: 2.082505
(Iteration 8 / 70) loss: 2.132747
(Epoch 4 / 35) train acc: 0.240000; val_acc: 0.113000
(Iteration 9 / 70) loss: 1.974502
(Iteration 10 / 70) loss: 2.234853
(Epoch 5 / 35) train acc: 0.270000; val_acc: 0.115000
(Iteration 11 / 70) loss: 2.062134
(Iteration 12 / 70) loss: 1.967815
(Epoch 6 / 35) train acc: 0.270000; val_acc: 0.115000
(Iteration 13 / 70) loss: 2.151717
(Iteration 14 / 70) loss: 1.962033
(Epoch 7 / 35) train acc: 0.330000; val_acc: 0.131000
(Iteration 15 / 70) loss: 1.905878
(Iteration 16 / 70) loss: 1.981501
(Epoch 8 / 35) train acc: 0.420000; val_acc: 0.144000
(Iteration 17 / 70) loss: 2.000987
(Iteration 18 / 70) loss: 1.943681
(Epoch 9 / 35) train acc: 0.420000; val_acc: 0.137000
(Iteration 19 / 70) loss: 1.894658
(Iteration 20 / 70) loss: 1.798240
(Epoch 10 / 35) train acc: 0.390000; val_acc: 0.137000
(Iteration 21 / 70) loss: 1.930483
(Iteration 22 / 70) loss: 1.848953
(Epoch 11 / 35) train acc: 0.460000; val_acc: 0.160000
(Iteration 23 / 70) loss: 1.733071
(Iteration 24 / 70) loss: 1.833933
(Epoch 12 / 35) train acc: 0.520000; val_acc: 0.167000
(Iteration 25 / 70) loss: 1.759339
(Iteration 26 / 70) loss: 1.707899
(Epoch 13 / 35) train acc: 0.530000; val_acc: 0.171000
(Iteration 27 / 70) loss: 1.668286
(Iteration 28 / 70) loss: 1.632742
(Epoch 14 / 35) train acc: 0.510000; val_acc: 0.173000
(Iteration 29 / 70) loss: 1.493473
(Iteration 30 / 70) loss: 1.852287
(Epoch 15 / 35) train acc: 0.590000; val_acc: 0.177000
(Iteration 31 / 70) loss: 1.544719
(Iteration 32 / 70) loss: 1.445474
(Epoch 16 / 35) train acc: 0.620000; val_acc: 0.167000
(Iteration 33 / 70) loss: 1.438357
(Iteration 34 / 70) loss: 1.558215
(Epoch 17 / 35) train acc: 0.550000; val_acc: 0.181000
(Iteration 35 / 70) loss: 1.457353
(Iteration 36 / 70) loss: 1.430685
(Epoch 18 / 35) train acc: 0.640000; val_acc: 0.177000
(Iteration 37 / 70) loss: 1.417343
```

```
(Iteration 38 / 70) loss: 1.224349
(Epoch 19 / 35) train acc: 0.560000; val_acc: 0.182000
(Iteration 39 / 70) loss: 1.358695
(Iteration 40 / 70) loss: 1.459283
(Epoch 20 / 35) train acc: 0.620000; val_acc: 0.171000
(Iteration 41 / 70) loss: 1.324597
(Iteration 42 / 70) loss: 1.141805
(Epoch 21 / 35) train acc: 0.710000; val_acc: 0.176000
(Iteration 43 / 70) loss: 1.251012
(Iteration 44 / 70) loss: 1.255930
(Epoch 22 / 35) train acc: 0.740000; val_acc: 0.183000
(Iteration 45 / 70) loss: 1.265682
(Iteration 46 / 70) loss: 1.241632
(Epoch 23 / 35) train acc: 0.800000; val_acc: 0.182000
(Iteration 47 / 70) loss: 1.088461
(Iteration 48 / 70) loss: 1.286929
(Epoch 24 / 35) train acc: 0.790000; val_acc: 0.187000
(Iteration 49 / 70) loss: 1.043943
(Iteration 50 / 70) loss: 1.232451
(Epoch 25 / 35) train acc: 0.830000; val_acc: 0.186000
(Iteration 51 / 70) loss: 1.166305
(Iteration 52 / 70) loss: 0.992921
(Epoch 26 / 35) train acc: 0.810000; val_acc: 0.183000
(Iteration 53 / 70) loss: 1.027397
(Iteration 54 / 70) loss: 1.034611
(Epoch 27 / 35) train acc: 0.870000; val_acc: 0.191000
(Iteration 55 / 70) loss: 1.074365
(Iteration 56 / 70) loss: 0.884611
(Epoch 28 / 35) train acc: 0.790000; val_acc: 0.180000
(Iteration 57 / 70) loss: 1.045844
(Iteration 58 / 70) loss: 0.771730
(Epoch 29 / 35) train acc: 0.850000; val_acc: 0.188000
(Iteration 59 / 70) loss: 0.964063
(Iteration 60 / 70) loss: 0.919592
(Epoch 30 / 35) train acc: 0.840000; val_acc: 0.190000
(Iteration 61 / 70) loss: 0.898468
(Iteration 62 / 70) loss: 0.837345
(Epoch 31 / 35) train acc: 0.890000; val_acc: 0.194000
(Iteration 63 / 70) loss: 0.866577
(Iteration 64 / 70) loss: 0.730397
(Epoch 32 / 35) train acc: 0.850000; val_acc: 0.188000
(Iteration 65 / 70) loss: 0.562069
(Iteration 66 / 70) loss: 0.911381
(Epoch 33 / 35) train acc: 0.910000; val_acc: 0.179000
(Iteration 67 / 70) loss: 0.662602
(Iteration 68 / 70) loss: 0.702882
(Epoch 34 / 35) train acc: 0.920000; val_acc: 0.182000
(Iteration 69 / 70) loss: 0.514115
```

```
(Iteration 70 / 70) loss: 0.786051
(Epoch 35 / 35) train acc: 0.900000; val_acc: 0.200000
```

[31]:
```python
# Print final training accuracy
print(
    "Small data training accuracy:",
    solver.check_accuracy(small_data['X_train'], small_data['y_train'])
)
```

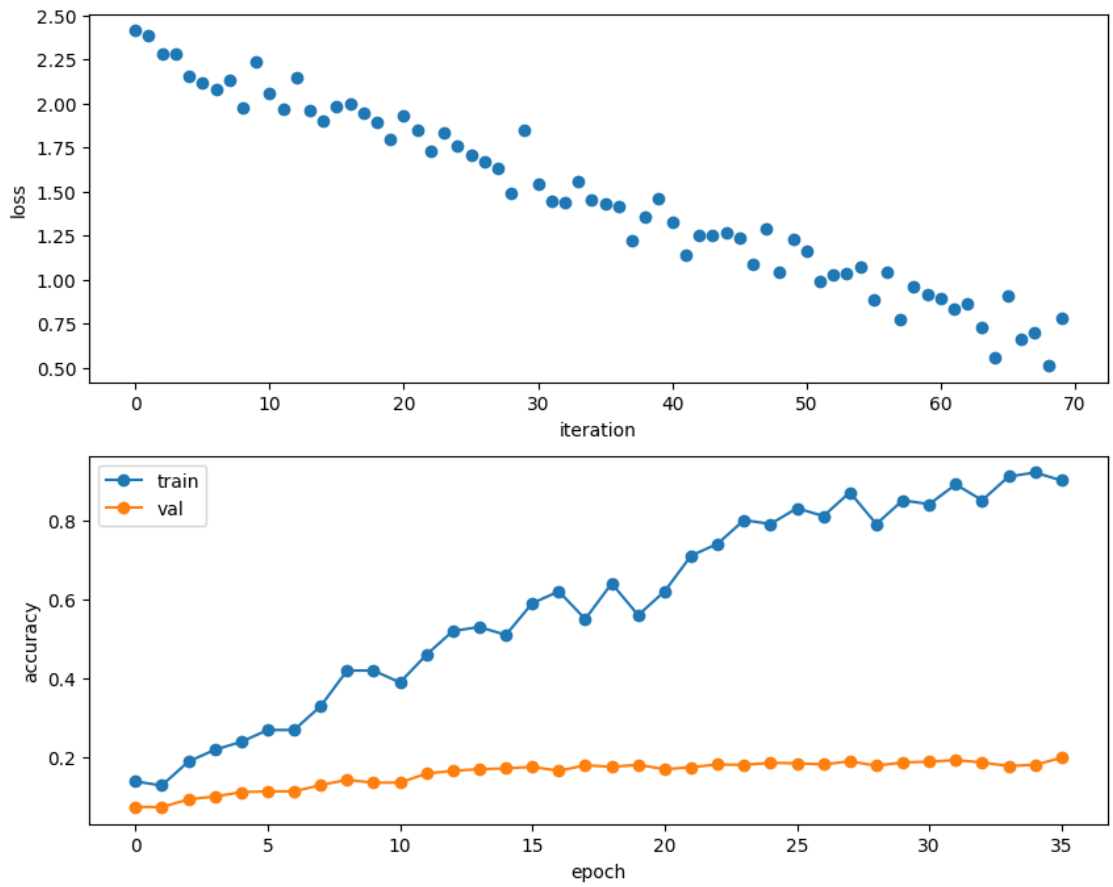
```
Small data training accuracy: 0.9
```

[32]:
```python
# Print final validation accuracy
print(
    "Small data validation accuracy:",
    solver.check_accuracy(small_data['X_val'], small_data['y_val'])
)
```

```
Small data validation accuracy: 0.2
```

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

[33]:
```python
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 30% accuracy on the training set with sgd, it should take 6 minuts. In the next part when we will learn other optimization tequnics we will get better accuracy in the same amount of time:

[21]:
```
model = ThreeLayerConvNet(weight_scale=0.001, hidden_dim=500, reg=0.001)

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

```
(Iteration 1 / 980) loss: 2.304876
(Epoch 0 / 1) train acc: 0.083000; val_acc: 0.086000
(Iteration 21 / 980) loss: 2.304521
```

```
(Iteration 41 / 980) loss: 2.304424
(Iteration 61 / 980) loss: 2.304157
(Iteration 81 / 980) loss: 2.304181
(Iteration 101 / 980) loss: 2.303648
(Iteration 121 / 980) loss: 2.302706
(Iteration 141 / 980) loss: 2.303352
(Iteration 161 / 980) loss: 2.301611
(Iteration 181 / 980) loss: 2.298818
(Iteration 201 / 980) loss: 2.293071
(Iteration 221 / 980) loss: 2.285592
(Iteration 241 / 980) loss: 2.272385
(Iteration 261 / 980) loss: 2.244782
(Iteration 281 / 980) loss: 2.208467
(Iteration 301 / 980) loss: 2.050966
(Iteration 321 / 980) loss: 2.058296
(Iteration 341 / 980) loss: 2.258100
(Iteration 361 / 980) loss: 2.037670
(Iteration 381 / 980) loss: 1.991332
(Iteration 401 / 980) loss: 1.982192
(Iteration 421 / 980) loss: 1.943203
(Iteration 441 / 980) loss: 2.018387
(Iteration 461 / 980) loss: 2.059734
(Iteration 481 / 980) loss: 1.910822
(Iteration 501 / 980) loss: 1.942802
(Iteration 521 / 980) loss: 1.786348
(Iteration 541 / 980) loss: 2.038088
(Iteration 561 / 980) loss: 1.912679
(Iteration 581 / 980) loss: 1.921920
(Iteration 601 / 980) loss: 1.987053
(Iteration 621 / 980) loss: 1.979135
(Iteration 641 / 980) loss: 1.866771
(Iteration 661 / 980) loss: 1.710859
(Iteration 681 / 980) loss: 2.107062
(Iteration 701 / 980) loss: 1.754281
(Iteration 721 / 980) loss: 1.917319
(Iteration 741 / 980) loss: 2.004374
(Iteration 761 / 980) loss: 1.546441
(Iteration 781 / 980) loss: 1.817538
(Iteration 801 / 980) loss: 1.697297
(Iteration 821 / 980) loss: 1.391700
(Iteration 841 / 980) loss: 1.776255
(Iteration 861 / 980) loss: 1.777225
(Iteration 881 / 980) loss: 1.706812
(Iteration 901 / 980) loss: 1.600886
(Iteration 921 / 980) loss: 1.496853
(Iteration 941 / 980) loss: 1.674209
(Iteration 961 / 980) loss: 1.514064
(Epoch 1 / 1) train acc: 0.402000; val_acc: 0.417000
```

[22]:
```
# Print final training accuracy
print(
    "Full data training accuracy:",
    solver.check_accuracy(small_data['X_train'], small_data['y_train'])
)
```

```
Full data training accuracy: 0.34
```

[23]:
```
# Print final validation accuracy
print(
    "Full data validation accuracy:",
    solver.check_accuracy(data['X_val'], data['y_val'])
)
```

```
Full data validation accuracy: 0.417
```

9.5 Visualize Filters

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

[24]:
```
from CV7062610.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()
```