BatchNormalization

January 21, 2026

[ ]:
```
# This mounts your Google Drive to the Colab VM.
from google.colab import drive
drive.mount('/content/drive')

# TODO: Enter the foldername in your Drive where you have saved the unzipped
# assignment folder, e.g. 'icv83551/assignments/assignment2/'
FOLDERNAME = 'icv83551/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 /content/drive/My\ Drive/$FOLDERNAME/icv83551/datasets/
!bash get_datasets.sh
%cd /content/drive/My\ Drive/$FOLDERNAME
```

```
Mounted at /content/drive
/content/drive/My Drive/icv83551/assignments/assignment2/icv83551/datasets
/content/drive/My Drive/icv83551/assignments/assignment2
```

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, proposed by [1] in 2015.

To understand the goal of batch normalization, it is important to first recognize that machine learning methods tend to perform better with input data consisting 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, they propose to insert into the network layers that normalize batches. At training time, such a 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.

[ ]:
```
# Setup cell.
import time
import numpy as np
import matplotlib.pyplot as plt
from icv83551.data_utils import get_CIFAR10_data
from icv83551.gradient_check import eval_numerical_gradient,␣
 ↪eval_numerical_gradient_array
from icv83551.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"

#%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(f"  means: {x.mean(axis=axis)}")
    print(f"  stds:  {x.std(axis=axis)}\n")
```

[ ]:
```
# Load the (preprocessed) CIFAR-10 data.
data = get_CIFAR10_data()
for k, v in list(data.items()):
    print(f"{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 Batch Normalization: Forward Pass

In the file `icv83551/layers.py`, implement the batch normalization forward pass in the function `batchnorm_forward`. Once you have done so, run the following to test your implementation.

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

[ ]:
```
from icv83551.layers import *

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

# 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: [5.32907052e-17 7.04991621e-17 1.85962357e-17]
  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]
```

[ ]:
```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)

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]
```

3 Batch Normalization: Backward Pass

Now implement the backward pass for batch normalization in the function `batchnorm_backward`.

To derive the backward pass you should write out the computation graph for batch normalization and backprop through each of the intermediate nodes. Some intermediates may have multiple outgoing branches; make sure to sum gradients across these branches in the backward pass. Referencing the paper linked to above in [1] may be helpful!

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

[ ]:
```
# 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:  1.7029227094228273e-09
dgamma error:  7.420414216247087e-13
dbeta error:  2.8795057655839487e-12
```

4 Batch Normalization: Alternative Backward Pass

In class we talked about two different implementations for the sigmoid backward pass. One strategy is to write out a computation graph composed of simple operations and backprop through all intermediate values. Another strategy is to work out the derivatives on paper. For example, you can derive a very simple formula for the sigmoid function's backward pass by simplifying gradients on paper.

Surprisingly, it turns out that you can do a similar simplification for the batch normalization

backward pass too!

In the forward pass, given a set of inputs $X = \begin{bmatrix} x_1 \\ x_2 \\ ... \\ x_N \end{bmatrix}$,

we first calculate the mean μ and variance v. With μ and v calculated, we can calculate the standard deviation σ and normalized data Y. The equations and graph illustration below describe the computation (y_i is the i-th element of the vector Y).

$$\mu = \frac{1}{N}\sum_{k=1}^{N} x_k \qquad v = \frac{1}{N}\sum_{k=1}^{N}(x_k - \mu)^2 \tag{1}$$

$$\sigma = \sqrt{v + \epsilon} \qquad y_i = \frac{x_i - \mu}{\sigma} \tag{2}$$

The meat of our problem during backpropagation is to compute $\frac{\partial L}{\partial X}$, given the upstream gradient we receive, $\frac{\partial L}{\partial Y}$. To do this, recall the chain rule in calculus gives us $\frac{\partial L}{\partial X} = \frac{\partial L}{\partial Y} \cdot \frac{\partial Y}{\partial X}$.

The unknown/hard part is $\frac{\partial Y}{\partial X}$. We can find this by first deriving step-by-step our local gradients at $\frac{\partial v}{\partial X}$, $\frac{\partial \mu}{\partial X}$, $\frac{\partial \sigma}{\partial v}$, $\frac{\partial Y}{\partial \sigma}$, and $\frac{\partial Y}{\partial \mu}$, and then use the chain rule to compose these gradients (which appear in the form of vectors!) appropriately to compute $\frac{\partial Y}{\partial X}$.

If it's challenging to directly reason about the gradients over X and Y which require matrix multiplication, try reasoning about the gradients in terms of individual elements x_i and y_i first: in that case, you will need to come up with the derivations for $\frac{\partial L}{\partial x_i}$, by relying on the Chain Rule to first calculate the intermediate $\frac{\partial \mu}{\partial x_i}$, $\frac{\partial v}{\partial x_i}$, $\frac{\partial \sigma}{\partial x_i}$, then assemble these pieces to calculate $\frac{\partial y_i}{\partial x_i}$.

You should make sure each of the intermediary gradient derivations are all as simplified as possible, for ease of implementation.

After doing so, implement the simplified batch normalization backward pass in the function `batchnorm_backward_alt` and compare the two implementations by running the following. Your two implementations should compute nearly identical results, but the alternative implementation should be a bit faster.

[ ]:
```
np.random.seed(231)
N, D = 100, 500
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'}
out, cache = batchnorm_forward(x, gamma, beta, bn_param)

t1 = time.time()
dx1, dgamma1, dbeta1 = batchnorm_backward(dout, cache)
t2 = time.time()
```

```
dx2, dgamma2, dbeta2 = batchnorm_backward_alt(dout, cache)
t3 = time.time()

print('dx difference: ', rel_error(dx1, dx2))
print('dgamma difference: ', rel_error(dgamma1, dgamma2))
print('dbeta difference: ', rel_error(dbeta1, dbeta2))
print('speedup: %.2fx' % ((t2 - t1) / (t3 - t2)))
```

```
dx difference:  1.618542846444811e-12
dgamma difference:  0.0
dbeta difference:  0.0
speedup: 3.64x
```

5 Fully Connected Networks with Batch Normalization

Now that you have a working implementation for batch normalization, go back to your `FullyConnectedNet` in the file `icv83551/classifiers/fc_net.py`. Recall that you implemented the network initialization, forward pass, and backward pass in Assignment 1. Copy that implementation here, and modify it to incorporate 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 `icv83551/layer_utils.py`.

[ ]:
```
from icv83551.classifiers.fc_net import *
from icv83551.gradient_check import *

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,))

# 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: 5.65e-06
W3 relative error: 4.14e-10
b1 relative error: 2.78e-09
b2 relative error: 5.55e-09
b3 relative error: 1.02e-10
beta1 relative error: 7.33e-09
beta2 relative error: 1.17e-09
gamma1 relative error: 7.47e-09
gamma2 relative error: 3.35e-09

Running check with reg =  3.14
Initial loss:  6.996533220108303
W1 relative error: 1.98e-06
W2 relative error: 2.29e-06
W3 relative error: 2.79e-08
b1 relative error: 5.55e-09
b2 relative error: 2.22e-08
b3 relative error: 2.10e-10
beta1 relative error: 6.32e-09
beta2 relative error: 3.48e-09
gamma1 relative error: 6.27e-09
gamma2 relative error: 4.14e-09
```

6 Batch Normalization 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.

[ ]:
```
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()
```

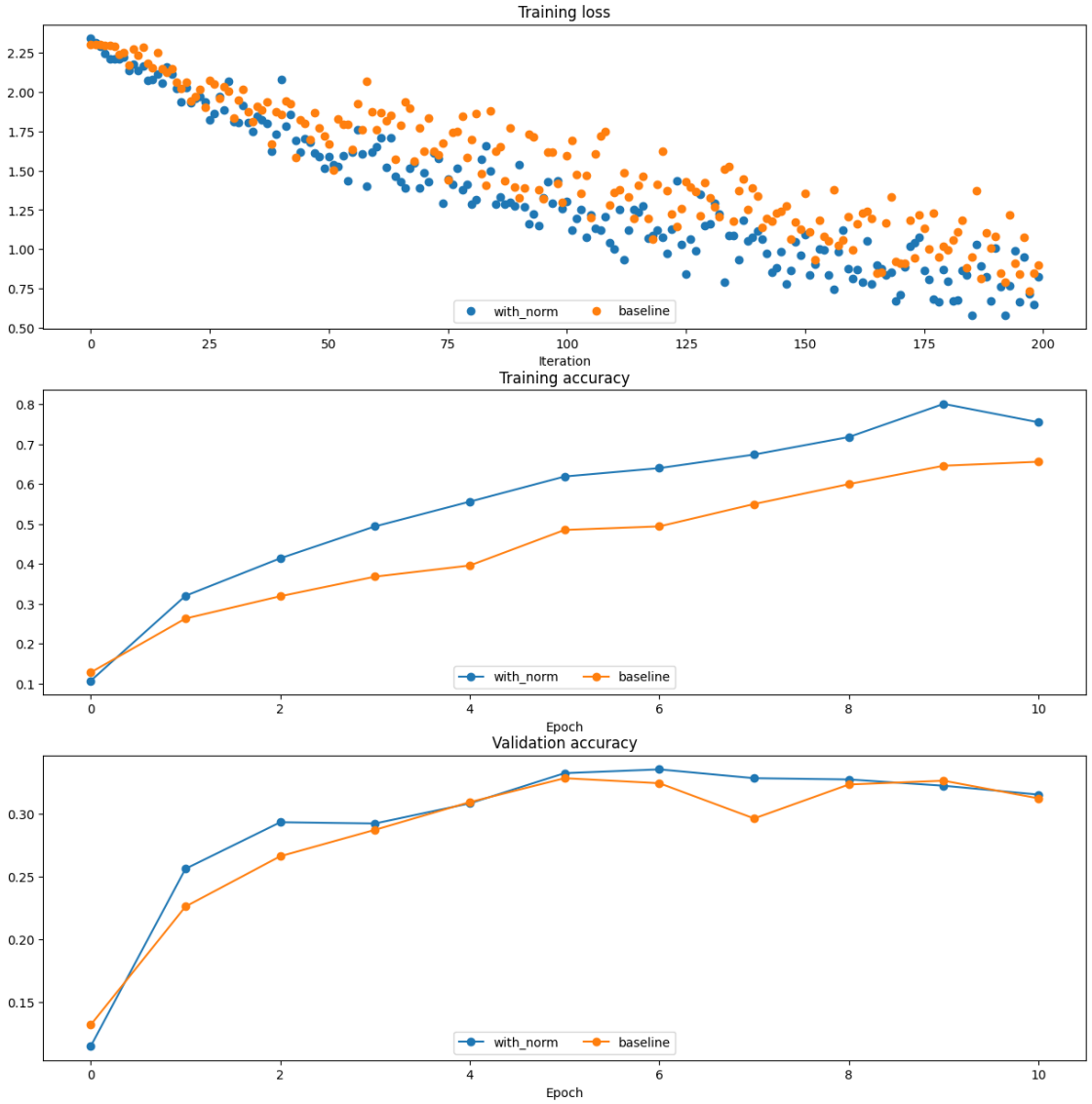
```
Solver with batch norm:
(Iteration 1 / 200) loss: 2.340974
(Epoch 0 / 10) train acc: 0.107000; val_acc: 0.115000
(Epoch 1 / 10) train acc: 0.320000; val_acc: 0.256000
(Iteration 21 / 200) loss: 2.027945
(Epoch 2 / 10) train acc: 0.414000; val_acc: 0.293000
(Iteration 41 / 200) loss: 2.078358
(Epoch 3 / 10) train acc: 0.494000; val_acc: 0.292000
(Iteration 61 / 200) loss: 1.654395
(Epoch 4 / 10) train acc: 0.556000; val_acc: 0.308000
(Iteration 81 / 200) loss: 1.289283
(Epoch 5 / 10) train acc: 0.619000; val_acc: 0.332000
(Iteration 101 / 200) loss: 1.303661
(Epoch 6 / 10) train acc: 0.640000; val_acc: 0.335000
(Iteration 121 / 200) loss: 1.075268
(Epoch 7 / 10) train acc: 0.674000; val_acc: 0.328000
(Iteration 141 / 200) loss: 1.114925
```

```
(Epoch 8 / 10) train acc: 0.718000; val_acc: 0.327000
(Iteration 161 / 200) loss: 0.815040
(Epoch 9 / 10) train acc: 0.801000; val_acc: 0.322000
(Iteration 181 / 200) loss: 0.796903
(Epoch 10 / 10) train acc: 0.755000; val_acc: 0.315000

Solver without batch norm:
(Iteration 1 / 200) loss: 2.302331
(Epoch 0 / 10) train acc: 0.128000; val_acc: 0.132000
(Epoch 1 / 10) train acc: 0.263000; val_acc: 0.226000
(Iteration 21 / 200) loss: 2.064354
(Epoch 2 / 10) train acc: 0.319000; val_acc: 0.266000
(Iteration 41 / 200) loss: 1.856846
(Epoch 3 / 10) train acc: 0.368000; val_acc: 0.287000
(Iteration 61 / 200) loss: 1.760862
(Epoch 4 / 10) train acc: 0.396000; val_acc: 0.309000
(Iteration 81 / 200) loss: 1.696757
(Epoch 5 / 10) train acc: 0.485000; val_acc: 0.328000
(Iteration 101 / 200) loss: 1.591938
(Epoch 6 / 10) train acc: 0.494000; val_acc: 0.324000
(Iteration 121 / 200) loss: 1.621612
(Epoch 7 / 10) train acc: 0.550000; val_acc: 0.296000
(Iteration 141 / 200) loss: 1.339807
(Epoch 8 / 10) train acc: 0.600000; val_acc: 0.323000
(Iteration 161 / 200) loss: 0.998247
(Epoch 9 / 10) train acc: 0.646000; val_acc: 0.326000
(Iteration 181 / 200) loss: 0.993196
(Epoch 10 / 10) train acc: 0.656000; val_acc: 0.312000
```

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.

[ ]:
```
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()
```



7 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 eight-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.

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

# Try training a very deep net with batchnorm.
```

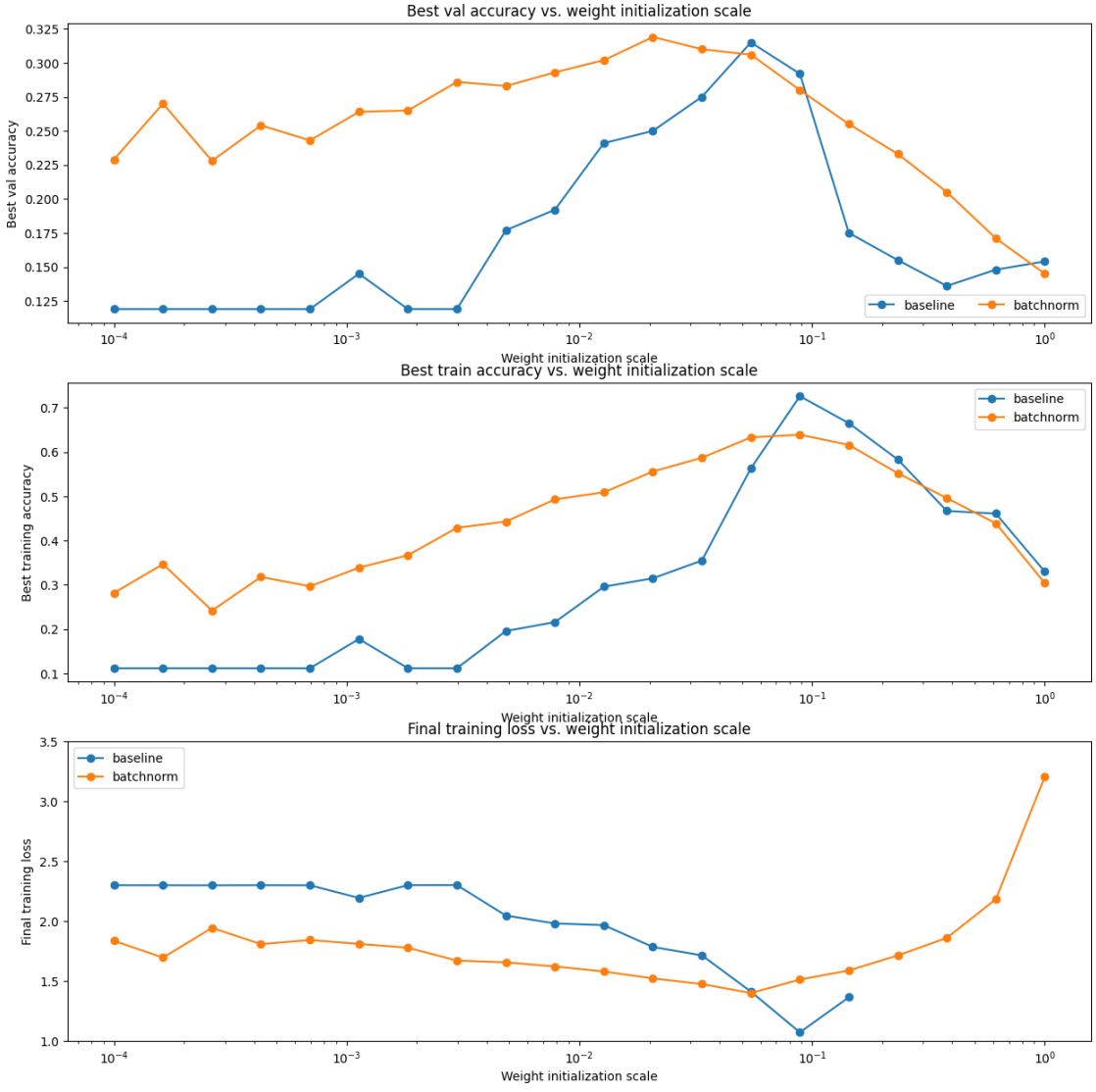
```
hidden_dims = [50, 50, 50, 50, 50, 50, 50]
num_train = 1000
small_data = {
  'X_train': data['X_train'][:num_train],
  'y_train': data['y_train'][:num_train],
  'X_val': data['X_val'],
  'y_val': data['y_val'],
}

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

/content/drive/My Drive/icv83551/assignments/assignment2/icv83551/layers.py:810:
RuntimeWarning: divide by zero encountered in log
  loss = (-np.sum(np.log(probs[np.arange(x.shape[0]), y])))/num_train

Running weight scale 17 / 20
Running weight scale 18 / 20
Running weight scale 19 / 20
Running weight scale 20 / 20
```

[ ]:
```python
# 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()
```



7.1 Inline Question 1:

Describe the results of this experiment. How does the weight initialization scale affect models with/without batch normalization differently, and why? ## Answer: the experements show that the model is very sensetive to the inizalized value of the weights. we can see that the convergence happens around a "sweet spot" scale while with the batch norm it has a much more smooth convergence range. this happens because if the wieght scale is to small, the graident vanishes, if too large, explodes (without batch norm). on the other hand as written above batch norm behaves in a "smooth" manner, converging on a wider set of wieghts, with stable loss and accuracy. this happens for these main resons: 1. Graident vanishing/exploding - the graident multiplies at ever layer, causing it to become unstable (explode/vanish). 2. Batch Norm shift - makes sure every level gets a stable distrabution of the wieghts (meaning no matter how the distrabution is acroos the earlier layer, its given to the next level stable) 3. removes the conection between the scale of the weights, and the direction of the weights. in conculssion: BN allows us a much wider range of "kosher" initilazation weights, BN removes the conection between the direction and size of the weight vector, keeps the graident flowing and not exploding/vanishing

8 Batch Normalization and Batch Size

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

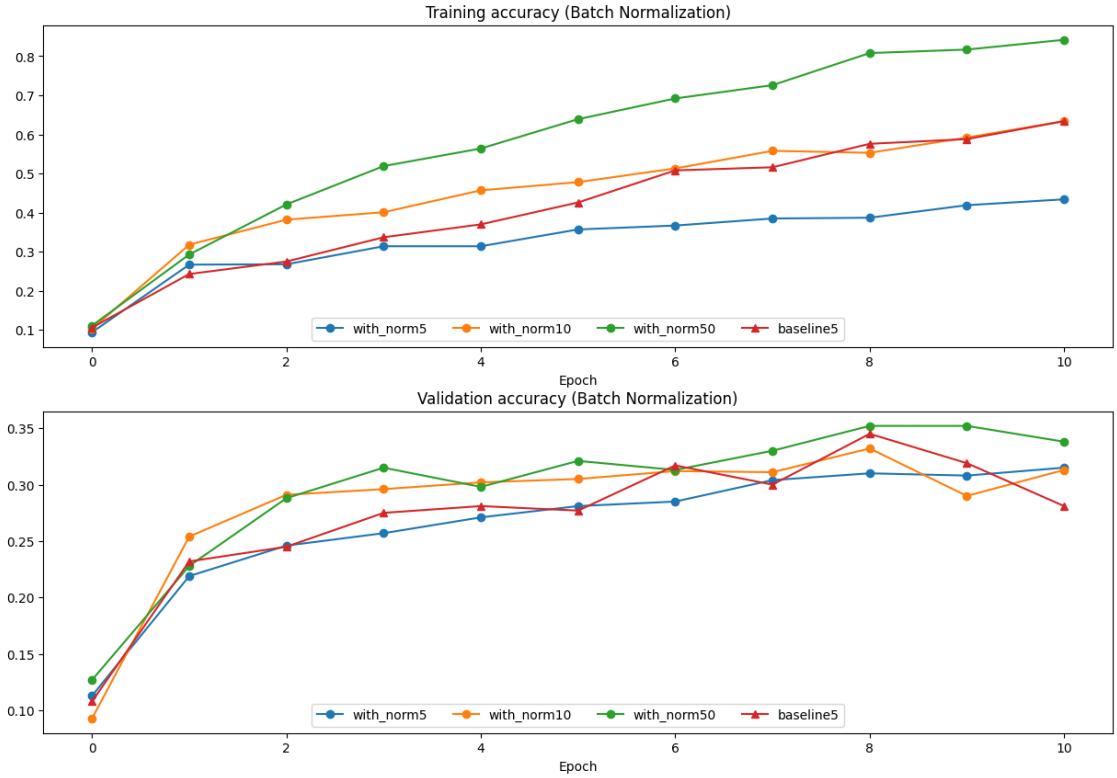
The first cell will train 6-layer networks both with and without batch normalization using different batch sizes. The second layer will plot training accuracy and validation set accuracy over time.

[ ]:
```
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
```

[ ]:
```
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()
```



8.1 Inline Question 2:

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

8.2 Answer:

We can see that the batch norm of size 5 underpreforms the baseline,10 very slightly overpreforms the baseline, and that 50 overpreforms the baseline consistently. the main reason for this, is that for larger groups we get a better distrebution of the data (meaning outlyers effect the norm much less - since BN uses batch statistics as a estimate) therefor or normalization is much more stable, giving us the wanted results. while small batches (5-10) if there is a outlier, Outliers move the activations (the data flowing through), which then creates a “garbage” gradient, which then moves the weights to a bad place, and therefor become less stable with worse results, we can see that BN is very dependent on the size of the batch.

9 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.

9.1 Inline Question 3:

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.

9.2 Answer:

Layer: 2 + (1 -> its a "subset" of layer-norm, as it normalizes locally across a row)

Batch: 3

10 Layer Normalization: Implementation

Now you'll implement layer normalization. This step should be relatively straightforward, as conceptually the implementation is almost identical to that of batch normalization. One significant difference though is that for layer normalization, we do not keep track of the moving moments, and the testing phase is identical to the training phase, where the mean and variance are directly calculated per datapoint.

Here's what you need to do:

- In `icv83551/layers.py`, implement the forward pass for layer normalization in the function `layernorm_forward`.

Run the cell below to check your results. * In `icv83551/layers.py`, implement the backward pass for layer normalization in the function `layernorm_backward`.

Run the second cell below to check your results. * Modify `icv83551/classifiers/fc_net.py` to add layer normalization to the `FullyConnectedNet`. When the `normalization` flag is set to `"layernorm"` in the constructor, you should insert a layer normalization layer before each ReLU nonlinearity.

Run the third cell below to run the batch size experiment on layer normalization.

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

```
# Simulate the forward pass for a two-layer network.
np.random.seed(231)
N, D1, D2, D3 =4, 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 layer normalization:')
print_mean_std(a,axis=1)

gamma = np.ones(D3)
beta = np.zeros(D3)

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

gamma = np.asarray([3.0,3.0,3.0])
beta = np.asarray([5.0,5.0,5.0])

# Now means should be close to beta and stds close to gamma.
print('After layer normalization (gamma=', gamma, ', beta=', beta, ')')
a_norm, _ = layernorm_forward(a, gamma, beta, {'mode': 'train'})
print_mean_std(a_norm,axis=1)
```

```
Before layer normalization:
  means: [-59.06673243 -47.60782686 -43.31137368 -26.40991744]
  stds:  [10.07429373 28.39478981 35.28360729  4.01831507]

After layer normalization (gamma=1, beta=0)
  means: [ 4.81096644e-16 -7.40148683e-17  2.22044605e-16 -5.92118946e-16]
  stds:  [0.99999995 0.99999999 1.         0.99999969]

After layer normalization (gamma= [3. 3. 3.] , beta= [5. 5. 5.] )
  means: [5. 5. 5. 5.]
  stds:  [2.99999985 2.99999998 2.99999999 2.99999907]
```

[ ]:
```
# 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)
```

```
ln_param = {}
fx = lambda x: layernorm_forward(x, gamma, beta, ln_param)[0]
fg = lambda a: layernorm_forward(x, a, beta, ln_param)[0]
fb = lambda b: layernorm_forward(x, gamma, b, ln_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 = layernorm_forward(x, gamma, beta, ln_param)
dx, dgamma, dbeta = layernorm_backward(dout, cache)

# You should expect to see relative errors between 1e-12 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:  2.107279036881856e-09
dgamma error:  4.519489546032799e-12
dbeta error:  2.5842537629899423e-12
```

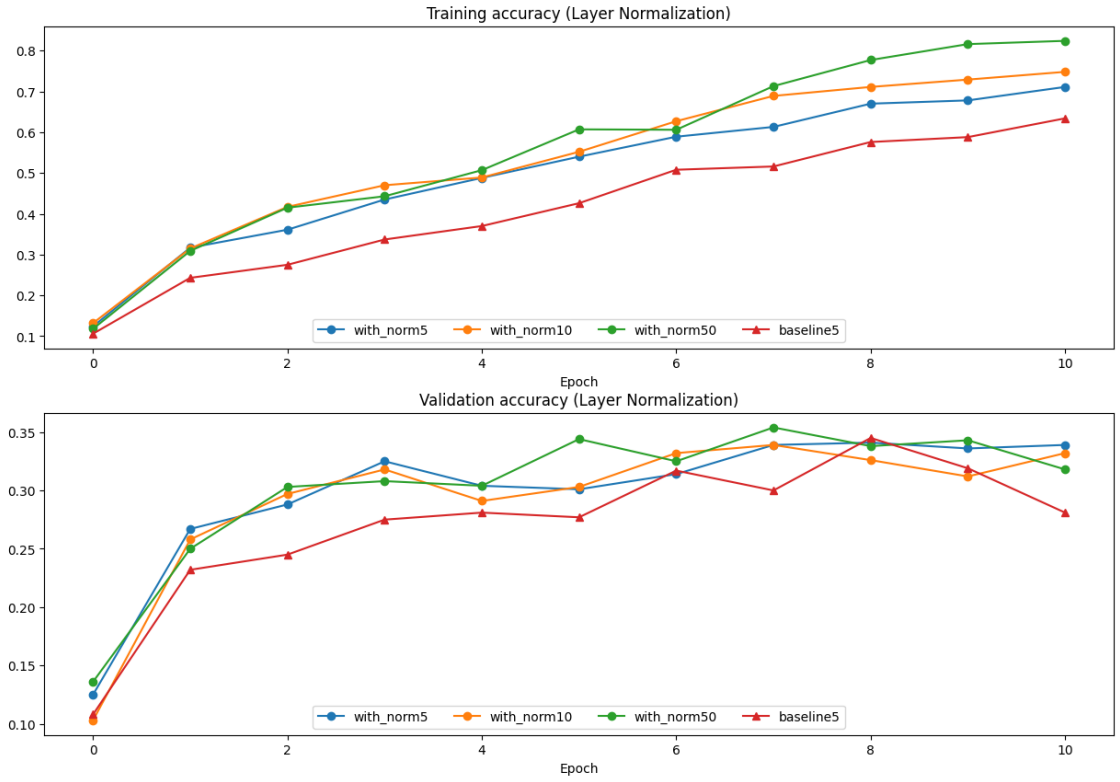
11 Layer Normalization and Batch Size

We will now run the previous batch size experiment with layer normalization instead of batch normalization. Compared to the previous experiment, you should see a markedly smaller influence of batch size on the training history!

[ ]:
```
ln_solvers_bsize, solver_bsize, batch_sizes = run_batchsize_experiments('layernorm')

plt.subplot(2, 1, 1)
plot_training_history('Training accuracy (Layer Normalization)','Epoch', solver_bsize, ln_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 (Layer Normalization)','Epoch', solver_bsize, ln_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()
```

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

```
Normalization: batch size =  10
Normalization: batch size =  50
```



11.1 Inline Question 4:

When is layer normalization likely to not work well, and why?

1. Using it in a very deep network
2. Having a very small dimension of features
3. Having a high regularization term

11.2 Answer:

2 - it is the analogy of small data group in batch-norm

[ ]:

Dropout

January 21, 2026

[ ]:
```
# This mounts your Google Drive to the Colab VM.
from google.colab import drive
drive.mount('/content/drive')

# TODO: Enter the foldername in your Drive where you have saved the unzipped
# assignment folder, e.g. 'icv83551/assignments/assignment2/'
FOLDERNAME = 'icv83551/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 /content/drive/My\ Drive/$FOLDERNAME/icv83551/datasets/
!bash get_datasets.sh
%cd /content/drive/My\ Drive/$FOLDERNAME
```

```
Mounted at /content/drive
/content/drive/My Drive/icv83551/assignments/assignment2/icv83551/datasets
/content/drive/My Drive/icv83551/assignments/assignment2
```

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

[ ]:
```
# Setup cell.
import time
import numpy as np
import matplotlib.pyplot as plt
```

```
from icv83551.classifiers.fc_net import *
from icv83551.data_utils import get_CIFAR10_data
from icv83551.gradient_check import eval_numerical_gradient,␣
 ↪eval_numerical_gradient_array
from icv83551.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"

#%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))))
```

[ ]:
```
# Load the (preprocessed) CIFAR-10 data.
data = get_CIFAR10_data()
for k, v in list(data.items()):
    print(f"{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 `icv83551/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.

[ ]:
```
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 `icv83551/layers.py`, implement the backward pass for dropout. After doing so, run the following cell to numerically gradient-check your implementation.

[ ]:
```
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:

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

3.2 Answer:

if we dont divide by p during training, we create a scale mismatch between the training and testing phases. because dropout randomly removes neurons (zero's them out) the total amount of "signals" passed during training is reduced by p. if we dont scale the rest up, we will get weight that are tuned to these "artifically" smaller input. if we didnt do this, during test when all the neurons are activated the signal strength will be higher then that what the model was trained to handel. this can cause numerical instability and poor predictions as it will cause higher and unexpected activation levels.

4 Fully Connected Networks with Dropout

In the file `icv83551/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_keep_ratio` 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.

[ ]:
```
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_keep_ratio in [1, 0.75, 0.5]:
    print('Running check with dropout = ', dropout_keep_ratio)
    model = FullyConnectedNet(
        [H1, H2],
        input_dim=D,
        num_classes=C,
        weight_scale=5e-2,
        dtype=np.float64,
        dropout_keep_ratio=dropout_keep_ratio,
        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_keep_ratio=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:  2.300479089768492
W1 relative error: 1.03e-07
W2 relative error: 2.21e-05
W3 relative error: 4.56e-07
b1 relative error: 4.66e-09
b2 relative error: 2.09e-09
b3 relative error: 1.69e-10

Running check with dropout =  0.75
Initial loss:  2.302371489704412
W1 relative error: 1.85e-07
W2 relative error: 2.15e-06
W3 relative error: 4.56e-08
b1 relative error: 1.16e-08
b2 relative error: 1.82e-09
b3 relative error: 1.48e-10

Running check with dropout =  0.5
Initial loss:  2.30427592207859
W1 relative error: 3.11e-07
W2 relative error: 2.48e-08
W3 relative error: 6.43e-08
b1 relative error: 5.37e-09
b2 relative error: 1.91e-09
b3 relative error: 1.85e-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.

[ ]:
```
# 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'],
```

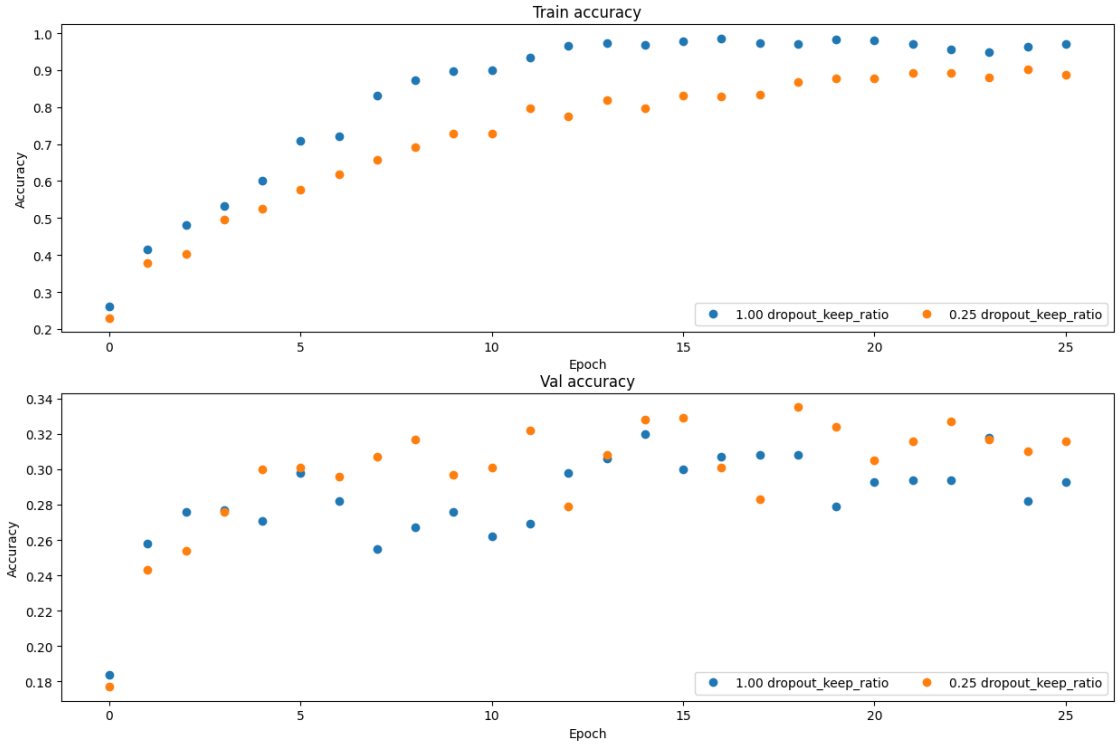
```
    'y_val': data['y_val'],
}

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

    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_keep_ratio] = solver
    print()
```

```
1
(Iteration 1 / 125) loss: 7.856644
(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: 0.710000; val_acc: 0.298000
(Epoch 6 / 25) train acc: 0.720000; val_acc: 0.282000
(Epoch 7 / 25) train acc: 0.832000; val_acc: 0.255000
(Epoch 8 / 25) train acc: 0.874000; val_acc: 0.267000
(Epoch 9 / 25) train acc: 0.898000; val_acc: 0.276000
(Epoch 10 / 25) train acc: 0.900000; val_acc: 0.262000
(Epoch 11 / 25) train acc: 0.934000; val_acc: 0.269000
(Epoch 12 / 25) train acc: 0.966000; val_acc: 0.298000
(Epoch 13 / 25) train acc: 0.974000; val_acc: 0.306000
(Epoch 14 / 25) train acc: 0.968000; val_acc: 0.320000
(Epoch 15 / 25) train acc: 0.978000; val_acc: 0.300000
(Epoch 16 / 25) train acc: 0.986000; val_acc: 0.307000
(Epoch 17 / 25) train acc: 0.974000; val_acc: 0.308000
(Epoch 18 / 25) train acc: 0.970000; val_acc: 0.308000
```

```
(Epoch 19 / 25) train acc: 0.984000; val_acc: 0.279000
(Epoch 20 / 25) train acc: 0.980000; val_acc: 0.293000
(Iteration 101 / 125) loss: 0.449588
(Epoch 21 / 25) train acc: 0.972000; val_acc: 0.294000
(Epoch 22 / 25) train acc: 0.956000; val_acc: 0.294000
(Epoch 23 / 25) train acc: 0.950000; val_acc: 0.318000
(Epoch 24 / 25) train acc: 0.964000; val_acc: 0.282000
(Epoch 25 / 25) train acc: 0.970000; val_acc: 0.293000

0.25
(Iteration 1 / 125) loss: 17.318478
(Epoch 0 / 25) train acc: 0.230000; val_acc: 0.177000
/content/drive/My Drive/icv83551/assignments/assignment2/icv83551/layers.py:810:
RuntimeWarning: divide by zero encountered in log
  loss = (-np.sum(np.log(probs[np.arange(x.shape[0]), y])))/num_train
(Epoch 1 / 25) train acc: 0.378000; val_acc: 0.243000
(Epoch 2 / 25) train acc: 0.404000; val_acc: 0.254000
(Epoch 3 / 25) train acc: 0.496000; val_acc: 0.276000
(Epoch 4 / 25) train acc: 0.526000; val_acc: 0.300000
(Epoch 5 / 25) train acc: 0.576000; val_acc: 0.301000
(Epoch 6 / 25) train acc: 0.618000; val_acc: 0.296000
(Epoch 7 / 25) train acc: 0.658000; val_acc: 0.307000
(Epoch 8 / 25) train acc: 0.692000; val_acc: 0.317000
(Epoch 9 / 25) train acc: 0.728000; val_acc: 0.297000
(Epoch 10 / 25) train acc: 0.728000; val_acc: 0.301000
(Epoch 11 / 25) train acc: 0.798000; val_acc: 0.322000
(Epoch 12 / 25) train acc: 0.774000; val_acc: 0.279000
(Epoch 13 / 25) train acc: 0.820000; val_acc: 0.308000
(Epoch 14 / 25) train acc: 0.798000; val_acc: 0.328000
(Epoch 15 / 25) train acc: 0.832000; val_acc: 0.329000
(Epoch 16 / 25) train acc: 0.828000; val_acc: 0.301000
(Epoch 17 / 25) train acc: 0.834000; val_acc: 0.283000
(Epoch 18 / 25) train acc: 0.868000; val_acc: 0.335000
(Epoch 19 / 25) train acc: 0.878000; val_acc: 0.324000
(Epoch 20 / 25) train acc: 0.878000; val_acc: 0.305000
(Iteration 101 / 125) loss: 5.331102
(Epoch 21 / 25) train acc: 0.892000; val_acc: 0.316000
(Epoch 22 / 25) train acc: 0.892000; val_acc: 0.327000
(Epoch 23 / 25) train acc: 0.880000; val_acc: 0.317000
(Epoch 24 / 25) train acc: 0.902000; val_acc: 0.310000
(Epoch 25 / 25) train acc: 0.888000; val_acc: 0.316000
```

[ ]:
```
# Plot train and validation accuracies of the two models.
train_accs = []
val_accs = []
```

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

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

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

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

5.2 Answer:

we can see that the training accuracy is lower, while on average the validation accuracy is higher, that means dropout is a good regulizer against overfitting. drop out is a form of essembaly of experts, meaning we get some "average" of the diffrent neurons that where turned on and off, therefor, its less prone to overfiiting.

[ ]:

ConvolutionalNetworks

January 21, 2026

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

# TODO: Enter the foldername in your Drive where you have saved the unzipped
# assignment folder, e.g. 'icv83551/assignments/assignment2/'
FOLDERNAME = 'icv83551/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 /content/drive/My\ Drive/$FOLDERNAME/icv83551/datasets/
!bash get_datasets.sh
%cd /content/drive/My\ Drive/$FOLDERNAME
```

```
Mounted at /content/drive
/content/drive/My Drive/icv83551/assignments/assignment2/icv83551/datasets
/content/drive/My Drive/icv83551/assignments/assignment2
```

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]:
```
# Setup cell.
import numpy as np
import matplotlib.pyplot as plt
```

```
from icv83551.classifiers.cnn import *
from icv83551.data_utils import get_CIFAR10_data
from icv83551.gradient_check import eval_numerical_gradient_array,␣
 ↪eval_numerical_gradient
from icv83551.layers import *
from icv83551.fast_layers import *
from icv83551.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) CIFAR-10 data.
data = get_CIFAR10_data()
for k, v in list(data.items()):
    print(f"{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 `icv83551/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
```

2.1 Aside: Image Processing via Convolutions

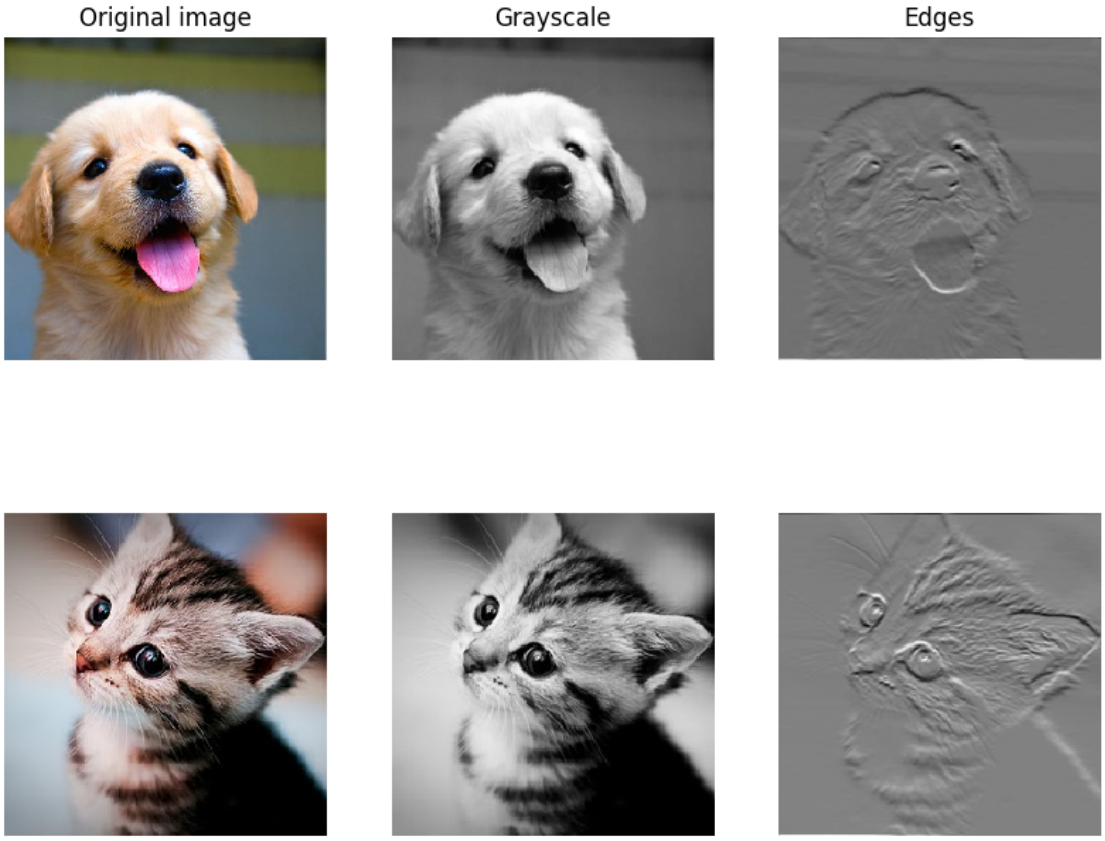
As fun way to both check your implementation and gain a better understanding of the type of operation that convolutional layers can perform, we will set up an input containing two images and manually set up filters that perform common image processing operations (grayscale conversion and edge detection).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

[5]:
```
from imageio import imread
from PIL import Image

kitten = imread('icv83551/notebook_images/kitten.jpg')
puppy = imread('icv83551/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()
```

```
/tmp/ipython-input-1439264293.py: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('icv83551/notebook_images/kitten.jpg')
/tmp/ipython-input-1439264293.py: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('icv83551/notebook_images/puppy.jpg')
```



3 Convolution: Naive Backward Pass

Implement the backward pass for the convolution operation in the function `conv_backward_naive` in the file `icv83551/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.

[6]:
```
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
```

4 Max-Pooling: Naive Forward Pass

Implement the forward pass for the max-pooling operation in the function `max_pool_forward_naive` in the file `icv83551/layers.py`. Again, don't worry too much about computational efficiency.

Check your implementation by running the following:

[7]:
```
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
```

5 Max-Pooling: Naive Backward

Implement the backward pass for the max-pooling operation in the function `max_pool_backward_naive` in the file `icv83551/layers.py`. You don't need to worry about computational efficiency.

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

[8]:
```
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
```

6 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 `icv83551/fast_layers.py`.

6.0.1 Execute the below cell, save the notebook, and restart the runtime

The fast convolution implementation depends on a Cython extension; to compile it, run the cell below. Next, save the Colab notebook (`File > Save`) and **restart the runtime** (`Runtime > Restart runtime`). You can then re-execute the preceeding cells from top to bottom and skip the cell below as you only need to run it once for the compilation step.

[9]:
```
# Remember to restart the runtime after executing this cell!
%cd /content/drive/My\ Drive/$FOLDERNAME/icv83551/
!python setup.py build_ext --inplace
%cd /content/drive/My\ Drive/$FOLDERNAME/
```

```
/content/drive/My Drive/icv83551/assignments/assignment2/icv83551
/content/drive/My Drive/icv83551/assignments/assignment2
```

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 icv83551.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: 5.236882s
Fast: 0.011023s
Speedup: 475.095170x
Difference:  4.926407851494105e-11

Testing conv_backward_fast:
Naive: 8.314782s
Fast: 0.076719s
Speedup: 108.379972x
dx difference:  1.949764775345631e-11
dw difference:  3.681156828004736e-13
db difference:  0.0
```

[11]:
```
# Relative errors should be close to 0.0.
from icv83551.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: 0.633891s
fast: 0.007035s
speedup: 90.111269x
difference:  0.0

Testing pool_backward_fast:
Naive: 0.655887s
fast: 0.013220s
speedup: 49.612996x
dx difference:  0.0
```

7 Convolutional "Sandwich" Layers

In the previous assignment, we introduced the concept of "sandwich" layers that combine multiple operations into commonly used patterns. In the file `icv83551/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 their usage.

[12]:
```
from icv83551.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 icv83551.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
```

8 Three-Layer Convolutional Network

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

Open the file `icv83551/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:

8.1 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):  2.508255638232932
```

8.2 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: 3.053965e-04
W2 max relative error: 1.822723e-02
W3 max relative error: 3.422399e-04
b1 max relative error: 3.397321e-06
b2 max relative error: 2.517459e-03
b3 max relative error: 9.711800e-10
```

8.3 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.

[16]:
```
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)

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: 3.102719
(Epoch 1 / 15) train acc: 0.140000; val_acc: 0.087000
(Iteration 3 / 30) loss: 2.270332
(Iteration 4 / 30) loss: 2.099074
(Epoch 2 / 15) train acc: 0.230000; val_acc: 0.093000
(Iteration 5 / 30) loss: 1.841253
(Iteration 6 / 30) loss: 1.935296
(Epoch 3 / 15) train acc: 0.490000; val_acc: 0.168000
(Iteration 7 / 30) loss: 1.828834
(Iteration 8 / 30) loss: 1.652295
(Epoch 4 / 15) train acc: 0.520000; val_acc: 0.182000
(Iteration 9 / 30) loss: 1.332530
(Iteration 10 / 30) loss: 1.772358
(Epoch 5 / 15) train acc: 0.640000; val_acc: 0.171000
(Iteration 11 / 30) loss: 1.029629
(Iteration 12 / 30) loss: 1.038692
(Epoch 6 / 15) train acc: 0.720000; val_acc: 0.226000
(Iteration 13 / 30) loss: 1.152896
(Iteration 14 / 30) loss: 0.834351
(Epoch 7 / 15) train acc: 0.810000; val_acc: 0.248000
(Iteration 15 / 30) loss: 0.584665
(Iteration 16 / 30) loss: 0.644552
(Epoch 8 / 15) train acc: 0.830000; val_acc: 0.240000
(Iteration 17 / 30) loss: 0.811508
(Iteration 18 / 30) loss: 0.430228
(Epoch 9 / 15) train acc: 0.840000; val_acc: 0.175000
(Iteration 19 / 30) loss: 0.421580
(Iteration 20 / 30) loss: 0.555581
(Epoch 10 / 15) train acc: 0.930000; val_acc: 0.197000
(Iteration 21 / 30) loss: 0.364954
(Iteration 22 / 30) loss: 0.271303
(Epoch 11 / 15) train acc: 0.860000; val_acc: 0.215000
(Iteration 23 / 30) loss: 0.405969
(Iteration 24 / 30) loss: 0.385744
(Epoch 12 / 15) train acc: 0.950000; val_acc: 0.207000
(Iteration 25 / 30) loss: 0.109979
(Iteration 26 / 30) loss: 0.113894
(Epoch 13 / 15) train acc: 0.960000; val_acc: 0.218000
(Iteration 27 / 30) loss: 0.123754
(Iteration 28 / 30) loss: 0.172242
(Epoch 14 / 15) train acc: 0.990000; val_acc: 0.222000
(Iteration 29 / 30) loss: 0.123923
(Iteration 30 / 30) loss: 0.070897
(Epoch 15 / 15) train acc: 0.990000; val_acc: 0.218000
```

[17]:
```
# Print final training accuracy.
print(
    "Small data training accuracy:",
    solver.check_accuracy(small_data['X_train'], small_data['y_train'])
)
```

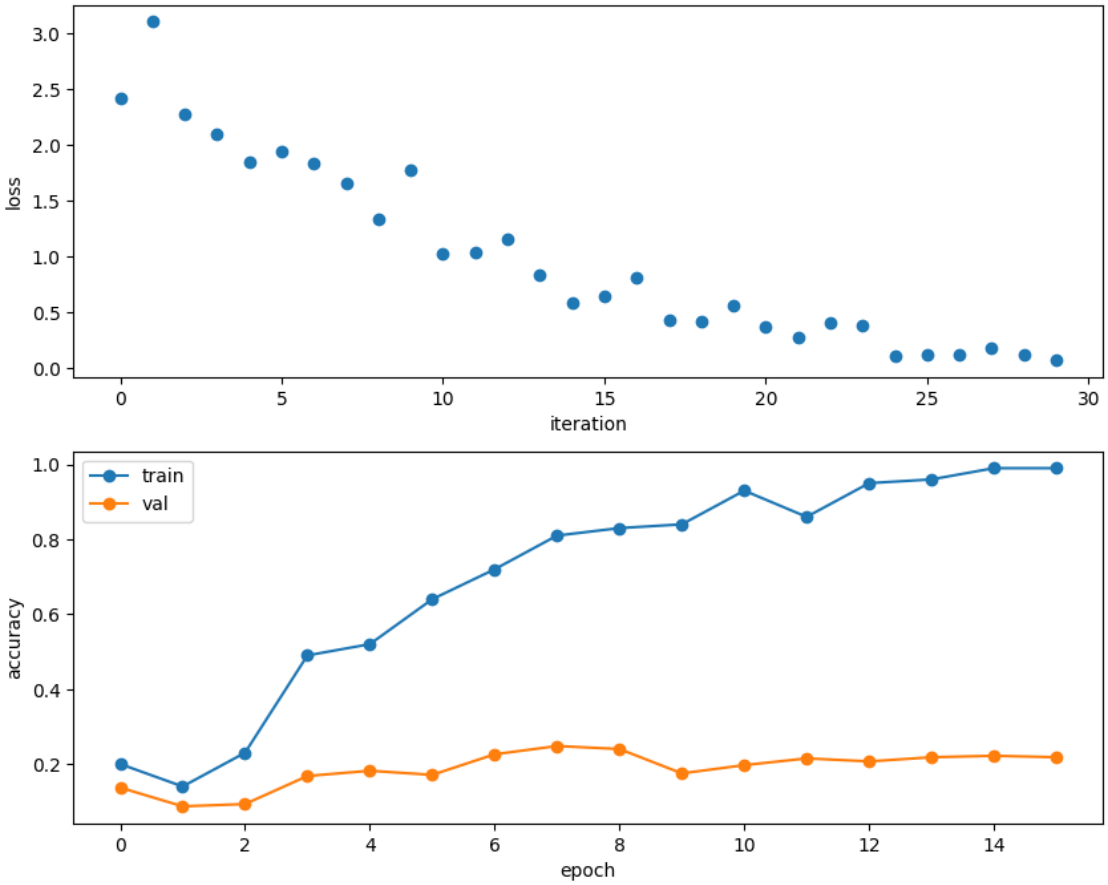
```
Small data training accuracy: 0.81
```

[18]:
```
# Print final validation accuracy.
print(
    "Small data validation accuracy:",
    solver.check_accuracy(small_data['X_val'], small_data['y_val'])
)
```

```
Small data validation accuracy: 0.248
```

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

[19]:
```
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()
```



8.4 Train the Network

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

[20]:
```
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: 2.304740
(Epoch 0 / 1) train acc: 0.103000; val_acc: 0.107000
(Iteration 21 / 980) loss: 2.129645
(Iteration 41 / 980) loss: 1.945061
(Iteration 61 / 980) loss: 1.770560
(Iteration 81 / 980) loss: 1.901148
(Iteration 101 / 980) loss: 1.919195
(Iteration 121 / 980) loss: 1.765398
(Iteration 141 / 980) loss: 1.898770
(Iteration 161 / 980) loss: 1.738502
(Iteration 181 / 980) loss: 1.843249
(Iteration 201 / 980) loss: 2.066862
(Iteration 221 / 980) loss: 1.990459
(Iteration 241 / 980) loss: 1.828815
(Iteration 261 / 980) loss: 1.604638
(Iteration 281 / 980) loss: 1.692068
(Iteration 301 / 980) loss: 1.754931
(Iteration 321 / 980) loss: 1.742302
(Iteration 341 / 980) loss: 1.699758
(Iteration 361 / 980) loss: 1.723792
(Iteration 381 / 980) loss: 1.542635
(Iteration 401 / 980) loss: 1.738328
(Iteration 421 / 980) loss: 1.427555
(Iteration 441 / 980) loss: 1.759026
(Iteration 461 / 980) loss: 1.879609
(Iteration 481 / 980) loss: 1.413088
(Iteration 501 / 980) loss: 1.367136
(Iteration 521 / 980) loss: 1.637779
(Iteration 541 / 980) loss: 1.749722
(Iteration 561 / 980) loss: 1.645201
(Iteration 581 / 980) loss: 1.373341
(Iteration 601 / 980) loss: 1.573957
(Iteration 621 / 980) loss: 1.570977
(Iteration 641 / 980) loss: 1.683598
(Iteration 661 / 980) loss: 1.755739
(Iteration 681 / 980) loss: 1.741579
(Iteration 701 / 980) loss: 1.627704
(Iteration 721 / 980) loss: 1.655453
(Iteration 741 / 980) loss: 1.634793
(Iteration 761 / 980) loss: 1.447560
(Iteration 781 / 980) loss: 1.793672
(Iteration 801 / 980) loss: 1.627485
(Iteration 821 / 980) loss: 1.656835
(Iteration 841 / 980) loss: 1.351238
(Iteration 861 / 980) loss: 1.745392
(Iteration 881 / 980) loss: 1.552356
(Iteration 901 / 980) loss: 1.539406
(Iteration 921 / 980) loss: 1.492501
```

```
(Iteration 941 / 980) loss: 1.683674
(Iteration 961 / 980) loss: 1.638435
(Epoch 1 / 1) train acc: 0.480000; val_acc: 0.485000
```

[21]:
```python
# Print final training accuracy.
print(
    "Full data training accuracy:",
    solver.check_accuracy(data['X_train'], data['y_train'])
)
```

```
Full data training accuracy: 0.46477551020408164
```

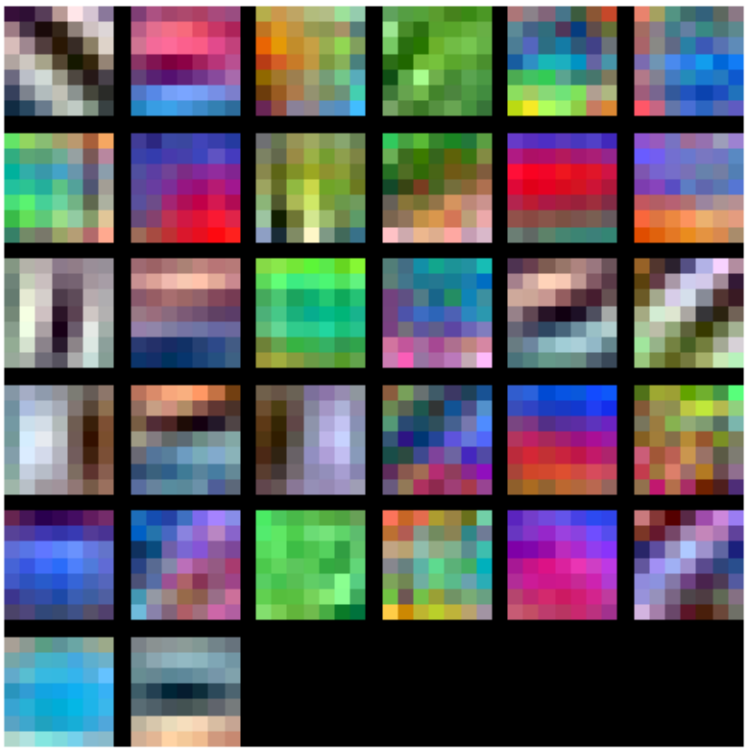
[22]:
```python
# Print final validation accuracy.
print(
    "Full data validation accuracy:",
    solver.check_accuracy(data['X_val'], data['y_val'])
)
```

```
Full data validation accuracy: 0.485
```

8.5 Visualize Filters

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

[23]:
```python
from icv83551.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()
```



9 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 Spatial Batch Normalization: Forward Pass

In the file `icv83551/layers.py`, implement the forward pass for spatial batch normalization in the function `spatial_batchnorm_forward`. Check your implementation by running the following:

[24]:
```
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:  [ 6.18949336e-16  5.99520433e-16 -1.22124533e-16]
  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]
```

[25]:
```
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]
```

11 Spatial Batch Normalization: Backward Pass

In the file `icv83551/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)

#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:  2.786648193872555e-07
dgamma error:  7.0974817113608705e-12
dbeta error:  3.275608725278405e-12
```

12 Spatial Group Normalization

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.

[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.

13 Spatial Group Normalization: Forward Pass

In the file `icv83551/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]
After spatial group normalization:
  shape:  (2, 6, 4, 5)
  means:  [-2.14643118e-16  5.25505565e-16  2.65528340e-16 -3.38618023e-16]
  stds:  [0.99999963 0.99999948 0.99999973 0.99999968]
```

14 Spatial Group Normalization: Backward Pass

In the file `icv83551/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:

[28]:
```
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 and 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))
```

```
dx error:  7.413109365088547e-08
dgamma error:  9.468195772749234e-12
dbeta error:  3.354494437653335e-12
```

[28]:

PyTorch

January 21, 2026

[16]:
```
# This mounts your Google Drive to the Colab VM.
from google.colab import drive
drive.mount('/content/drive')

# TODO: Enter the foldername in your Drive where you have saved the unzipped
# assignment folder, e.g. 'icv83551/assignments/assignment2/'
FOLDERNAME = 'icv83551/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 /content/drive/My\ Drive/$FOLDERNAME/icv83551/datasets/
!bash get_datasets.sh
%cd /content/drive/My\ Drive/$FOLDERNAME
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
/content/drive/My Drive/icv83551/assignments/assignment2/icv83551/datasets
/content/drive/My Drive/icv83551/assignments/assignment2
```

1 Introduction to PyTorch

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.

1.1 Why do we use deep learning frameworks?

- Our code will now run on GPUs! This will allow our models to train much faster. When using a framework like PyTorch 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).
- In 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! PyTorch is an excellent frameworks that will make your lives a lot easier, and now that you understand their guts, you are free to use them :)
- Finally, we want you to be exposed to the sort of deep learning code you might run into in academia or industry.

1.2 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.

1.3 How do I learn PyTorch?

One of our former instructors, Justin Johnson, 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.

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

API	Flexibility	Convenience
`nn.Sequential`	Low	High

3 GPU

You can manually switch to a GPU device on Colab by clicking `Runtime -> Change runtime type` and selecting `GPU` under `Hardware Accelerator`. You should do this before running the following cells to import packages, since the kernel gets restarted upon switching runtimes.

[17]:
```
import torch
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

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)
```

```
using device: cuda
```

4 Part I. Preparation

Now, let's 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.

[18]:
```
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('./icv83551/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('./icv83551/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('./icv83551/datasets', train=False, download=True,
                            transform=transform)
loader_test = DataLoader(cifar10_test, batch_size=64)
```

5 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.

5.0.1 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).

[19]:
```
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()
```

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


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

5.0.2 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.

[20]:
```
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()
```

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

5.0.3 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!

[21]:
```
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.             ␣
↪    #
  ␣
↪################################################################################
    #x = flatten(x)
    x= F.relu(F.conv2d(x, conv_w1, conv_b1,padding=2))
    x =F.relu(F.conv2d(x, conv_w2, conv_b2,padding=1))
    x = flatten(x)
    scores = x.mm(fc_w) + fc_b
  ␣
↪################################################################################
    #                                 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).

[22]:
```
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()
```

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

5.0.4 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

[23]:
```
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))
```

[23]:
```
tensor([[-0.2618, -0.7051,  0.2961,  0.2186, -1.5298],
        [ 0.0281, -1.8424, -2.1079,  0.0190,  1.0839],
        [ 0.3596,  0.1986, -1.3243,  1.2846,  0.7297]], device='cuda:0',
       requires_grad=True)
```

5.0.5 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.

[24]:
```
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))
```

5.0.6 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.

[25]:
```
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()
```

5.0.7 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.

[26]:
```
hidden_layer_size = 4000
learning_rate = 1e-2

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

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

```
Iteration 0, loss = 2.6088
Checking accuracy on the val set
Got 194 / 1000 correct (19.40%)

Iteration 100, loss = 2.0992
Checking accuracy on the val set
Got 347 / 1000 correct (34.70%)

Iteration 200, loss = 2.0662
Checking accuracy on the val set
Got 349 / 1000 correct (34.90%)

Iteration 300, loss = 2.2073
Checking accuracy on the val set
Got 405 / 1000 correct (40.50%)
```

```
Iteration 400, loss = 1.7707
Checking accuracy on the val set
Got 397 / 1000 correct (39.70%)

Iteration 500, loss = 1.5852
Checking accuracy on the val set
Got 434 / 1000 correct (43.40%)

Iteration 600, loss = 1.7638
Checking accuracy on the val set
Got 452 / 1000 correct (45.20%)

Iteration 700, loss = 1.6435
Checking accuracy on the val set
Got 413 / 1000 correct (41.30%)
```

5.0.8 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.

[27]:
```
learning_rate = 3e-3

channel_1 = 32
channel_2 = 16

device = 'cuda' if torch.cuda.is_available() else 'cpu'
conv_w1 = random_weight((channel_1,3, 5,5)).to(device)
conv_b1 = torch.zeros((channel_1 ,)).to(device)
conv_w2 = random_weight((channel_2,channel_1, 3,3)).to(device)
conv_b2 = torch.zeros((channel_2,)).to(device)
fc_w = torch.zeros((channel_2*32*32, 10)).to(device)
fc_b = torch.zeros(10).to(device)

################################################################################
# TODO: Initialize the parameters of a three-layer ConvNet.                    #
```

```
################################################################################

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

params = [conv_w1, conv_b1, conv_w2, conv_b2, fc_w, fc_b]
params = [p.to(device).detach() for p in params]

for p in params:
    p.requires_grad = True
train_part2(three_layer_convnet, params, learning_rate)
```

```
Iteration 0, loss = 2.3026
Checking accuracy on the val set
Got 107 / 1000 correct (10.70%)

Iteration 100, loss = 1.6958
Checking accuracy on the val set
Got 396 / 1000 correct (39.60%)

Iteration 200, loss = 1.4827
Checking accuracy on the val set
Got 437 / 1000 correct (43.70%)

Iteration 300, loss = 1.3729
Checking accuracy on the val set
Got 460 / 1000 correct (46.00%)

Iteration 400, loss = 1.4293
Checking accuracy on the val set
Got 497 / 1000 correct (49.70%)

Iteration 500, loss = 1.1980
Checking accuracy on the val set
Got 499 / 1000 correct (49.90%)

Iteration 600, loss = 1.4925
Checking accuracy on the val set
Got 482 / 1000 correct (48.20%)

Iteration 700, loss = 1.5036
Checking accuracy on the val set
Got 515 / 1000 correct (51.50%)
```

6 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.

6.0.1 Module API: Two-Layer Network

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

[28]:
```
class TwoLayerFC(nn.Module):
    def __init__(self, input_size, hidden_size, num_classes):
        super().__init__()
        # assign layer objects to class attributes
        self.fc1 = nn.Linear(input_size, hidden_size)
        # nn.init package contains convenient initialization methods
        # http://pytorch.org/docs/master/nn.html#torch-nn-init
        nn.init.kaiming_normal_(self.fc1.weight)
        self.fc2 = nn.Linear(hidden_size, num_classes)
        nn.init.kaiming_normal_(self.fc2.weight)

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

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

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

6.0.2 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.

[29]:
```
class ThreeLayerConvNet(nn.Module):
    def __init__(self, in_channel, channel_1, channel_2, num_classes):
        super().__init__()
        self.conv1 = nn.Conv2d(in_channel, channel_1, kernel_size=5, padding=2)
        self.Relu1 = nn.ReLU()
        self.conv2 = nn.Conv2d(channel_1, channel_2, kernel_size=3, padding=1)
        self.Relu2 = nn.ReLU()
        self.fc = nn.Linear(channel_2*32*32, num_classes)
        ########################################################################
        # TODO: Set up the layers you need for a three-layer ConvNet with the  #
        # architecture defined above.                                          #
        ########################################################################

        ########################################################################
        #                           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()                            #
        ########################################################################
        x = self.conv1(x)
        x = self.Relu1(x)
        x = self.conv2(x)
        x = self.Relu2(x)
        x = torch.flatten(x, 1)
        scores = self.fc(x)
        ########################################################################
        #                                END OF YOUR CODE                      #
        ########################################################################
        return scores


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

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

6.0.3 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.

[30]:
```
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))
        return acc
```

6.0.4 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.

[31]:
```
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()
```

6.0.5 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.

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

train_part34(model, optimizer)
```

```
Iteration 0, loss = 3.0620
Checking accuracy on validation set
Got 135 / 1000 correct (13.50)

Iteration 100, loss = 2.2843
Checking accuracy on validation set
Got 291 / 1000 correct (29.10)

Iteration 200, loss = 2.3982
Checking accuracy on validation set
Got 389 / 1000 correct (38.90)

Iteration 300, loss = 1.7339
Checking accuracy on validation set
Got 399 / 1000 correct (39.90)

Iteration 400, loss = 1.8412
Checking accuracy on validation set
Got 444 / 1000 correct (44.40)

Iteration 500, loss = 1.8003
Checking accuracy on validation set
```

```
Got 436 / 1000 correct (43.60)

Iteration 600, loss = 1.5286
Checking accuracy on validation set
Got 432 / 1000 correct (43.20)

Iteration 700, loss = 1.4743
Checking accuracy on validation set
Got 435 / 1000 correct (43.50)
```

6.0.6 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.

[33]:
```
learning_rate = 3e-3
channel_1 = 32
channel_2 = 16

model = None
optimizer = None
################################################################################
# TODO: Instantiate your ThreeLayerConvNet model and a corresponding optimizer #
################################################################################
model = ThreeLayerConvNet(in_channel =3,␣
  ↪channel_1=channel_1,channel_2=channel_2,num_classes=10)
optimizer = optim.SGD(model.parameters(), lr=learning_rate)
################################################################################
#                                 END OF YOUR CODE                             #
################################################################################

train_part34(model, optimizer)
```

```
Iteration 0, loss = 2.2974
Checking accuracy on validation set
Got 111 / 1000 correct (11.10)

Iteration 100, loss = 2.1139
Checking accuracy on validation set
Got 314 / 1000 correct (31.40)

Iteration 200, loss = 1.8557
Checking accuracy on validation set
Got 323 / 1000 correct (32.30)
```

```
Iteration 300, loss = 1.8479
Checking accuracy on validation set
Got 373 / 1000 correct (37.30)

Iteration 400, loss = 1.6830
Checking accuracy on validation set
Got 394 / 1000 correct (39.40)

Iteration 500, loss = 1.7428
Checking accuracy on validation set
Got 400 / 1000 correct (40.00)

Iteration 600, loss = 1.8777
Checking accuracy on validation set
Got 426 / 1000 correct (42.60)

Iteration 700, loss = 1.7689
Checking accuracy on validation set
Got 444 / 1000 correct (44.40)
```

7 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.

7.0.1 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.

[34]:
```
# We need to wrap `flatten` function in a module in order to stack it
# in nn.Sequential
class Flatten(nn.Module):
    def forward(self, x):
        return flatten(x)

hidden_layer_size = 4000
```

```
learning_rate = 1e-2

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

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

train_part34(model, optimizer)
```

```
Iteration 0, loss = 2.2611
Checking accuracy on validation set
Got 145 / 1000 correct (14.50)

Iteration 100, loss = 1.8084
Checking accuracy on validation set
Got 381 / 1000 correct (38.10)

Iteration 200, loss = 1.7253
Checking accuracy on validation set
Got 398 / 1000 correct (39.80)

Iteration 300, loss = 1.6227
Checking accuracy on validation set
Got 430 / 1000 correct (43.00)

Iteration 400, loss = 1.5654
Checking accuracy on validation set
Got 431 / 1000 correct (43.10)

Iteration 500, loss = 1.9176
Checking accuracy on validation set
Got 395 / 1000 correct (39.50)

Iteration 600, loss = 1.6072
Checking accuracy on validation set
Got 432 / 1000 correct (43.20)

Iteration 700, loss = 1.9812
Checking accuracy on validation set
Got 422 / 1000 correct (42.20)
```

7.0.2 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 can use the default PyTorch weight initialization.

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.

[38]:
```
channel_1 = 32
channel_2 = 16
learning_rate = 1e-2

model = nn.Sequential(
    nn.Conv2d(3, channel_1, kernel_size=5, padding=2),
    nn.ReLU(),
    nn.Conv2d(channel_1, channel_2, kernel_size=3, padding=1),
    nn.ReLU(),
    nn.Flatten(),
    nn.Linear(channel_2*32*32, 10)
)
optimizer = optim.SGD(model.parameters(), lr=learning_rate,
                      momentum=0.9, nesterov=True)
################################################################################
# TODO: Rewrite the 2-layer ConvNet with bias from Part III with the           #
# Sequential API.                                                              #
################################################################################

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

train_part34(model, optimizer)
```

```
Iteration 0, loss = 2.3136
Checking accuracy on validation set
Got 141 / 1000 correct (14.10)

Iteration 100, loss = 1.4481
Checking accuracy on validation set
Got 440 / 1000 correct (44.00)
```

```
Iteration 200, loss = 1.4108
Checking accuracy on validation set
Got 499 / 1000 correct (49.90)

Iteration 300, loss = 1.4819
Checking accuracy on validation set
Got 522 / 1000 correct (52.20)

Iteration 400, loss = 1.2802
Checking accuracy on validation set
Got 553 / 1000 correct (55.30)

Iteration 500, loss = 1.1858
Checking accuracy on validation set
Got 572 / 1000 correct (57.20)

Iteration 600, loss = 1.3704
Checking accuracy on validation set
Got 574 / 1000 correct (57.40)

Iteration 700, loss = 1.0234
Checking accuracy on validation set
Got 564 / 1000 correct (56.40)
```

8 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

8.0.1 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.

8.0.2 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.

8.0.3 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

8.0.4 Have fun and happy training!

[39]:
```
################################################################################
# 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.   #
################################################################################
top_acc = 0.0
best_model = None
optimizer = None
models = []
filter_size = 64
model_acc = {}
experiments = [
        {"name": "Adam", "opt": optim.Adam, "lr": 1e-3, "wd": 1e-4},
        {"name": "RMSprop",       "opt": optim.RMSprop, "lr": 1e-3, "wd": 1e-4},
        {"name": "SGD_momentum",  "opt": optim.SGD, "lr": 1e-2, "wd": 1e-4}
    ]
for n in [3, 4, 5]:
  for m in [2, 3]:
    for experiment in experiments:
      model1 = nn.Sequential(
          *[nn.Sequential(
              nn.Conv2d(3 if i == 0 else filter_size, filter_size, 3,␣
 ↪padding=1),
              nn.BatchNorm2d(filter_size),
              nn.ReLU(),
              nn.MaxPool2d(2)
          ) for i in range(n)],
          nn.AdaptiveAvgPool2d(1),
          nn.Flatten(),
          *[nn.Sequential(
              nn.Linear(filter_size if i == 0 else 128, 128),
              nn.BatchNorm1d(128),
              nn.ReLU()
          ) for i in range(m)],
          nn.Linear(128, 10))
      model2 = nn.Sequential(
          *[nn.Sequential(
              nn.Conv2d(3 if i == 0 else filter_size, filter_size, 3,␣
 ↪padding=1),
```

```
            nn.ReLU(),
            nn.Conv2d(filter_size, filter_size, 3, padding=1),
            nn.BatchNorm2d(filter_size),
            nn.ReLU(),
            nn.MaxPool2d(2)
        ) for i in range(n)],
        nn.AdaptiveAvgPool2d(1),
        nn.Flatten(),
        *[nn.Sequential(nn.Linear(filter_size if i == 0 else 128, 128), nn.
↪BatchNorm1d(128), nn.ReLU()) for i in range(m)],
        nn.Linear(128, 10)
    )
    model3 = nn.Sequential(
        nn.Conv2d(3, filter_size, 3, padding=1),
        *[nn.Sequential(
            nn.BatchNorm2d(filter_size),
            nn.ReLU(),
            nn.Conv2d(filter_size, filter_size, 3, padding=1)
        ) for _ in range(n)],
        nn.AdaptiveAvgPool2d(1),
        nn.Flatten(),
        *[nn.Sequential(nn.Linear(filter_size if i == 0 else 128, 128), nn.
↪BatchNorm1d(128), nn.ReLU()) for i in range(m)],
        nn.Linear(128, 10)
    )
    models = [model1, model2, model3]
    for model,indx in zip(models, range(1,4)):
      model = model.to(device)
      optimizer = experiment["opt"](model.parameters(), lr=experiment["lr"],␣
↪weight_decay=experiment["wd"])
      train_part34(model, optimizer, epochs=10)
      acc = check_accuracy_part34(loader_val, model)
      model_acc[acc] = {
          "n": n,
          "m": m,
          "opt": experiment["opt"],
          "lr": experiment["lr"],
          "wd": experiment["wd"],
          "type": indx,
      }
      if acc> top_acc:
        top_acc = acc
        best_model = model
        print(f"--- NEW BEST ACCURACY: {top_acc:.2f}% ---")
top_acc_final3=0.0
sorted_r = sorted(model_acc.items(), key=lambda x: x[0], reverse=True)
top_3 = sorted_r[:3]
```

```
for acc, mode in top_3:
  if mode["type"] == 1:
    model = nn.Sequential(
            *[nn.Sequential(
                nn.Conv2d(3 if i == 0 else filter_size, filter_size, 3,␣
 ↪padding=1),
                nn.BatchNorm2d(filter_size),
                nn.ReLU(),
                nn.MaxPool2d(2)
            ) for i in range(mode["n"])],
            nn.AdaptiveAvgPool2d(1),
            nn.Flatten(),
            *[nn.Sequential(
                nn.Linear(filter_size if i == 0 else 128, 128),
                nn.BatchNorm1d(128),
                nn.ReLU()
            ) for i in range(mode["m"])],
            nn.Linear(128, 10))
  if mode["type"] == 2:
    model = nn.Sequential(
        *[nn.Sequential(
            nn.Conv2d(3 if i == 0 else filter_size, filter_size, 3, padding=1),
            nn.ReLU(),
            nn.Conv2d(filter_size, filter_size, 3, padding=1),
            nn.BatchNorm2d(filter_size),
            nn.ReLU(),
            nn.MaxPool2d(2)
        ) for i in range(mode["n"])],
        nn.AdaptiveAvgPool2d(1),
        nn.Flatten(),
        *[nn.Sequential(nn.Linear(filter_size if i == 0 else 128, 128), nn.
 ↪BatchNorm1d(128), nn.ReLU()) for i in range(mode["m"])],
        nn.Linear(128, 10)
    )
  if mode["type"] == 3:
    model = nn.Sequential(
        nn.Conv2d(3, filter_size, 3, padding=1),
        *[nn.Sequential(
            nn.BatchNorm2d(filter_size),
            nn.ReLU(),
            nn.Conv2d(filter_size, filter_size, 3, padding=1)
        ) for _ in range(mode["n"])],
        nn.AdaptiveAvgPool2d(1),
        nn.Flatten(),
        *[nn.Sequential(nn.Linear(filter_size if i == 0 else 128, 128), nn.
 ↪BatchNorm1d(128), nn.ReLU()) for i in range(mode["m"])],
        nn.Linear(128, 10)
```

```
    )
  optimizer =mode["opt"](model.parameters(), lr=mode["lr"],␣
 ↪weight_decay=mode["wd"])
  train_part34(model, optimizer, epochs=10)
  acc = check_accuracy_part34(loader_val, model)
  if acc >= 0.7 and acc >= top_acc_final3:
    top_acc_final3 = acc
    best_model = model
    print(f"you did it Noam, the accuracy is: {acc}")
model = best_model
################################################################################
#                                END OF YOUR CODE                              #
################################################################################

# You should get at least 70% accuracy
```

```
Streaming output truncated to the last 5000 lines.
Got 624 / 1000 correct (62.40)

Iteration 700, loss = 0.8091
Checking accuracy on validation set
Got 626 / 1000 correct (62.60)

Iteration 0, loss = 1.3780
Checking accuracy on validation set
Got 631 / 1000 correct (63.10)

Iteration 100, loss = 0.7460
Checking accuracy on validation set
Got 697 / 1000 correct (69.70)

Iteration 200, loss = 0.6674
Checking accuracy on validation set
Got 616 / 1000 correct (61.60)

Iteration 300, loss = 0.6845
Checking accuracy on validation set
Got 518 / 1000 correct (51.80)

Iteration 400, loss = 0.7441
Checking accuracy on validation set
Got 665 / 1000 correct (66.50)

Iteration 500, loss = 0.7830
Checking accuracy on validation set
Got 549 / 1000 correct (54.90)
```

```
Iteration 600, loss = 0.6592
Checking accuracy on validation set
Got 707 / 1000 correct (70.70)

Iteration 700, loss = 0.5016
Checking accuracy on validation set
Got 643 / 1000 correct (64.30)

Iteration 0, loss = 0.8472
Checking accuracy on validation set
Got 647 / 1000 correct (64.70)

Iteration 100, loss = 0.7251
Checking accuracy on validation set
Got 664 / 1000 correct (66.40)

Iteration 200, loss = 0.5995
Checking accuracy on validation set
Got 697 / 1000 correct (69.70)

Iteration 300, loss = 0.6653
Checking accuracy on validation set
Got 692 / 1000 correct (69.20)

Iteration 400, loss = 0.6043
Checking accuracy on validation set
Got 694 / 1000 correct (69.40)

Iteration 500, loss = 0.6204
Checking accuracy on validation set
Got 719 / 1000 correct (71.90)

Iteration 600, loss = 0.9274
Checking accuracy on validation set
Got 701 / 1000 correct (70.10)

Iteration 700, loss = 0.7882
Checking accuracy on validation set
Got 694 / 1000 correct (69.40)

Iteration 0, loss = 0.7047
Checking accuracy on validation set
Got 705 / 1000 correct (70.50)

Iteration 100, loss = 0.7382
Checking accuracy on validation set
Got 624 / 1000 correct (62.40)
```

```
Iteration 200, loss = 0.6833
Checking accuracy on validation set
Got 717 / 1000 correct (71.70)

Iteration 300, loss = 0.6806
Checking accuracy on validation set
Got 703 / 1000 correct (70.30)

Iteration 400, loss = 0.6256
Checking accuracy on validation set
Got 691 / 1000 correct (69.10)

Iteration 500, loss = 0.6992
Checking accuracy on validation set
Got 683 / 1000 correct (68.30)

Iteration 600, loss = 0.5713
Checking accuracy on validation set
Got 590 / 1000 correct (59.00)

Iteration 700, loss = 0.6245
Checking accuracy on validation set
Got 696 / 1000 correct (69.60)

Iteration 0, loss = 0.8037
Checking accuracy on validation set
Got 734 / 1000 correct (73.40)

Iteration 100, loss = 0.5251
Checking accuracy on validation set
Got 707 / 1000 correct (70.70)

Iteration 200, loss = 0.8234
Checking accuracy on validation set
Got 641 / 1000 correct (64.10)

Iteration 300, loss = 0.5946
Checking accuracy on validation set
Got 629 / 1000 correct (62.90)

Iteration 400, loss = 0.7263
Checking accuracy on validation set
Got 726 / 1000 correct (72.60)

Iteration 500, loss = 0.5655
Checking accuracy on validation set
Got 732 / 1000 correct (73.20)
```

```
Iteration 600, loss = 0.6083
Checking accuracy on validation set
Got 759 / 1000 correct (75.90)

Iteration 700, loss = 0.4143
Checking accuracy on validation set
Got 723 / 1000 correct (72.30)

Iteration 0, loss = 0.3991
Checking accuracy on validation set
Got 684 / 1000 correct (68.40)

Iteration 100, loss = 0.5800
Checking accuracy on validation set
Got 719 / 1000 correct (71.90)

Iteration 200, loss = 0.5876
Checking accuracy on validation set
Got 734 / 1000 correct (73.40)

Iteration 300, loss = 0.9189
Checking accuracy on validation set
Got 737 / 1000 correct (73.70)

Iteration 400, loss = 0.5250
Checking accuracy on validation set
Got 689 / 1000 correct (68.90)

Iteration 500, loss = 0.4335
Checking accuracy on validation set
Got 740 / 1000 correct (74.00)

Iteration 600, loss = 0.3854
Checking accuracy on validation set
Got 685 / 1000 correct (68.50)

Iteration 700, loss = 0.4554
Checking accuracy on validation set
Got 752 / 1000 correct (75.20)

Checking accuracy on validation set
Got 700 / 1000 correct (70.00)
Iteration 0, loss = 2.4518
Checking accuracy on validation set
Got 102 / 1000 correct (10.20)

Iteration 100, loss = 1.7874
Checking accuracy on validation set
```

```
Got 414 / 1000 correct (41.40)

Iteration 200, loss = 1.4211
Checking accuracy on validation set
Got 488 / 1000 correct (48.80)

Iteration 300, loss = 1.4563
Checking accuracy on validation set
Got 508 / 1000 correct (50.80)

Iteration 400, loss = 1.2928
Checking accuracy on validation set
Got 541 / 1000 correct (54.10)

Iteration 500, loss = 1.3326
Checking accuracy on validation set
Got 565 / 1000 correct (56.50)

Iteration 600, loss = 1.1842
Checking accuracy on validation set
Got 595 / 1000 correct (59.50)

Iteration 700, loss = 1.2220
Checking accuracy on validation set
Got 571 / 1000 correct (57.10)

Iteration 0, loss = 1.1364
Checking accuracy on validation set
Got 600 / 1000 correct (60.00)

Iteration 100, loss = 1.0316
Checking accuracy on validation set
Got 638 / 1000 correct (63.80)

Iteration 200, loss = 1.1403
Checking accuracy on validation set
Got 612 / 1000 correct (61.20)

Iteration 300, loss = 1.2177
Checking accuracy on validation set
Got 640 / 1000 correct (64.00)

Iteration 400, loss = 0.8691
Checking accuracy on validation set
Got 662 / 1000 correct (66.20)

Iteration 500, loss = 0.9020
Checking accuracy on validation set
```

```
Got 672 / 1000 correct (67.20)

Iteration 600, loss = 0.8761
Checking accuracy on validation set
Got 681 / 1000 correct (68.10)

Iteration 700, loss = 1.0979
Checking accuracy on validation set
Got 679 / 1000 correct (67.90)

Iteration 0, loss = 1.0163
Checking accuracy on validation set
Got 646 / 1000 correct (64.60)

Iteration 100, loss = 0.8779
Checking accuracy on validation set
Got 683 / 1000 correct (68.30)

Iteration 200, loss = 0.8258
Checking accuracy on validation set
Got 686 / 1000 correct (68.60)

Iteration 300, loss = 0.7784
Checking accuracy on validation set
Got 661 / 1000 correct (66.10)

Iteration 400, loss = 0.9462
Checking accuracy on validation set
Got 687 / 1000 correct (68.70)

Iteration 500, loss = 0.6685
Checking accuracy on validation set
Got 643 / 1000 correct (64.30)

Iteration 600, loss = 0.6342
Checking accuracy on validation set
Got 686 / 1000 correct (68.60)

Iteration 700, loss = 0.8442
Checking accuracy on validation set
Got 697 / 1000 correct (69.70)

Iteration 0, loss = 0.7584
Checking accuracy on validation set
Got 675 / 1000 correct (67.50)

Iteration 100, loss = 0.6500
Checking accuracy on validation set
```

```
Got 682 / 1000 correct (68.20)

Iteration 200, loss = 0.9458
Checking accuracy on validation set
Got 697 / 1000 correct (69.70)

Iteration 300, loss = 0.7045
Checking accuracy on validation set
Got 723 / 1000 correct (72.30)

Iteration 400, loss = 0.9822
Checking accuracy on validation set
Got 715 / 1000 correct (71.50)

Iteration 500, loss = 0.7520
Checking accuracy on validation set
Got 687 / 1000 correct (68.70)

Iteration 600, loss = 0.8207
Checking accuracy on validation set
Got 699 / 1000 correct (69.90)

Iteration 700, loss = 0.6969
Checking accuracy on validation set
Got 707 / 1000 correct (70.70)

Iteration 0, loss = 0.7626
Checking accuracy on validation set
Got 660 / 1000 correct (66.00)

Iteration 100, loss = 0.7040
Checking accuracy on validation set
Got 691 / 1000 correct (69.10)

Iteration 200, loss = 0.6459
Checking accuracy on validation set
Got 681 / 1000 correct (68.10)

Iteration 300, loss = 0.4182
Checking accuracy on validation set
Got 710 / 1000 correct (71.00)

Iteration 400, loss = 0.7798
Checking accuracy on validation set
Got 711 / 1000 correct (71.10)

Iteration 500, loss = 0.5916
Checking accuracy on validation set
```

```
Got 701 / 1000 correct (70.10)

Iteration 600, loss = 0.6563
Checking accuracy on validation set
Got 752 / 1000 correct (75.20)

Iteration 700, loss = 0.5764
Checking accuracy on validation set
Got 747 / 1000 correct (74.70)

Iteration 0, loss = 0.7577
Checking accuracy on validation set
Got 724 / 1000 correct (72.40)

Iteration 100, loss = 0.5241
Checking accuracy on validation set
Got 713 / 1000 correct (71.30)

Iteration 200, loss = 0.6670
Checking accuracy on validation set
Got 699 / 1000 correct (69.90)

Iteration 300, loss = 0.4454
Checking accuracy on validation set
Got 727 / 1000 correct (72.70)

Iteration 400, loss = 0.6398
Checking accuracy on validation set
Got 737 / 1000 correct (73.70)

Iteration 500, loss = 0.6312
Checking accuracy on validation set
Got 710 / 1000 correct (71.00)

Iteration 600, loss = 0.5900
Checking accuracy on validation set
Got 740 / 1000 correct (74.00)

Iteration 700, loss = 0.8503
Checking accuracy on validation set
Got 707 / 1000 correct (70.70)

Iteration 0, loss = 0.8190
Checking accuracy on validation set
Got 713 / 1000 correct (71.30)

Iteration 100, loss = 0.8354
Checking accuracy on validation set
```

```
Got 728 / 1000 correct (72.80)

Iteration 200, loss = 0.4341
Checking accuracy on validation set
Got 715 / 1000 correct (71.50)

Iteration 300, loss = 0.4341
Checking accuracy on validation set
Got 734 / 1000 correct (73.40)

Iteration 400, loss = 0.4675
Checking accuracy on validation set
Got 708 / 1000 correct (70.80)

Iteration 500, loss = 0.4875
Checking accuracy on validation set
Got 742 / 1000 correct (74.20)

Iteration 600, loss = 0.5365
Checking accuracy on validation set
Got 729 / 1000 correct (72.90)

Iteration 700, loss = 0.6749
Checking accuracy on validation set
Got 726 / 1000 correct (72.60)

Iteration 0, loss = 0.4765
Checking accuracy on validation set
Got 721 / 1000 correct (72.10)

Iteration 100, loss = 0.4325
Checking accuracy on validation set
Got 748 / 1000 correct (74.80)

Iteration 200, loss = 0.5451
Checking accuracy on validation set
Got 731 / 1000 correct (73.10)

Iteration 300, loss = 0.4950
Checking accuracy on validation set
Got 739 / 1000 correct (73.90)

Iteration 400, loss = 0.6748
Checking accuracy on validation set
Got 723 / 1000 correct (72.30)

Iteration 500, loss = 0.6324
Checking accuracy on validation set
```

```
Got 728 / 1000 correct (72.80)

Iteration 600, loss = 0.5863
Checking accuracy on validation set
Got 732 / 1000 correct (73.20)

Iteration 700, loss = 0.4528
Checking accuracy on validation set
Got 700 / 1000 correct (70.00)

Iteration 0, loss = 0.5565
Checking accuracy on validation set
Got 701 / 1000 correct (70.10)

Iteration 100, loss = 0.3469
Checking accuracy on validation set
Got 750 / 1000 correct (75.00)

Iteration 200, loss = 0.3881
Checking accuracy on validation set
Got 748 / 1000 correct (74.80)

Iteration 300, loss = 0.6235
Checking accuracy on validation set
Got 728 / 1000 correct (72.80)

Iteration 400, loss = 0.3642
Checking accuracy on validation set
Got 726 / 1000 correct (72.60)

Iteration 500, loss = 0.6159
Checking accuracy on validation set
Got 742 / 1000 correct (74.20)

Iteration 600, loss = 0.4238
Checking accuracy on validation set
Got 734 / 1000 correct (73.40)

Iteration 700, loss = 0.4318
Checking accuracy on validation set
Got 747 / 1000 correct (74.70)

Iteration 0, loss = 0.5988
Checking accuracy on validation set
Got 726 / 1000 correct (72.60)

Iteration 100, loss = 0.3319
Checking accuracy on validation set
```

```
Got 741 / 1000 correct (74.10)

Iteration 200, loss = 0.3620
Checking accuracy on validation set
Got 749 / 1000 correct (74.90)

Iteration 300, loss = 0.5602
Checking accuracy on validation set
Got 734 / 1000 correct (73.40)

Iteration 400, loss = 0.4111
Checking accuracy on validation set
Got 762 / 1000 correct (76.20)

Iteration 500, loss = 0.5683
Checking accuracy on validation set
Got 762 / 1000 correct (76.20)

Iteration 600, loss = 0.4440
Checking accuracy on validation set
Got 726 / 1000 correct (72.60)

Iteration 700, loss = 0.5605
Checking accuracy on validation set
Got 709 / 1000 correct (70.90)

Checking accuracy on validation set
Got 733 / 1000 correct (73.30)
Iteration 0, loss = 2.2726
Checking accuracy on validation set
Got 119 / 1000 correct (11.90)

Iteration 100, loss = 1.6862
Checking accuracy on validation set
Got 389 / 1000 correct (38.90)

Iteration 200, loss = 1.6236
Checking accuracy on validation set
Got 414 / 1000 correct (41.40)

Iteration 300, loss = 1.3233
Checking accuracy on validation set
Got 450 / 1000 correct (45.00)

Iteration 400, loss = 1.3443
Checking accuracy on validation set
Got 402 / 1000 correct (40.20)
```

```
Iteration 500, loss = 1.2475
Checking accuracy on validation set
Got 505 / 1000 correct (50.50)

Iteration 600, loss = 1.2625
Checking accuracy on validation set
Got 543 / 1000 correct (54.30)

Iteration 700, loss = 1.0810
Checking accuracy on validation set
Got 529 / 1000 correct (52.90)

Iteration 0, loss = 1.2554
Checking accuracy on validation set
Got 527 / 1000 correct (52.70)

Iteration 100, loss = 1.1616
Checking accuracy on validation set
Got 529 / 1000 correct (52.90)

Iteration 200, loss = 0.9514
Checking accuracy on validation set
Got 616 / 1000 correct (61.60)

Iteration 300, loss = 0.7863
Checking accuracy on validation set
Got 558 / 1000 correct (55.80)

Iteration 400, loss = 0.8891
Checking accuracy on validation set
Got 597 / 1000 correct (59.70)

Iteration 500, loss = 0.9796
Checking accuracy on validation set
Got 603 / 1000 correct (60.30)

Iteration 600, loss = 0.8911
Checking accuracy on validation set
Got 675 / 1000 correct (67.50)

Iteration 700, loss = 0.9330
Checking accuracy on validation set
Got 596 / 1000 correct (59.60)

Iteration 0, loss = 1.0095
Checking accuracy on validation set
Got 555 / 1000 correct (55.50)
```

```
Iteration 100, loss = 0.9035
Checking accuracy on validation set
Got 685 / 1000 correct (68.50)

Iteration 200, loss = 0.8494
Checking accuracy on validation set
Got 668 / 1000 correct (66.80)

Iteration 300, loss = 0.6183
Checking accuracy on validation set
Got 631 / 1000 correct (63.10)

Iteration 400, loss = 0.7296
Checking accuracy on validation set
Got 613 / 1000 correct (61.30)

Iteration 500, loss = 0.8724
Checking accuracy on validation set
Got 653 / 1000 correct (65.30)

Iteration 600, loss = 0.7692
Checking accuracy on validation set
Got 673 / 1000 correct (67.30)

Iteration 700, loss = 0.7695
Checking accuracy on validation set
Got 700 / 1000 correct (70.00)

Iteration 0, loss = 0.8085
Checking accuracy on validation set
Got 722 / 1000 correct (72.20)

Iteration 100, loss = 0.7989
Checking accuracy on validation set
Got 726 / 1000 correct (72.60)

Iteration 200, loss = 0.6001
Checking accuracy on validation set
Got 654 / 1000 correct (65.40)

Iteration 300, loss = 0.5447
Checking accuracy on validation set
Got 725 / 1000 correct (72.50)

Iteration 400, loss = 0.8344
Checking accuracy on validation set
Got 687 / 1000 correct (68.70)
```

```
Iteration 500, loss = 0.7696
Checking accuracy on validation set
Got 692 / 1000 correct (69.20)

Iteration 600, loss = 1.0632
Checking accuracy on validation set
Got 714 / 1000 correct (71.40)

Iteration 700, loss = 0.6424
Checking accuracy on validation set
Got 730 / 1000 correct (73.00)

Iteration 0, loss = 0.5430
Checking accuracy on validation set
Got 697 / 1000 correct (69.70)

Iteration 100, loss = 0.7304
Checking accuracy on validation set
Got 698 / 1000 correct (69.80)

Iteration 200, loss = 0.6776
Checking accuracy on validation set
Got 756 / 1000 correct (75.60)

Iteration 300, loss = 0.7536
Checking accuracy on validation set
Got 738 / 1000 correct (73.80)

Iteration 400, loss = 0.6375
Checking accuracy on validation set
Got 758 / 1000 correct (75.80)

Iteration 500, loss = 0.6038
Checking accuracy on validation set
Got 699 / 1000 correct (69.90)

Iteration 600, loss = 0.5098
Checking accuracy on validation set
Got 683 / 1000 correct (68.30)

Iteration 700, loss = 0.4166
Checking accuracy on validation set
Got 714 / 1000 correct (71.40)

Iteration 0, loss = 0.5165
Checking accuracy on validation set
Got 711 / 1000 correct (71.10)
```

```
Iteration 100, loss = 0.6064
Checking accuracy on validation set
Got 709 / 1000 correct (70.90)

Iteration 200, loss = 0.6445
Checking accuracy on validation set
Got 685 / 1000 correct (68.50)

Iteration 300, loss = 0.4284
Checking accuracy on validation set
Got 706 / 1000 correct (70.60)

Iteration 400, loss = 0.4650
Checking accuracy on validation set
Got 706 / 1000 correct (70.60)

Iteration 500, loss = 0.4697
Checking accuracy on validation set
Got 722 / 1000 correct (72.20)

Iteration 600, loss = 0.5502
Checking accuracy on validation set
Got 736 / 1000 correct (73.60)

Iteration 700, loss = 0.5299
Checking accuracy on validation set
Got 758 / 1000 correct (75.80)

Iteration 0, loss = 0.4897
Checking accuracy on validation set
Got 753 / 1000 correct (75.30)

Iteration 100, loss = 0.5282
Checking accuracy on validation set
Got 748 / 1000 correct (74.80)

Iteration 200, loss = 0.4998
Checking accuracy on validation set
Got 752 / 1000 correct (75.20)

Iteration 300, loss = 0.4163
Checking accuracy on validation set
Got 744 / 1000 correct (74.40)

Iteration 400, loss = 0.4933
Checking accuracy on validation set
Got 720 / 1000 correct (72.00)
```

```
Iteration 500, loss = 0.4203
Checking accuracy on validation set
Got 709 / 1000 correct (70.90)

Iteration 600, loss = 0.6470
Checking accuracy on validation set
Got 711 / 1000 correct (71.10)

Iteration 700, loss = 0.6343
Checking accuracy on validation set
Got 745 / 1000 correct (74.50)

Iteration 0, loss = 0.4075
Checking accuracy on validation set
Got 758 / 1000 correct (75.80)

Iteration 100, loss = 0.3910
Checking accuracy on validation set
Got 743 / 1000 correct (74.30)

Iteration 200, loss = 0.4070
Checking accuracy on validation set
Got 788 / 1000 correct (78.80)

Iteration 300, loss = 0.4304
Checking accuracy on validation set
Got 780 / 1000 correct (78.00)

Iteration 400, loss = 0.5913
Checking accuracy on validation set
Got 712 / 1000 correct (71.20)

Iteration 500, loss = 0.3516
Checking accuracy on validation set
Got 724 / 1000 correct (72.40)

Iteration 600, loss = 0.5252
Checking accuracy on validation set
Got 765 / 1000 correct (76.50)

Iteration 700, loss = 0.4638
Checking accuracy on validation set
Got 777 / 1000 correct (77.70)

Iteration 0, loss = 0.4937
Checking accuracy on validation set
Got 759 / 1000 correct (75.90)
```

```
Iteration 100, loss = 0.4080
Checking accuracy on validation set
Got 742 / 1000 correct (74.20)

Iteration 200, loss = 0.6037
Checking accuracy on validation set
Got 751 / 1000 correct (75.10)

Iteration 300, loss = 0.6036
Checking accuracy on validation set
Got 762 / 1000 correct (76.20)

Iteration 400, loss = 0.4926
Checking accuracy on validation set
Got 761 / 1000 correct (76.10)

Iteration 500, loss = 0.3887
Checking accuracy on validation set
Got 672 / 1000 correct (67.20)

Iteration 600, loss = 0.4217
Checking accuracy on validation set
Got 749 / 1000 correct (74.90)

Iteration 700, loss = 0.2723
Checking accuracy on validation set
Got 784 / 1000 correct (78.40)

Iteration 0, loss = 0.4493
Checking accuracy on validation set
Got 737 / 1000 correct (73.70)

Iteration 100, loss = 0.3037
Checking accuracy on validation set
Got 761 / 1000 correct (76.10)

Iteration 200, loss = 0.4885
Checking accuracy on validation set
Got 697 / 1000 correct (69.70)

Iteration 300, loss = 0.5007
Checking accuracy on validation set
Got 794 / 1000 correct (79.40)

Iteration 400, loss = 0.3235
Checking accuracy on validation set
Got 795 / 1000 correct (79.50)
```

```
Iteration 500, loss = 0.5169
Checking accuracy on validation set
Got 755 / 1000 correct (75.50)

Iteration 600, loss = 0.4727
Checking accuracy on validation set
Got 813 / 1000 correct (81.30)

Iteration 700, loss = 0.5485
Checking accuracy on validation set
Got 737 / 1000 correct (73.70)

Checking accuracy on validation set
Got 772 / 1000 correct (77.20)
Iteration 0, loss = 2.3743
Checking accuracy on validation set
Got 79 / 1000 correct (7.90)

Iteration 100, loss = 1.8389
Checking accuracy on validation set
Got 345 / 1000 correct (34.50)

Iteration 200, loss = 1.5912
Checking accuracy on validation set
Got 442 / 1000 correct (44.20)

Iteration 300, loss = 1.5009
Checking accuracy on validation set
Got 386 / 1000 correct (38.60)

Iteration 400, loss = 1.4033
Checking accuracy on validation set
Got 458 / 1000 correct (45.80)

Iteration 500, loss = 1.4114
Checking accuracy on validation set
Got 423 / 1000 correct (42.30)

Iteration 600, loss = 1.3464
Checking accuracy on validation set
Got 282 / 1000 correct (28.20)

Iteration 700, loss = 1.2145
Checking accuracy on validation set
Got 473 / 1000 correct (47.30)

Iteration 0, loss = 1.2752
Checking accuracy on validation set
```

```
Got 432 / 1000 correct (43.20)

Iteration 100, loss = 1.1689
Checking accuracy on validation set
Got 421 / 1000 correct (42.10)

Iteration 200, loss = 1.1000
Checking accuracy on validation set
Got 473 / 1000 correct (47.30)

Iteration 300, loss = 1.1167
Checking accuracy on validation set
Got 502 / 1000 correct (50.20)

Iteration 400, loss = 1.1464
Checking accuracy on validation set
Got 521 / 1000 correct (52.10)

Iteration 500, loss = 1.1698
Checking accuracy on validation set
Got 490 / 1000 correct (49.00)

Iteration 600, loss = 1.1023
Checking accuracy on validation set
Got 574 / 1000 correct (57.40)

Iteration 700, loss = 1.0884
Checking accuracy on validation set
Got 521 / 1000 correct (52.10)

Iteration 0, loss = 1.0588
Checking accuracy on validation set
Got 300 / 1000 correct (30.00)

Iteration 100, loss = 1.0965
Checking accuracy on validation set
Got 559 / 1000 correct (55.90)

Iteration 200, loss = 0.7822
Checking accuracy on validation set
Got 471 / 1000 correct (47.10)

Iteration 300, loss = 1.1415
Checking accuracy on validation set
Got 404 / 1000 correct (40.40)

Iteration 400, loss = 1.0315
Checking accuracy on validation set
```

```
Got 535 / 1000 correct (53.50)

Iteration 500, loss = 0.8751
Checking accuracy on validation set
Got 498 / 1000 correct (49.80)

Iteration 600, loss = 0.8084
Checking accuracy on validation set
Got 596 / 1000 correct (59.60)

Iteration 700, loss = 1.0740
Checking accuracy on validation set
Got 526 / 1000 correct (52.60)

Iteration 0, loss = 1.1433
Checking accuracy on validation set
Got 524 / 1000 correct (52.40)

Iteration 100, loss = 0.7856
Checking accuracy on validation set
Got 585 / 1000 correct (58.50)

Iteration 200, loss = 0.8392
Checking accuracy on validation set
Got 584 / 1000 correct (58.40)

Iteration 300, loss = 0.9889
Checking accuracy on validation set
Got 537 / 1000 correct (53.70)

Iteration 400, loss = 0.8927
Checking accuracy on validation set
Got 654 / 1000 correct (65.40)

Iteration 500, loss = 0.8711
Checking accuracy on validation set
Got 480 / 1000 correct (48.00)

Iteration 600, loss = 1.1309
Checking accuracy on validation set
Got 488 / 1000 correct (48.80)

Iteration 700, loss = 0.9413
Checking accuracy on validation set
Got 524 / 1000 correct (52.40)

Iteration 0, loss = 0.9740
Checking accuracy on validation set
```

```
Got 590 / 1000 correct (59.00)

Iteration 100, loss = 0.9187
Checking accuracy on validation set
Got 652 / 1000 correct (65.20)

Iteration 200, loss = 0.8521
Checking accuracy on validation set
Got 510 / 1000 correct (51.00)

Iteration 300, loss = 0.8083
Checking accuracy on validation set
Got 413 / 1000 correct (41.30)

Iteration 400, loss = 0.9560
Checking accuracy on validation set
Got 470 / 1000 correct (47.00)

Iteration 500, loss = 0.7709
Checking accuracy on validation set
Got 496 / 1000 correct (49.60)

Iteration 600, loss = 0.5789
Checking accuracy on validation set
Got 482 / 1000 correct (48.20)

Iteration 700, loss = 0.7596
Checking accuracy on validation set
Got 522 / 1000 correct (52.20)

Iteration 0, loss = 0.8228
Checking accuracy on validation set
Got 652 / 1000 correct (65.20)

Iteration 100, loss = 0.8332
Checking accuracy on validation set
Got 622 / 1000 correct (62.20)

Iteration 200, loss = 0.9157
Checking accuracy on validation set
Got 685 / 1000 correct (68.50)

Iteration 300, loss = 0.7470
Checking accuracy on validation set
Got 675 / 1000 correct (67.50)

Iteration 400, loss = 0.5895
Checking accuracy on validation set
```

```
Got 642 / 1000 correct (64.20)

Iteration 500, loss = 0.6836
Checking accuracy on validation set
Got 611 / 1000 correct (61.10)

Iteration 600, loss = 0.6866
Checking accuracy on validation set
Got 675 / 1000 correct (67.50)

Iteration 700, loss = 0.9933
Checking accuracy on validation set
Got 535 / 1000 correct (53.50)

Iteration 0, loss = 0.7893
Checking accuracy on validation set
Got 540 / 1000 correct (54.00)

Iteration 100, loss = 0.8066
Checking accuracy on validation set
Got 456 / 1000 correct (45.60)

Iteration 200, loss = 0.8367
Checking accuracy on validation set
Got 548 / 1000 correct (54.80)

Iteration 300, loss = 1.1102
Checking accuracy on validation set
Got 456 / 1000 correct (45.60)

Iteration 400, loss = 0.7984
Checking accuracy on validation set
Got 659 / 1000 correct (65.90)

Iteration 500, loss = 0.6118
Checking accuracy on validation set
Got 616 / 1000 correct (61.60)

Iteration 600, loss = 0.6750
Checking accuracy on validation set
Got 675 / 1000 correct (67.50)

Iteration 700, loss = 0.7984
Checking accuracy on validation set
Got 648 / 1000 correct (64.80)

Iteration 0, loss = 1.1270
Checking accuracy on validation set
```

```
Got 532 / 1000 correct (53.20)

Iteration 100, loss = 0.6973
Checking accuracy on validation set
Got 589 / 1000 correct (58.90)

Iteration 200, loss = 0.4330
Checking accuracy on validation set
Got 658 / 1000 correct (65.80)

Iteration 300, loss = 0.7126
Checking accuracy on validation set
Got 671 / 1000 correct (67.10)

Iteration 400, loss = 0.6559
Checking accuracy on validation set
Got 624 / 1000 correct (62.40)

Iteration 500, loss = 0.8999
Checking accuracy on validation set
Got 635 / 1000 correct (63.50)

Iteration 600, loss = 0.8190
Checking accuracy on validation set
Got 667 / 1000 correct (66.70)

Iteration 700, loss = 0.5299
Checking accuracy on validation set
Got 725 / 1000 correct (72.50)

Iteration 0, loss = 0.5305
Checking accuracy on validation set
Got 620 / 1000 correct (62.00)

Iteration 100, loss = 0.5574
Checking accuracy on validation set
Got 701 / 1000 correct (70.10)

Iteration 200, loss = 0.5759
Checking accuracy on validation set
Got 612 / 1000 correct (61.20)

Iteration 300, loss = 0.6128
Checking accuracy on validation set
Got 517 / 1000 correct (51.70)

Iteration 400, loss = 0.5938
Checking accuracy on validation set
```

```
Got 644 / 1000 correct (64.40)

Iteration 500, loss = 0.6153
Checking accuracy on validation set
Got 431 / 1000 correct (43.10)

Iteration 600, loss = 0.6565
Checking accuracy on validation set
Got 527 / 1000 correct (52.70)

Iteration 700, loss = 0.6013
Checking accuracy on validation set
Got 612 / 1000 correct (61.20)

Iteration 0, loss = 0.5153
Checking accuracy on validation set
Got 578 / 1000 correct (57.80)

Iteration 100, loss = 0.9032
Checking accuracy on validation set
Got 668 / 1000 correct (66.80)

Iteration 200, loss = 0.6499
Checking accuracy on validation set
Got 668 / 1000 correct (66.80)

Iteration 300, loss = 0.6675
Checking accuracy on validation set
Got 634 / 1000 correct (63.40)

Iteration 400, loss = 0.5432
Checking accuracy on validation set
Got 595 / 1000 correct (59.50)

Iteration 500, loss = 0.7574
Checking accuracy on validation set
Got 603 / 1000 correct (60.30)

Iteration 600, loss = 0.6857
Checking accuracy on validation set
Got 676 / 1000 correct (67.60)

Iteration 700, loss = 0.7050
Checking accuracy on validation set
Got 590 / 1000 correct (59.00)

Checking accuracy on validation set
Got 676 / 1000 correct (67.60)
```

```
Iteration 0, loss = 2.2794
Checking accuracy on validation set
Got 78 / 1000 correct (7.80)

Iteration 100, loss = 1.6265
Checking accuracy on validation set
Got 394 / 1000 correct (39.40)

Iteration 200, loss = 1.7030
Checking accuracy on validation set
Got 453 / 1000 correct (45.30)

Iteration 300, loss = 1.3525
Checking accuracy on validation set
Got 548 / 1000 correct (54.80)

Iteration 400, loss = 1.1169
Checking accuracy on validation set
Got 580 / 1000 correct (58.00)

Iteration 500, loss = 0.8600
Checking accuracy on validation set
Got 582 / 1000 correct (58.20)

Iteration 600, loss = 1.0076
Checking accuracy on validation set
Got 653 / 1000 correct (65.30)

Iteration 700, loss = 1.1401
Checking accuracy on validation set
Got 646 / 1000 correct (64.60)

Iteration 0, loss = 0.9443
Checking accuracy on validation set
Got 626 / 1000 correct (62.60)

Iteration 100, loss = 0.9315
Checking accuracy on validation set
Got 652 / 1000 correct (65.20)

Iteration 200, loss = 0.7600
Checking accuracy on validation set
Got 671 / 1000 correct (67.10)

Iteration 300, loss = 0.7684
Checking accuracy on validation set
Got 664 / 1000 correct (66.40)
```

```
Iteration 400, loss = 1.2210
Checking accuracy on validation set
Got 700 / 1000 correct (70.00)

Iteration 500, loss = 0.7224
Checking accuracy on validation set
Got 704 / 1000 correct (70.40)

Iteration 600, loss = 1.0002
Checking accuracy on validation set
Got 681 / 1000 correct (68.10)

Iteration 700, loss = 0.7810
Checking accuracy on validation set
Got 744 / 1000 correct (74.40)

Iteration 0, loss = 0.5592
Checking accuracy on validation set
Got 670 / 1000 correct (67.00)

Iteration 100, loss = 0.8165
Checking accuracy on validation set
Got 719 / 1000 correct (71.90)

Iteration 200, loss = 0.8876
Checking accuracy on validation set
Got 706 / 1000 correct (70.60)

Iteration 300, loss = 0.6107
Checking accuracy on validation set
Got 728 / 1000 correct (72.80)

Iteration 400, loss = 0.9121
Checking accuracy on validation set
Got 721 / 1000 correct (72.10)

Iteration 500, loss = 0.6729
Checking accuracy on validation set
Got 746 / 1000 correct (74.60)

Iteration 600, loss = 0.6713
Checking accuracy on validation set
Got 692 / 1000 correct (69.20)

Iteration 700, loss = 0.6112
Checking accuracy on validation set
Got 754 / 1000 correct (75.40)
```

```
Iteration 0, loss = 0.5519
Checking accuracy on validation set
Got 739 / 1000 correct (73.90)

Iteration 100, loss = 0.4871
Checking accuracy on validation set
Got 724 / 1000 correct (72.40)

Iteration 200, loss = 0.6376
Checking accuracy on validation set
Got 740 / 1000 correct (74.00)

Iteration 300, loss = 0.4940
Checking accuracy on validation set
Got 727 / 1000 correct (72.70)

Iteration 400, loss = 0.5271
Checking accuracy on validation set
Got 731 / 1000 correct (73.10)

Iteration 500, loss = 0.3857
Checking accuracy on validation set
Got 738 / 1000 correct (73.80)

Iteration 600, loss = 0.7622
Checking accuracy on validation set
Got 763 / 1000 correct (76.30)

Iteration 700, loss = 0.4049
Checking accuracy on validation set
Got 754 / 1000 correct (75.40)

Iteration 0, loss = 0.6047
Checking accuracy on validation set
Got 732 / 1000 correct (73.20)

Iteration 100, loss = 0.5683
Checking accuracy on validation set
Got 763 / 1000 correct (76.30)

Iteration 200, loss = 0.4806
Checking accuracy on validation set
Got 747 / 1000 correct (74.70)

Iteration 300, loss = 0.5870
Checking accuracy on validation set
Got 757 / 1000 correct (75.70)
```

```
Iteration 400, loss = 0.7412
Checking accuracy on validation set
Got 761 / 1000 correct (76.10)

Iteration 500, loss = 0.3943
Checking accuracy on validation set
Got 755 / 1000 correct (75.50)

Iteration 600, loss = 0.5895
Checking accuracy on validation set
Got 744 / 1000 correct (74.40)

Iteration 700, loss = 0.6059
Checking accuracy on validation set
Got 732 / 1000 correct (73.20)

Iteration 0, loss = 0.5128
Checking accuracy on validation set
Got 759 / 1000 correct (75.90)

Iteration 100, loss = 0.2587
Checking accuracy on validation set
Got 752 / 1000 correct (75.20)

Iteration 200, loss = 0.4423
Checking accuracy on validation set
Got 734 / 1000 correct (73.40)

Iteration 300, loss = 0.6088
Checking accuracy on validation set
Got 765 / 1000 correct (76.50)

Iteration 400, loss = 0.4178
Checking accuracy on validation set
Got 760 / 1000 correct (76.00)

Iteration 500, loss = 0.7909
Checking accuracy on validation set
Got 762 / 1000 correct (76.20)

Iteration 600, loss = 0.3505
Checking accuracy on validation set
Got 774 / 1000 correct (77.40)

Iteration 700, loss = 0.4300
Checking accuracy on validation set
Got 752 / 1000 correct (75.20)
```

```
Iteration 0, loss = 0.5371
Checking accuracy on validation set
Got 781 / 1000 correct (78.10)

Iteration 100, loss = 0.3897
Checking accuracy on validation set
Got 771 / 1000 correct (77.10)

Iteration 200, loss = 0.3987
Checking accuracy on validation set
Got 744 / 1000 correct (74.40)

Iteration 300, loss = 0.6429
Checking accuracy on validation set
Got 744 / 1000 correct (74.40)

Iteration 400, loss = 0.5353
Checking accuracy on validation set
Got 772 / 1000 correct (77.20)

Iteration 500, loss = 0.2916
Checking accuracy on validation set
Got 741 / 1000 correct (74.10)

Iteration 600, loss = 0.3828
Checking accuracy on validation set
Got 767 / 1000 correct (76.70)

Iteration 700, loss = 0.4712
Checking accuracy on validation set
Got 763 / 1000 correct (76.30)

Iteration 0, loss = 0.3861
Checking accuracy on validation set
Got 786 / 1000 correct (78.60)

Iteration 100, loss = 0.3704
Checking accuracy on validation set
Got 787 / 1000 correct (78.70)

Iteration 200, loss = 0.3738
Checking accuracy on validation set
Got 744 / 1000 correct (74.40)

Iteration 300, loss = 0.5907
Checking accuracy on validation set
Got 762 / 1000 correct (76.20)
```

```
Iteration 400, loss = 0.5044
Checking accuracy on validation set
Got 756 / 1000 correct (75.60)

Iteration 500, loss = 0.3659
Checking accuracy on validation set
Got 772 / 1000 correct (77.20)

Iteration 600, loss = 0.3058
Checking accuracy on validation set
Got 777 / 1000 correct (77.70)

Iteration 700, loss = 0.6992
Checking accuracy on validation set
Got 762 / 1000 correct (76.20)

Iteration 0, loss = 0.7345
Checking accuracy on validation set
Got 769 / 1000 correct (76.90)

Iteration 100, loss = 0.6361
Checking accuracy on validation set
Got 756 / 1000 correct (75.60)

Iteration 200, loss = 0.3954
Checking accuracy on validation set
Got 771 / 1000 correct (77.10)

Iteration 300, loss = 0.3678
Checking accuracy on validation set
Got 771 / 1000 correct (77.10)

Iteration 400, loss = 0.3981
Checking accuracy on validation set
Got 770 / 1000 correct (77.00)

Iteration 500, loss = 0.2697
Checking accuracy on validation set
Got 772 / 1000 correct (77.20)

Iteration 600, loss = 0.6045
Checking accuracy on validation set
Got 760 / 1000 correct (76.00)

Iteration 700, loss = 0.3558
Checking accuracy on validation set
Got 747 / 1000 correct (74.70)
```

```
Iteration 0, loss = 0.2080
Checking accuracy on validation set
Got 777 / 1000 correct (77.70)

Iteration 100, loss = 0.3176
Checking accuracy on validation set
Got 774 / 1000 correct (77.40)

Iteration 200, loss = 0.4917
Checking accuracy on validation set
Got 770 / 1000 correct (77.00)

Iteration 300, loss = 0.3167
Checking accuracy on validation set
Got 746 / 1000 correct (74.60)

Iteration 400, loss = 0.3391
Checking accuracy on validation set
Got 775 / 1000 correct (77.50)

Iteration 500, loss = 0.2123
Checking accuracy on validation set
Got 771 / 1000 correct (77.10)

Iteration 600, loss = 0.3450
Checking accuracy on validation set
Got 769 / 1000 correct (76.90)

Iteration 700, loss = 0.4832
Checking accuracy on validation set
Got 774 / 1000 correct (77.40)

Checking accuracy on validation set
Got 773 / 1000 correct (77.30)
Iteration 0, loss = 2.3736
Checking accuracy on validation set
Got 105 / 1000 correct (10.50)

Iteration 100, loss = 1.4777
Checking accuracy on validation set
Got 323 / 1000 correct (32.30)

Iteration 200, loss = 1.2798
Checking accuracy on validation set
Got 368 / 1000 correct (36.80)

Iteration 300, loss = 1.1820
Checking accuracy on validation set
```

```
Got 387 / 1000 correct (38.70)

Iteration 400, loss = 1.2596
Checking accuracy on validation set
Got 543 / 1000 correct (54.30)

Iteration 500, loss = 1.0908
Checking accuracy on validation set
Got 604 / 1000 correct (60.40)

Iteration 600, loss = 1.0316
Checking accuracy on validation set
Got 457 / 1000 correct (45.70)

Iteration 700, loss = 1.0627
Checking accuracy on validation set
Got 514 / 1000 correct (51.40)

Iteration 0, loss = 1.3904
Checking accuracy on validation set
Got 573 / 1000 correct (57.30)

Iteration 100, loss = 0.9445
Checking accuracy on validation set
Got 501 / 1000 correct (50.10)

Iteration 200, loss = 0.8285
Checking accuracy on validation set
Got 662 / 1000 correct (66.20)

Iteration 300, loss = 1.1204
Checking accuracy on validation set
Got 581 / 1000 correct (58.10)

Iteration 400, loss = 0.6940
Checking accuracy on validation set
Got 647 / 1000 correct (64.70)

Iteration 500, loss = 0.9237
Checking accuracy on validation set
Got 679 / 1000 correct (67.90)

Iteration 600, loss = 1.0642
Checking accuracy on validation set
Got 652 / 1000 correct (65.20)

Iteration 700, loss = 0.8241
Checking accuracy on validation set
```

```
Got 697 / 1000 correct (69.70)

Iteration 0, loss = 0.6917
Checking accuracy on validation set
Got 692 / 1000 correct (69.20)

Iteration 100, loss = 0.8343
Checking accuracy on validation set
Got 737 / 1000 correct (73.70)

Iteration 200, loss = 0.6655
Checking accuracy on validation set
Got 665 / 1000 correct (66.50)

Iteration 300, loss = 0.8808
Checking accuracy on validation set
Got 652 / 1000 correct (65.20)

Iteration 400, loss = 0.6120
Checking accuracy on validation set
Got 740 / 1000 correct (74.00)

Iteration 500, loss = 0.6128
Checking accuracy on validation set
Got 719 / 1000 correct (71.90)

Iteration 600, loss = 0.7157
Checking accuracy on validation set
Got 693 / 1000 correct (69.30)

Iteration 700, loss = 0.7126
Checking accuracy on validation set
Got 665 / 1000 correct (66.50)

Iteration 0, loss = 0.6628
Checking accuracy on validation set
Got 717 / 1000 correct (71.70)

Iteration 100, loss = 0.6806
Checking accuracy on validation set
Got 667 / 1000 correct (66.70)

Iteration 200, loss = 0.5621
Checking accuracy on validation set
Got 676 / 1000 correct (67.60)

Iteration 300, loss = 0.5295
Checking accuracy on validation set
```

```
Got 687 / 1000 correct (68.70)

Iteration 400, loss = 0.6346
Checking accuracy on validation set
Got 772 / 1000 correct (77.20)

Iteration 500, loss = 0.6509
Checking accuracy on validation set
Got 711 / 1000 correct (71.10)

Iteration 600, loss = 0.5751
Checking accuracy on validation set
Got 745 / 1000 correct (74.50)

Iteration 700, loss = 0.6351
Checking accuracy on validation set
Got 734 / 1000 correct (73.40)

Iteration 0, loss = 0.6711
Checking accuracy on validation set
Got 748 / 1000 correct (74.80)

Iteration 100, loss = 0.6721
Checking accuracy on validation set
Got 754 / 1000 correct (75.40)

Iteration 200, loss = 0.5843
Checking accuracy on validation set
Got 742 / 1000 correct (74.20)

Iteration 300, loss = 0.4767
Checking accuracy on validation set
Got 738 / 1000 correct (73.80)

Iteration 400, loss = 0.6478
Checking accuracy on validation set
Got 749 / 1000 correct (74.90)

Iteration 500, loss = 0.4906
Checking accuracy on validation set
Got 776 / 1000 correct (77.60)

Iteration 600, loss = 0.5893
Checking accuracy on validation set
Got 772 / 1000 correct (77.20)

Iteration 700, loss = 0.5736
Checking accuracy on validation set
```

```
Got 756 / 1000 correct (75.60)

Iteration 0, loss = 0.4843
Checking accuracy on validation set
Got 768 / 1000 correct (76.80)

Iteration 100, loss = 0.3850
Checking accuracy on validation set
Got 793 / 1000 correct (79.30)

Iteration 200, loss = 0.4174
Checking accuracy on validation set
Got 766 / 1000 correct (76.60)

Iteration 300, loss = 0.4805
Checking accuracy on validation set
Got 766 / 1000 correct (76.60)

Iteration 400, loss = 0.6927
Checking accuracy on validation set
Got 760 / 1000 correct (76.00)

Iteration 500, loss = 0.4267
Checking accuracy on validation set
Got 723 / 1000 correct (72.30)

Iteration 600, loss = 0.5778
Checking accuracy on validation set
Got 776 / 1000 correct (77.60)

Iteration 700, loss = 0.2558
Checking accuracy on validation set
Got 749 / 1000 correct (74.90)

Iteration 0, loss = 0.4061
Checking accuracy on validation set
Got 779 / 1000 correct (77.90)

Iteration 100, loss = 0.4237
Checking accuracy on validation set
Got 814 / 1000 correct (81.40)

Iteration 200, loss = 0.3609
Checking accuracy on validation set
Got 777 / 1000 correct (77.70)

Iteration 300, loss = 0.6151
Checking accuracy on validation set
```

```
Got 763 / 1000 correct (76.30)

Iteration 400, loss = 0.5114
Checking accuracy on validation set
Got 754 / 1000 correct (75.40)

Iteration 500, loss = 0.5159
Checking accuracy on validation set
Got 786 / 1000 correct (78.60)

Iteration 600, loss = 0.6059
Checking accuracy on validation set
Got 786 / 1000 correct (78.60)

Iteration 700, loss = 0.7083
Checking accuracy on validation set
Got 789 / 1000 correct (78.90)

Iteration 0, loss = 0.3384
Checking accuracy on validation set
Got 800 / 1000 correct (80.00)

Iteration 100, loss = 0.6023
Checking accuracy on validation set
Got 805 / 1000 correct (80.50)

Iteration 200, loss = 0.3602
Checking accuracy on validation set
Got 817 / 1000 correct (81.70)

Iteration 300, loss = 0.4000
Checking accuracy on validation set
Got 786 / 1000 correct (78.60)

Iteration 400, loss = 0.3744
Checking accuracy on validation set
Got 802 / 1000 correct (80.20)

Iteration 500, loss = 0.4620
Checking accuracy on validation set
Got 795 / 1000 correct (79.50)

Iteration 600, loss = 0.2620
Checking accuracy on validation set
Got 801 / 1000 correct (80.10)

Iteration 700, loss = 0.3656
Checking accuracy on validation set
```

```
Got 814 / 1000 correct (81.40)

Iteration 0, loss = 0.2438
Checking accuracy on validation set
Got 822 / 1000 correct (82.20)

Iteration 100, loss = 0.5495
Checking accuracy on validation set
Got 810 / 1000 correct (81.00)

Iteration 200, loss = 0.2987
Checking accuracy on validation set
Got 808 / 1000 correct (80.80)

Iteration 300, loss = 0.3715
Checking accuracy on validation set
Got 797 / 1000 correct (79.70)

Iteration 400, loss = 0.3854
Checking accuracy on validation set
Got 813 / 1000 correct (81.30)

Iteration 500, loss = 0.2797
Checking accuracy on validation set
Got 816 / 1000 correct (81.60)

Iteration 600, loss = 0.4988
Checking accuracy on validation set
Got 757 / 1000 correct (75.70)

Iteration 700, loss = 0.2349
Checking accuracy on validation set
Got 811 / 1000 correct (81.10)

Iteration 0, loss = 0.5160
Checking accuracy on validation set
Got 817 / 1000 correct (81.70)

Iteration 100, loss = 0.3643
Checking accuracy on validation set
Got 782 / 1000 correct (78.20)

Iteration 200, loss = 0.3323
Checking accuracy on validation set
Got 809 / 1000 correct (80.90)

Iteration 300, loss = 0.2393
Checking accuracy on validation set
```

```
Got 810 / 1000 correct (81.00)

Iteration 400, loss = 0.4672
Checking accuracy on validation set
Got 833 / 1000 correct (83.30)

Iteration 500, loss = 0.4411
Checking accuracy on validation set
Got 825 / 1000 correct (82.50)

Iteration 600, loss = 0.3599
Checking accuracy on validation set
Got 800 / 1000 correct (80.00)

Iteration 700, loss = 0.5027
Checking accuracy on validation set
Got 809 / 1000 correct (80.90)

Checking accuracy on validation set
Got 820 / 1000 correct (82.00)
Iteration 0, loss = 2.4119
Checking accuracy on validation set
Got 78 / 1000 correct (7.80)

Iteration 100, loss = 1.8186
Checking accuracy on validation set
Got 331 / 1000 correct (33.10)

Iteration 200, loss = 1.7167
Checking accuracy on validation set
Got 388 / 1000 correct (38.80)

Iteration 300, loss = 1.5094
Checking accuracy on validation set
Got 385 / 1000 correct (38.50)

Iteration 400, loss = 1.5162
Checking accuracy on validation set
Got 403 / 1000 correct (40.30)

Iteration 500, loss = 1.4886
Checking accuracy on validation set
Got 486 / 1000 correct (48.60)

Iteration 600, loss = 1.4865
Checking accuracy on validation set
Got 420 / 1000 correct (42.00)
```

```
Iteration 700, loss = 1.4383
Checking accuracy on validation set
Got 470 / 1000 correct (47.00)

Iteration 0, loss = 1.1954
Checking accuracy on validation set
Got 450 / 1000 correct (45.00)

Iteration 100, loss = 1.2674
Checking accuracy on validation set
Got 558 / 1000 correct (55.80)

Iteration 200, loss = 1.1530
Checking accuracy on validation set
Got 491 / 1000 correct (49.10)

Iteration 300, loss = 0.8783
Checking accuracy on validation set
Got 578 / 1000 correct (57.80)

Iteration 400, loss = 1.0882
Checking accuracy on validation set
Got 597 / 1000 correct (59.70)

Iteration 500, loss = 1.0154
Checking accuracy on validation set
Got 540 / 1000 correct (54.00)

Iteration 600, loss = 1.0233
Checking accuracy on validation set
Got 540 / 1000 correct (54.00)

Iteration 700, loss = 1.1365
Checking accuracy on validation set
Got 576 / 1000 correct (57.60)

Iteration 0, loss = 1.1320
Checking accuracy on validation set
Got 526 / 1000 correct (52.60)

Iteration 100, loss = 0.7661
Checking accuracy on validation set
Got 539 / 1000 correct (53.90)

Iteration 200, loss = 0.9455
Checking accuracy on validation set
Got 539 / 1000 correct (53.90)
```

```
Iteration 300, loss = 0.8913
Checking accuracy on validation set
Got 636 / 1000 correct (63.60)

Iteration 400, loss = 0.7835
Checking accuracy on validation set
Got 534 / 1000 correct (53.40)

Iteration 500, loss = 1.1925
Checking accuracy on validation set
Got 525 / 1000 correct (52.50)

Iteration 600, loss = 1.0240
Checking accuracy on validation set
Got 597 / 1000 correct (59.70)

Iteration 700, loss = 1.1603
Checking accuracy on validation set
Got 669 / 1000 correct (66.90)

Iteration 0, loss = 0.9618
Checking accuracy on validation set
Got 626 / 1000 correct (62.60)

Iteration 100, loss = 0.9881
Checking accuracy on validation set
Got 614 / 1000 correct (61.40)

Iteration 200, loss = 0.9673
Checking accuracy on validation set
Got 660 / 1000 correct (66.00)

Iteration 300, loss = 0.9204
Checking accuracy on validation set
Got 642 / 1000 correct (64.20)

Iteration 400, loss = 0.8432
Checking accuracy on validation set
Got 664 / 1000 correct (66.40)

Iteration 500, loss = 0.8760
Checking accuracy on validation set
Got 654 / 1000 correct (65.40)

Iteration 600, loss = 0.7179
Checking accuracy on validation set
Got 706 / 1000 correct (70.60)
```

```
Iteration 700, loss = 0.9010
Checking accuracy on validation set
Got 683 / 1000 correct (68.30)

Iteration 0, loss = 0.7502
Checking accuracy on validation set
Got 653 / 1000 correct (65.30)

Iteration 100, loss = 0.8823
Checking accuracy on validation set
Got 669 / 1000 correct (66.90)

Iteration 200, loss = 0.8010
Checking accuracy on validation set
Got 630 / 1000 correct (63.00)

Iteration 300, loss = 1.2539
Checking accuracy on validation set
Got 646 / 1000 correct (64.60)

Iteration 400, loss = 0.6906
Checking accuracy on validation set
Got 682 / 1000 correct (68.20)

Iteration 500, loss = 0.7377
Checking accuracy on validation set
Got 650 / 1000 correct (65.00)

Iteration 600, loss = 0.6188
Checking accuracy on validation set
Got 576 / 1000 correct (57.60)

Iteration 700, loss = 0.7202
Checking accuracy on validation set
Got 665 / 1000 correct (66.50)

Iteration 0, loss = 0.7146
Checking accuracy on validation set
Got 625 / 1000 correct (62.50)

Iteration 100, loss = 0.8498
Checking accuracy on validation set
Got 662 / 1000 correct (66.20)

Iteration 200, loss = 0.8130
Checking accuracy on validation set
Got 684 / 1000 correct (68.40)
```

```
Iteration 300, loss = 0.5946
Checking accuracy on validation set
Got 713 / 1000 correct (71.30)

Iteration 400, loss = 0.6680
Checking accuracy on validation set
Got 632 / 1000 correct (63.20)

Iteration 500, loss = 0.6591
Checking accuracy on validation set
Got 709 / 1000 correct (70.90)

Iteration 600, loss = 0.9359
Checking accuracy on validation set
Got 694 / 1000 correct (69.40)

Iteration 700, loss = 1.1261
Checking accuracy on validation set
Got 662 / 1000 correct (66.20)

Iteration 0, loss = 0.6091
Checking accuracy on validation set
Got 686 / 1000 correct (68.60)

Iteration 100, loss = 0.5825
Checking accuracy on validation set
Got 668 / 1000 correct (66.80)

Iteration 200, loss = 0.6305
Checking accuracy on validation set
Got 678 / 1000 correct (67.80)

Iteration 300, loss = 0.6846
Checking accuracy on validation set
Got 677 / 1000 correct (67.70)

Iteration 400, loss = 0.9833
Checking accuracy on validation set
Got 629 / 1000 correct (62.90)

Iteration 500, loss = 0.7238
Checking accuracy on validation set
Got 677 / 1000 correct (67.70)

Iteration 600, loss = 0.8457
Checking accuracy on validation set
Got 711 / 1000 correct (71.10)
```

```
Iteration 700, loss = 0.5641
Checking accuracy on validation set
Got 733 / 1000 correct (73.30)

Iteration 0, loss = 0.6187
Checking accuracy on validation set
Got 681 / 1000 correct (68.10)

Iteration 100, loss = 0.3994
Checking accuracy on validation set
Got 740 / 1000 correct (74.00)

Iteration 200, loss = 0.5592
Checking accuracy on validation set
Got 676 / 1000 correct (67.60)

Iteration 300, loss = 0.5735
Checking accuracy on validation set
Got 664 / 1000 correct (66.40)

Iteration 400, loss = 0.5426
Checking accuracy on validation set
Got 656 / 1000 correct (65.60)

Iteration 500, loss = 0.6542
Checking accuracy on validation set
Got 655 / 1000 correct (65.50)

Iteration 600, loss = 0.6088
Checking accuracy on validation set
Got 685 / 1000 correct (68.50)

Iteration 700, loss = 1.0581
Checking accuracy on validation set
Got 698 / 1000 correct (69.80)

Iteration 0, loss = 0.4353
Checking accuracy on validation set
Got 636 / 1000 correct (63.60)

Iteration 100, loss = 0.6225
Checking accuracy on validation set
Got 713 / 1000 correct (71.30)

Iteration 200, loss = 0.7866
Checking accuracy on validation set
Got 694 / 1000 correct (69.40)
```

```
Iteration 300, loss = 0.5191
Checking accuracy on validation set
Got 759 / 1000 correct (75.90)

Iteration 400, loss = 0.6539
Checking accuracy on validation set
Got 689 / 1000 correct (68.90)

Iteration 500, loss = 0.6852
Checking accuracy on validation set
Got 697 / 1000 correct (69.70)

Iteration 600, loss = 0.7164
Checking accuracy on validation set
Got 722 / 1000 correct (72.20)

Iteration 700, loss = 0.3628
Checking accuracy on validation set
Got 737 / 1000 correct (73.70)

Iteration 0, loss = 0.5772
Checking accuracy on validation set
Got 668 / 1000 correct (66.80)

Iteration 100, loss = 0.5729
Checking accuracy on validation set
Got 711 / 1000 correct (71.10)

Iteration 200, loss = 0.6644
Checking accuracy on validation set
Got 675 / 1000 correct (67.50)

Iteration 300, loss = 0.5747
Checking accuracy on validation set
Got 736 / 1000 correct (73.60)

Iteration 400, loss = 0.7161
Checking accuracy on validation set
Got 727 / 1000 correct (72.70)

Iteration 500, loss = 0.6030
Checking accuracy on validation set
Got 754 / 1000 correct (75.40)

Iteration 600, loss = 0.7907
Checking accuracy on validation set
Got 655 / 1000 correct (65.50)
```

```
Iteration 700, loss = 0.5246
Checking accuracy on validation set
Got 732 / 1000 correct (73.20)

Checking accuracy on validation set
Got 724 / 1000 correct (72.40)
Iteration 0, loss = 2.3931
Checking accuracy on validation set
Got 108 / 1000 correct (10.80)

Iteration 100, loss = 1.3033
Checking accuracy on validation set
Got 473 / 1000 correct (47.30)

Iteration 200, loss = 1.3337
Checking accuracy on validation set
Got 517 / 1000 correct (51.70)

Iteration 300, loss = 1.1615
Checking accuracy on validation set
Got 574 / 1000 correct (57.40)

Iteration 400, loss = 1.3067
Checking accuracy on validation set
Got 622 / 1000 correct (62.20)

Iteration 500, loss = 1.1863
Checking accuracy on validation set
Got 544 / 1000 correct (54.40)

Iteration 600, loss = 1.1359
Checking accuracy on validation set
Got 606 / 1000 correct (60.60)

Iteration 700, loss = 0.8912
Checking accuracy on validation set
Got 645 / 1000 correct (64.50)

Iteration 0, loss = 0.9673
Checking accuracy on validation set
Got 552 / 1000 correct (55.20)

Iteration 100, loss = 1.2079
Checking accuracy on validation set
Got 622 / 1000 correct (62.20)

Iteration 200, loss = 0.6398
Checking accuracy on validation set
```

```
Got 622 / 1000 correct (62.20)

Iteration 300, loss = 0.7911
Checking accuracy on validation set
Got 686 / 1000 correct (68.60)

Iteration 400, loss = 0.9804
Checking accuracy on validation set
Got 728 / 1000 correct (72.80)

Iteration 500, loss = 1.0787
Checking accuracy on validation set
Got 633 / 1000 correct (63.30)

Iteration 600, loss = 0.5709
Checking accuracy on validation set
Got 677 / 1000 correct (67.70)

Iteration 700, loss = 0.9083
Checking accuracy on validation set
Got 691 / 1000 correct (69.10)

Iteration 0, loss = 0.7571
Checking accuracy on validation set
Got 659 / 1000 correct (65.90)

Iteration 100, loss = 0.9850
Checking accuracy on validation set
Got 694 / 1000 correct (69.40)

Iteration 200, loss = 0.5721
Checking accuracy on validation set
Got 749 / 1000 correct (74.90)

Iteration 300, loss = 0.7967
Checking accuracy on validation set
Got 715 / 1000 correct (71.50)

Iteration 400, loss = 0.7139
Checking accuracy on validation set
Got 748 / 1000 correct (74.80)

Iteration 500, loss = 0.8225
Checking accuracy on validation set
Got 703 / 1000 correct (70.30)

Iteration 600, loss = 0.5372
Checking accuracy on validation set
```

```
Got 735 / 1000 correct (73.50)

Iteration 700, loss = 0.6187
Checking accuracy on validation set
Got 765 / 1000 correct (76.50)

Iteration 0, loss = 0.6099
Checking accuracy on validation set
Got 734 / 1000 correct (73.40)

Iteration 100, loss = 0.6551
Checking accuracy on validation set
Got 762 / 1000 correct (76.20)

Iteration 200, loss = 0.6623
Checking accuracy on validation set
Got 754 / 1000 correct (75.40)

Iteration 300, loss = 0.6746
Checking accuracy on validation set
Got 741 / 1000 correct (74.10)

Iteration 400, loss = 0.5818
Checking accuracy on validation set
Got 748 / 1000 correct (74.80)

Iteration 500, loss = 0.7240
Checking accuracy on validation set
Got 729 / 1000 correct (72.90)

Iteration 600, loss = 0.6425
Checking accuracy on validation set
Got 753 / 1000 correct (75.30)

Iteration 700, loss = 0.5641
Checking accuracy on validation set
Got 772 / 1000 correct (77.20)

Iteration 0, loss = 0.6139
Checking accuracy on validation set
Got 754 / 1000 correct (75.40)

Iteration 100, loss = 0.5930
Checking accuracy on validation set
Got 754 / 1000 correct (75.40)

Iteration 200, loss = 0.4831
Checking accuracy on validation set
```

```
Got 763 / 1000 correct (76.30)

Iteration 300, loss = 0.6588
Checking accuracy on validation set
Got 762 / 1000 correct (76.20)

Iteration 400, loss = 0.4640
Checking accuracy on validation set
Got 776 / 1000 correct (77.60)

Iteration 500, loss = 0.6589
Checking accuracy on validation set
Got 763 / 1000 correct (76.30)

Iteration 600, loss = 0.4897
Checking accuracy on validation set
Got 717 / 1000 correct (71.70)

Iteration 700, loss = 0.6389
Checking accuracy on validation set
Got 755 / 1000 correct (75.50)

Iteration 0, loss = 0.3968
Checking accuracy on validation set
Got 781 / 1000 correct (78.10)

Iteration 100, loss = 0.5574
Checking accuracy on validation set
Got 769 / 1000 correct (76.90)

Iteration 200, loss = 0.2645
Checking accuracy on validation set
Got 800 / 1000 correct (80.00)

Iteration 300, loss = 0.5501
Checking accuracy on validation set
Got 777 / 1000 correct (77.70)

Iteration 400, loss = 0.3856
Checking accuracy on validation set
Got 788 / 1000 correct (78.80)

Iteration 500, loss = 0.3306
Checking accuracy on validation set
Got 779 / 1000 correct (77.90)

Iteration 600, loss = 0.4080
Checking accuracy on validation set
```

```
Got 786 / 1000 correct (78.60)

Iteration 700, loss = 0.3414
Checking accuracy on validation set
Got 754 / 1000 correct (75.40)

Iteration 0, loss = 0.4202
Checking accuracy on validation set
Got 744 / 1000 correct (74.40)

Iteration 100, loss = 0.4291
Checking accuracy on validation set
Got 773 / 1000 correct (77.30)

Iteration 200, loss = 0.5140
Checking accuracy on validation set
Got 761 / 1000 correct (76.10)

Iteration 300, loss = 0.4553
Checking accuracy on validation set
Got 780 / 1000 correct (78.00)

Iteration 400, loss = 0.4273
Checking accuracy on validation set
Got 781 / 1000 correct (78.10)

Iteration 500, loss = 0.4479
Checking accuracy on validation set
Got 791 / 1000 correct (79.10)

Iteration 600, loss = 0.5102
Checking accuracy on validation set
Got 813 / 1000 correct (81.30)

Iteration 700, loss = 0.2887
Checking accuracy on validation set
Got 807 / 1000 correct (80.70)

Iteration 0, loss = 0.4272
Checking accuracy on validation set
Got 790 / 1000 correct (79.00)

Iteration 100, loss = 0.2876
Checking accuracy on validation set
Got 797 / 1000 correct (79.70)

Iteration 200, loss = 0.5248
Checking accuracy on validation set
```

```
Got 790 / 1000 correct (79.00)

Iteration 300, loss = 0.4216
Checking accuracy on validation set
Got 808 / 1000 correct (80.80)

Iteration 400, loss = 0.4653
Checking accuracy on validation set
Got 776 / 1000 correct (77.60)

Iteration 500, loss = 0.3146
Checking accuracy on validation set
Got 778 / 1000 correct (77.80)

Iteration 600, loss = 0.4397
Checking accuracy on validation set
Got 759 / 1000 correct (75.90)

Iteration 700, loss = 0.4418
Checking accuracy on validation set
Got 786 / 1000 correct (78.60)

Iteration 0, loss = 0.3205
Checking accuracy on validation set
Got 792 / 1000 correct (79.20)

Iteration 100, loss = 0.3579
Checking accuracy on validation set
Got 806 / 1000 correct (80.60)

Iteration 200, loss = 0.4214
Checking accuracy on validation set
Got 765 / 1000 correct (76.50)

Iteration 300, loss = 0.6124
Checking accuracy on validation set
Got 793 / 1000 correct (79.30)

Iteration 400, loss = 0.4337
Checking accuracy on validation set
Got 779 / 1000 correct (77.90)

Iteration 500, loss = 0.4550
Checking accuracy on validation set
Got 768 / 1000 correct (76.80)

Iteration 600, loss = 0.3241
Checking accuracy on validation set
```

```
Got 767 / 1000 correct (76.70)

Iteration 700, loss = 0.4194
Checking accuracy on validation set
Got 792 / 1000 correct (79.20)

Iteration 0, loss = 0.1556
Checking accuracy on validation set
Got 796 / 1000 correct (79.60)

Iteration 100, loss = 0.2768
Checking accuracy on validation set
Got 791 / 1000 correct (79.10)

Iteration 200, loss = 0.4280
Checking accuracy on validation set
Got 790 / 1000 correct (79.00)

Iteration 300, loss = 0.3093
Checking accuracy on validation set
Got 795 / 1000 correct (79.50)

Iteration 400, loss = 0.3364
Checking accuracy on validation set
Got 797 / 1000 correct (79.70)

Iteration 500, loss = 0.2453
Checking accuracy on validation set
Got 785 / 1000 correct (78.50)

Iteration 600, loss = 0.3089
Checking accuracy on validation set
Got 779 / 1000 correct (77.90)

Iteration 700, loss = 0.6182
Checking accuracy on validation set
Got 775 / 1000 correct (77.50)

Checking accuracy on validation set
Got 786 / 1000 correct (78.60)
Iteration 0, loss = 2.3125
Checking accuracy on validation set
Got 119 / 1000 correct (11.90)

Iteration 100, loss = 1.8691
Checking accuracy on validation set
Got 237 / 1000 correct (23.70)
```

```
Iteration 200, loss = 1.4935
Checking accuracy on validation set
Got 379 / 1000 correct (37.90)

Iteration 300, loss = 1.5125
Checking accuracy on validation set
Got 434 / 1000 correct (43.40)

Iteration 400, loss = 1.1221
Checking accuracy on validation set
Got 448 / 1000 correct (44.80)

Iteration 500, loss = 1.2085
Checking accuracy on validation set
Got 464 / 1000 correct (46.40)

Iteration 600, loss = 1.0081
Checking accuracy on validation set
Got 547 / 1000 correct (54.70)

Iteration 700, loss = 1.2322
Checking accuracy on validation set
Got 410 / 1000 correct (41.00)

Iteration 0, loss = 1.1133
Checking accuracy on validation set
Got 536 / 1000 correct (53.60)

Iteration 100, loss = 1.2350
Checking accuracy on validation set
Got 582 / 1000 correct (58.20)

Iteration 200, loss = 1.1161
Checking accuracy on validation set
Got 470 / 1000 correct (47.00)

Iteration 300, loss = 0.8248
Checking accuracy on validation set
Got 627 / 1000 correct (62.70)

Iteration 400, loss = 0.7342
Checking accuracy on validation set
Got 582 / 1000 correct (58.20)

Iteration 500, loss = 1.3079
Checking accuracy on validation set
Got 618 / 1000 correct (61.80)
```

```
Iteration 600, loss = 1.0257
Checking accuracy on validation set
Got 654 / 1000 correct (65.40)

Iteration 700, loss = 0.9202
Checking accuracy on validation set
Got 675 / 1000 correct (67.50)

Iteration 0, loss = 0.9015
Checking accuracy on validation set
Got 622 / 1000 correct (62.20)

Iteration 100, loss = 0.8328
Checking accuracy on validation set
Got 658 / 1000 correct (65.80)

Iteration 200, loss = 1.1566
Checking accuracy on validation set
Got 665 / 1000 correct (66.50)

Iteration 300, loss = 0.8176
Checking accuracy on validation set
Got 690 / 1000 correct (69.00)

Iteration 400, loss = 0.8143
Checking accuracy on validation set
Got 644 / 1000 correct (64.40)

Iteration 500, loss = 0.7270
Checking accuracy on validation set
Got 720 / 1000 correct (72.00)

Iteration 600, loss = 0.7530
Checking accuracy on validation set
Got 526 / 1000 correct (52.60)

Iteration 700, loss = 0.9701
Checking accuracy on validation set
Got 662 / 1000 correct (66.20)

Iteration 0, loss = 0.6155
Checking accuracy on validation set
Got 690 / 1000 correct (69.00)

Iteration 100, loss = 0.9685
Checking accuracy on validation set
Got 689 / 1000 correct (68.90)
```

```
Iteration 200, loss = 0.7613
Checking accuracy on validation set
Got 738 / 1000 correct (73.80)

Iteration 300, loss = 0.7228
Checking accuracy on validation set
Got 717 / 1000 correct (71.70)

Iteration 400, loss = 0.8792
Checking accuracy on validation set
Got 716 / 1000 correct (71.60)

Iteration 500, loss = 0.6667
Checking accuracy on validation set
Got 748 / 1000 correct (74.80)

Iteration 600, loss = 0.7187
Checking accuracy on validation set
Got 740 / 1000 correct (74.00)

Iteration 700, loss = 0.4531
Checking accuracy on validation set
Got 745 / 1000 correct (74.50)

Iteration 0, loss = 0.4252
Checking accuracy on validation set
Got 706 / 1000 correct (70.60)

Iteration 100, loss = 0.6850
Checking accuracy on validation set
Got 648 / 1000 correct (64.80)

Iteration 200, loss = 0.5400
Checking accuracy on validation set
Got 772 / 1000 correct (77.20)

Iteration 300, loss = 0.7074
Checking accuracy on validation set
Got 723 / 1000 correct (72.30)

Iteration 400, loss = 0.7877
Checking accuracy on validation set
Got 738 / 1000 correct (73.80)

Iteration 500, loss = 0.7234
Checking accuracy on validation set
Got 765 / 1000 correct (76.50)
```

```
Iteration 600, loss = 0.4701
Checking accuracy on validation set
Got 750 / 1000 correct (75.00)

Iteration 700, loss = 0.6979
Checking accuracy on validation set
Got 676 / 1000 correct (67.60)

Iteration 0, loss = 0.4764
Checking accuracy on validation set
Got 703 / 1000 correct (70.30)

Iteration 100, loss = 0.7769
Checking accuracy on validation set
Got 730 / 1000 correct (73.00)

Iteration 200, loss = 0.7606
Checking accuracy on validation set
Got 763 / 1000 correct (76.30)

Iteration 300, loss = 0.5715
Checking accuracy on validation set
Got 777 / 1000 correct (77.70)

Iteration 400, loss = 0.4285
Checking accuracy on validation set
Got 733 / 1000 correct (73.30)

Iteration 500, loss = 0.6540
Checking accuracy on validation set
Got 737 / 1000 correct (73.70)

Iteration 600, loss = 0.3781
Checking accuracy on validation set
Got 747 / 1000 correct (74.70)

Iteration 700, loss = 0.7082
Checking accuracy on validation set
Got 783 / 1000 correct (78.30)

Iteration 0, loss = 0.6361
Checking accuracy on validation set
Got 779 / 1000 correct (77.90)

Iteration 100, loss = 0.5295
Checking accuracy on validation set
Got 770 / 1000 correct (77.00)
```

```
Iteration 200, loss = 0.4272
Checking accuracy on validation set
Got 800 / 1000 correct (80.00)

Iteration 300, loss = 0.5193
Checking accuracy on validation set
Got 771 / 1000 correct (77.10)

Iteration 400, loss = 0.5145
Checking accuracy on validation set
Got 790 / 1000 correct (79.00)

Iteration 500, loss = 0.3587
Checking accuracy on validation set
Got 768 / 1000 correct (76.80)

Iteration 600, loss = 0.4920
Checking accuracy on validation set
Got 796 / 1000 correct (79.60)

Iteration 700, loss = 0.3771
Checking accuracy on validation set
Got 810 / 1000 correct (81.00)

Iteration 0, loss = 0.3440
Checking accuracy on validation set
Got 798 / 1000 correct (79.80)

Iteration 100, loss = 0.3956
Checking accuracy on validation set
Got 766 / 1000 correct (76.60)

Iteration 200, loss = 0.5694
Checking accuracy on validation set
Got 809 / 1000 correct (80.90)

Iteration 300, loss = 0.7383
Checking accuracy on validation set
Got 796 / 1000 correct (79.60)

Iteration 400, loss = 0.4174
Checking accuracy on validation set
Got 760 / 1000 correct (76.00)

Iteration 500, loss = 0.3025
Checking accuracy on validation set
Got 820 / 1000 correct (82.00)
```

```
Iteration 600, loss = 0.4627
Checking accuracy on validation set
Got 756 / 1000 correct (75.60)

Iteration 700, loss = 0.3433
Checking accuracy on validation set
Got 821 / 1000 correct (82.10)

Iteration 0, loss = 0.3383
Checking accuracy on validation set
Got 809 / 1000 correct (80.90)

Iteration 100, loss = 0.3819
Checking accuracy on validation set
Got 808 / 1000 correct (80.80)

Iteration 200, loss = 0.3555
Checking accuracy on validation set
Got 792 / 1000 correct (79.20)

Iteration 300, loss = 0.2604
Checking accuracy on validation set
Got 821 / 1000 correct (82.10)

Iteration 400, loss = 0.3168
Checking accuracy on validation set
Got 721 / 1000 correct (72.10)

Iteration 500, loss = 0.3223
Checking accuracy on validation set
Got 814 / 1000 correct (81.40)

Iteration 600, loss = 0.4652
Checking accuracy on validation set
Got 830 / 1000 correct (83.00)

Iteration 700, loss = 0.6095
Checking accuracy on validation set
Got 760 / 1000 correct (76.00)

Iteration 0, loss = 0.3073
Checking accuracy on validation set
Got 798 / 1000 correct (79.80)

Iteration 100, loss = 0.3589
Checking accuracy on validation set
Got 781 / 1000 correct (78.10)
```

```
Iteration 200, loss = 0.4955
Checking accuracy on validation set
Got 802 / 1000 correct (80.20)

Iteration 300, loss = 0.2301
Checking accuracy on validation set
Got 793 / 1000 correct (79.30)

Iteration 400, loss = 0.3016
Checking accuracy on validation set
Got 809 / 1000 correct (80.90)

Iteration 500, loss = 0.3482
Checking accuracy on validation set
Got 817 / 1000 correct (81.70)

Iteration 600, loss = 0.2497
Checking accuracy on validation set
Got 798 / 1000 correct (79.80)

Iteration 700, loss = 0.3503
Checking accuracy on validation set
Got 781 / 1000 correct (78.10)

Checking accuracy on validation set
Got 776 / 1000 correct (77.60)
Iteration 0, loss = 2.3207
Checking accuracy on validation set
Got 133 / 1000 correct (13.30)

Iteration 100, loss = 1.8746
Checking accuracy on validation set
Got 281 / 1000 correct (28.10)

Iteration 200, loss = 1.6236
Checking accuracy on validation set
Got 359 / 1000 correct (35.90)

Iteration 300, loss = 1.4759
Checking accuracy on validation set
Got 384 / 1000 correct (38.40)

Iteration 400, loss = 1.3717
Checking accuracy on validation set
Got 432 / 1000 correct (43.20)

Iteration 500, loss = 1.6380
Checking accuracy on validation set
```

```
Got 447 / 1000 correct (44.70)

Iteration 600, loss = 1.4021
Checking accuracy on validation set
Got 465 / 1000 correct (46.50)

Iteration 700, loss = 1.1208
Checking accuracy on validation set
Got 447 / 1000 correct (44.70)

Iteration 0, loss = 1.1927
Checking accuracy on validation set
Got 331 / 1000 correct (33.10)

Iteration 100, loss = 1.4262
Checking accuracy on validation set
Got 504 / 1000 correct (50.40)

Iteration 200, loss = 1.1550
Checking accuracy on validation set
Got 521 / 1000 correct (52.10)

Iteration 300, loss = 1.3036
Checking accuracy on validation set
Got 513 / 1000 correct (51.30)

Iteration 400, loss = 1.1712
Checking accuracy on validation set
Got 528 / 1000 correct (52.80)

Iteration 500, loss = 1.0491
Checking accuracy on validation set
Got 432 / 1000 correct (43.20)

Iteration 600, loss = 0.8410
Checking accuracy on validation set
Got 552 / 1000 correct (55.20)

Iteration 700, loss = 1.1026
Checking accuracy on validation set
Got 595 / 1000 correct (59.50)

Iteration 0, loss = 1.2735
Checking accuracy on validation set
Got 560 / 1000 correct (56.00)

Iteration 100, loss = 1.2511
Checking accuracy on validation set
```

```
Got 593 / 1000 correct (59.30)

Iteration 200, loss = 1.1309
Checking accuracy on validation set
Got 630 / 1000 correct (63.00)

Iteration 300, loss = 0.9778
Checking accuracy on validation set
Got 511 / 1000 correct (51.10)

Iteration 400, loss = 1.0097
Checking accuracy on validation set
Got 599 / 1000 correct (59.90)

Iteration 500, loss = 1.0918
Checking accuracy on validation set
Got 563 / 1000 correct (56.30)

Iteration 600, loss = 0.7692
Checking accuracy on validation set
Got 570 / 1000 correct (57.00)

Iteration 700, loss = 1.1128
Checking accuracy on validation set
Got 644 / 1000 correct (64.40)

Iteration 0, loss = 0.9623
Checking accuracy on validation set
Got 564 / 1000 correct (56.40)

Iteration 100, loss = 1.1284
Checking accuracy on validation set
Got 595 / 1000 correct (59.50)

Iteration 200, loss = 0.9187
Checking accuracy on validation set
Got 626 / 1000 correct (62.60)

Iteration 300, loss = 0.9903
Checking accuracy on validation set
Got 610 / 1000 correct (61.00)

Iteration 400, loss = 1.1158
Checking accuracy on validation set
Got 528 / 1000 correct (52.80)

Iteration 500, loss = 0.9466
Checking accuracy on validation set
```

```
Got 609 / 1000 correct (60.90)

Iteration 600, loss = 0.9567
Checking accuracy on validation set
Got 569 / 1000 correct (56.90)

Iteration 700, loss = 0.7811
Checking accuracy on validation set
Got 674 / 1000 correct (67.40)

Iteration 0, loss = 1.0036
Checking accuracy on validation set
Got 583 / 1000 correct (58.30)

Iteration 100, loss = 1.1377
Checking accuracy on validation set
Got 659 / 1000 correct (65.90)

Iteration 200, loss = 1.0972
Checking accuracy on validation set
Got 588 / 1000 correct (58.80)

Iteration 300, loss = 0.9065
Checking accuracy on validation set
Got 603 / 1000 correct (60.30)

Iteration 400, loss = 0.6922
Checking accuracy on validation set
Got 644 / 1000 correct (64.40)

Iteration 500, loss = 0.8078
Checking accuracy on validation set
Got 633 / 1000 correct (63.30)

Iteration 600, loss = 1.0110
Checking accuracy on validation set
Got 655 / 1000 correct (65.50)

Iteration 700, loss = 0.7888
Checking accuracy on validation set
Got 655 / 1000 correct (65.50)

Iteration 0, loss = 1.1553
Checking accuracy on validation set
Got 677 / 1000 correct (67.70)

Iteration 100, loss = 0.8621
Checking accuracy on validation set
```

```
Got 643 / 1000 correct (64.30)

Iteration 200, loss = 0.7053
Checking accuracy on validation set
Got 682 / 1000 correct (68.20)

Iteration 300, loss = 0.7667
Checking accuracy on validation set
Got 671 / 1000 correct (67.10)

Iteration 400, loss = 0.9296
Checking accuracy on validation set
Got 652 / 1000 correct (65.20)

Iteration 500, loss = 0.8731
Checking accuracy on validation set
Got 646 / 1000 correct (64.60)

Iteration 600, loss = 0.8498
Checking accuracy on validation set
Got 709 / 1000 correct (70.90)

Iteration 700, loss = 0.9199
Checking accuracy on validation set
Got 643 / 1000 correct (64.30)

Iteration 0, loss = 1.0859
Checking accuracy on validation set
Got 726 / 1000 correct (72.60)

Iteration 100, loss = 0.7105
Checking accuracy on validation set
Got 623 / 1000 correct (62.30)

Iteration 200, loss = 0.8198
Checking accuracy on validation set
Got 689 / 1000 correct (68.90)

Iteration 300, loss = 0.7094
Checking accuracy on validation set
Got 718 / 1000 correct (71.80)

Iteration 400, loss = 0.9358
Checking accuracy on validation set
Got 699 / 1000 correct (69.90)

Iteration 500, loss = 0.5717
Checking accuracy on validation set
```

```
Got 665 / 1000 correct (66.50)

Iteration 600, loss = 0.6197
Checking accuracy on validation set
Got 724 / 1000 correct (72.40)

Iteration 700, loss = 0.6636
Checking accuracy on validation set
Got 703 / 1000 correct (70.30)

Iteration 0, loss = 0.7760
Checking accuracy on validation set
Got 720 / 1000 correct (72.00)

Iteration 100, loss = 0.6933
Checking accuracy on validation set
Got 709 / 1000 correct (70.90)

Iteration 200, loss = 0.4953
Checking accuracy on validation set
Got 652 / 1000 correct (65.20)

Iteration 300, loss = 0.5651
Checking accuracy on validation set
Got 643 / 1000 correct (64.30)

Iteration 400, loss = 0.6613
Checking accuracy on validation set
Got 746 / 1000 correct (74.60)

Iteration 500, loss = 0.9007
Checking accuracy on validation set
Got 696 / 1000 correct (69.60)

Iteration 600, loss = 0.6753
Checking accuracy on validation set
Got 758 / 1000 correct (75.80)

Iteration 700, loss = 0.7599
Checking accuracy on validation set
Got 640 / 1000 correct (64.00)

Iteration 0, loss = 0.6140
Checking accuracy on validation set
Got 699 / 1000 correct (69.90)

Iteration 100, loss = 0.5586
Checking accuracy on validation set
```

```
Got 704 / 1000 correct (70.40)

Iteration 200, loss = 0.6523
Checking accuracy on validation set
Got 682 / 1000 correct (68.20)

Iteration 300, loss = 0.7077
Checking accuracy on validation set
Got 753 / 1000 correct (75.30)

Iteration 400, loss = 0.7155
Checking accuracy on validation set
Got 635 / 1000 correct (63.50)

Iteration 500, loss = 0.8172
Checking accuracy on validation set
Got 647 / 1000 correct (64.70)

Iteration 600, loss = 0.7301
Checking accuracy on validation set
Got 665 / 1000 correct (66.50)

Iteration 700, loss = 0.5044
Checking accuracy on validation set
Got 734 / 1000 correct (73.40)

Iteration 0, loss = 0.5601
Checking accuracy on validation set
Got 721 / 1000 correct (72.10)

Iteration 100, loss = 0.6727
Checking accuracy on validation set
Got 698 / 1000 correct (69.80)

Iteration 200, loss = 1.0082
Checking accuracy on validation set
Got 677 / 1000 correct (67.70)

Iteration 300, loss = 0.8066
Checking accuracy on validation set
Got 714 / 1000 correct (71.40)

Iteration 400, loss = 0.5767
Checking accuracy on validation set
Got 703 / 1000 correct (70.30)

Iteration 500, loss = 0.4533
Checking accuracy on validation set
```

```
Got 704 / 1000 correct (70.40)

Iteration 600, loss = 0.5830
Checking accuracy on validation set
Got 670 / 1000 correct (67.00)

Iteration 700, loss = 0.6522
Checking accuracy on validation set
Got 755 / 1000 correct (75.50)

Checking accuracy on validation set
Got 671 / 1000 correct (67.10)
Iteration 0, loss = 2.3745
Checking accuracy on validation set
Got 119 / 1000 correct (11.90)

Iteration 100, loss = 1.7706
Checking accuracy on validation set
Got 426 / 1000 correct (42.60)

Iteration 200, loss = 1.6169
Checking accuracy on validation set
Got 455 / 1000 correct (45.50)

Iteration 300, loss = 1.4493
Checking accuracy on validation set
Got 499 / 1000 correct (49.90)

Iteration 400, loss = 1.2694
Checking accuracy on validation set
Got 556 / 1000 correct (55.60)

Iteration 500, loss = 1.3344
Checking accuracy on validation set
Got 545 / 1000 correct (54.50)

Iteration 600, loss = 1.1977
Checking accuracy on validation set
Got 518 / 1000 correct (51.80)

Iteration 700, loss = 1.4564
Checking accuracy on validation set
Got 573 / 1000 correct (57.30)

Iteration 0, loss = 1.1040
Checking accuracy on validation set
Got 585 / 1000 correct (58.50)
```

```
Iteration 100, loss = 1.1259
Checking accuracy on validation set
Got 585 / 1000 correct (58.50)

Iteration 200, loss = 0.9758
Checking accuracy on validation set
Got 587 / 1000 correct (58.70)

Iteration 300, loss = 1.0260
Checking accuracy on validation set
Got 648 / 1000 correct (64.80)

Iteration 400, loss = 1.0647
Checking accuracy on validation set
Got 622 / 1000 correct (62.20)

Iteration 500, loss = 0.8718
Checking accuracy on validation set
Got 619 / 1000 correct (61.90)

Iteration 600, loss = 0.9695
Checking accuracy on validation set
Got 637 / 1000 correct (63.70)

Iteration 700, loss = 1.0300
Checking accuracy on validation set
Got 612 / 1000 correct (61.20)

Iteration 0, loss = 1.0700
Checking accuracy on validation set
Got 632 / 1000 correct (63.20)

Iteration 100, loss = 1.0267
Checking accuracy on validation set
Got 667 / 1000 correct (66.70)

Iteration 200, loss = 0.8202
Checking accuracy on validation set
Got 653 / 1000 correct (65.30)

Iteration 300, loss = 0.6758
Checking accuracy on validation set
Got 677 / 1000 correct (67.70)

Iteration 400, loss = 0.6429
Checking accuracy on validation set
Got 677 / 1000 correct (67.70)
```

```
Iteration 500, loss = 0.8339
Checking accuracy on validation set
Got 653 / 1000 correct (65.30)

Iteration 600, loss = 0.9892
Checking accuracy on validation set
Got 677 / 1000 correct (67.70)

Iteration 700, loss = 0.9808
Checking accuracy on validation set
Got 687 / 1000 correct (68.70)

Iteration 0, loss = 1.0309
Checking accuracy on validation set
Got 674 / 1000 correct (67.40)

Iteration 100, loss = 0.8943
Checking accuracy on validation set
Got 698 / 1000 correct (69.80)

Iteration 200, loss = 0.7320
Checking accuracy on validation set
Got 697 / 1000 correct (69.70)

Iteration 300, loss = 0.7564
Checking accuracy on validation set
Got 683 / 1000 correct (68.30)

Iteration 400, loss = 0.6615
Checking accuracy on validation set
Got 701 / 1000 correct (70.10)

Iteration 500, loss = 0.7794
Checking accuracy on validation set
Got 646 / 1000 correct (64.60)

Iteration 600, loss = 0.8015
Checking accuracy on validation set
Got 690 / 1000 correct (69.00)

Iteration 700, loss = 0.9754
Checking accuracy on validation set
Got 677 / 1000 correct (67.70)

Iteration 0, loss = 0.4378
Checking accuracy on validation set
Got 706 / 1000 correct (70.60)
```

```
Iteration 100, loss = 0.8136
Checking accuracy on validation set
Got 710 / 1000 correct (71.00)

Iteration 200, loss = 0.6882
Checking accuracy on validation set
Got 712 / 1000 correct (71.20)

Iteration 300, loss = 0.6639
Checking accuracy on validation set
Got 703 / 1000 correct (70.30)

Iteration 400, loss = 0.4902
Checking accuracy on validation set
Got 721 / 1000 correct (72.10)

Iteration 500, loss = 0.7137
Checking accuracy on validation set
Got 695 / 1000 correct (69.50)

Iteration 600, loss = 0.6779
Checking accuracy on validation set
Got 715 / 1000 correct (71.50)

Iteration 700, loss = 0.8165
Checking accuracy on validation set
Got 728 / 1000 correct (72.80)

Iteration 0, loss = 0.6764
Checking accuracy on validation set
Got 672 / 1000 correct (67.20)

Iteration 100, loss = 0.4650
Checking accuracy on validation set
Got 737 / 1000 correct (73.70)

Iteration 200, loss = 0.9071
Checking accuracy on validation set
Got 715 / 1000 correct (71.50)

Iteration 300, loss = 0.7632
Checking accuracy on validation set
Got 713 / 1000 correct (71.30)

Iteration 400, loss = 0.6463
Checking accuracy on validation set
Got 702 / 1000 correct (70.20)
```

```
Iteration 500, loss = 0.4955
Checking accuracy on validation set
Got 718 / 1000 correct (71.80)

Iteration 600, loss = 0.6341
Checking accuracy on validation set
Got 725 / 1000 correct (72.50)

Iteration 700, loss = 0.7507
Checking accuracy on validation set
Got 738 / 1000 correct (73.80)

Iteration 0, loss = 0.4537
Checking accuracy on validation set
Got 713 / 1000 correct (71.30)

Iteration 100, loss = 0.4111
Checking accuracy on validation set
Got 744 / 1000 correct (74.40)

Iteration 200, loss = 0.8558
Checking accuracy on validation set
Got 724 / 1000 correct (72.40)

Iteration 300, loss = 0.4991
Checking accuracy on validation set
Got 733 / 1000 correct (73.30)

Iteration 400, loss = 0.4610
Checking accuracy on validation set
Got 744 / 1000 correct (74.40)

Iteration 500, loss = 0.6250
Checking accuracy on validation set
Got 711 / 1000 correct (71.10)

Iteration 600, loss = 0.5653
Checking accuracy on validation set
Got 726 / 1000 correct (72.60)

Iteration 700, loss = 0.7290
Checking accuracy on validation set
Got 726 / 1000 correct (72.60)

Iteration 0, loss = 0.3762
Checking accuracy on validation set
Got 744 / 1000 correct (74.40)
```

```
Iteration 100, loss = 0.4404
Checking accuracy on validation set
Got 733 / 1000 correct (73.30)

Iteration 200, loss = 0.6857
Checking accuracy on validation set
Got 724 / 1000 correct (72.40)

Iteration 300, loss = 0.4520
Checking accuracy on validation set
Got 705 / 1000 correct (70.50)

Iteration 400, loss = 0.4028
Checking accuracy on validation set
Got 714 / 1000 correct (71.40)

Iteration 500, loss = 0.5669
Checking accuracy on validation set
Got 722 / 1000 correct (72.20)

Iteration 600, loss = 0.6852
Checking accuracy on validation set
Got 733 / 1000 correct (73.30)

Iteration 700, loss = 0.6657
Checking accuracy on validation set
Got 748 / 1000 correct (74.80)

Iteration 0, loss = 0.3757
Checking accuracy on validation set
Got 759 / 1000 correct (75.90)

Iteration 100, loss = 0.4898
Checking accuracy on validation set
Got 701 / 1000 correct (70.10)

Iteration 200, loss = 0.2853
Checking accuracy on validation set
Got 740 / 1000 correct (74.00)

Iteration 300, loss = 0.4349
Checking accuracy on validation set
Got 765 / 1000 correct (76.50)

Iteration 400, loss = 0.4973
Checking accuracy on validation set
Got 737 / 1000 correct (73.70)
```

```
Iteration 500, loss = 0.4677
Checking accuracy on validation set
Got 747 / 1000 correct (74.70)

Iteration 600, loss = 0.6012
Checking accuracy on validation set
Got 730 / 1000 correct (73.00)

Iteration 700, loss = 0.5249
Checking accuracy on validation set
Got 750 / 1000 correct (75.00)

Iteration 0, loss = 0.5733
Checking accuracy on validation set
Got 739 / 1000 correct (73.90)

Iteration 100, loss = 0.3677
Checking accuracy on validation set
Got 766 / 1000 correct (76.60)

Iteration 200, loss = 0.4496
Checking accuracy on validation set
Got 743 / 1000 correct (74.30)

Iteration 300, loss = 0.2669
Checking accuracy on validation set
Got 766 / 1000 correct (76.60)

Iteration 400, loss = 0.6395
Checking accuracy on validation set
Got 753 / 1000 correct (75.30)

Iteration 500, loss = 0.5063
Checking accuracy on validation set
Got 750 / 1000 correct (75.00)

Iteration 600, loss = 0.5888
Checking accuracy on validation set
Got 743 / 1000 correct (74.30)

Iteration 700, loss = 0.3305
Checking accuracy on validation set
Got 754 / 1000 correct (75.40)

Checking accuracy on validation set
Got 744 / 1000 correct (74.40)
Iteration 0, loss = 2.3990
Checking accuracy on validation set
```

```
Got 78 / 1000 correct (7.80)

Iteration 100, loss = 1.8724
Checking accuracy on validation set
Got 249 / 1000 correct (24.90)

Iteration 200, loss = 1.6700
Checking accuracy on validation set
Got 352 / 1000 correct (35.20)

Iteration 300, loss = 1.3528
Checking accuracy on validation set
Got 439 / 1000 correct (43.90)

Iteration 400, loss = 1.5379
Checking accuracy on validation set
Got 488 / 1000 correct (48.80)

Iteration 500, loss = 1.4722
Checking accuracy on validation set
Got 505 / 1000 correct (50.50)

Iteration 600, loss = 1.2241
Checking accuracy on validation set
Got 535 / 1000 correct (53.50)

Iteration 700, loss = 1.2037
Checking accuracy on validation set
Got 535 / 1000 correct (53.50)

Iteration 0, loss = 1.1085
Checking accuracy on validation set
Got 519 / 1000 correct (51.90)

Iteration 100, loss = 1.0676
Checking accuracy on validation set
Got 613 / 1000 correct (61.30)

Iteration 200, loss = 1.3825
Checking accuracy on validation set
Got 550 / 1000 correct (55.00)

Iteration 300, loss = 0.8045
Checking accuracy on validation set
Got 594 / 1000 correct (59.40)

Iteration 400, loss = 1.1334
Checking accuracy on validation set
```

```
Got 631 / 1000 correct (63.10)

Iteration 500, loss = 0.6184
Checking accuracy on validation set
Got 639 / 1000 correct (63.90)

Iteration 600, loss = 1.0300
Checking accuracy on validation set
Got 575 / 1000 correct (57.50)

Iteration 700, loss = 0.7989
Checking accuracy on validation set
Got 646 / 1000 correct (64.60)

Iteration 0, loss = 1.0594
Checking accuracy on validation set
Got 610 / 1000 correct (61.00)

Iteration 100, loss = 0.9141
Checking accuracy on validation set
Got 661 / 1000 correct (66.10)

Iteration 200, loss = 0.9551
Checking accuracy on validation set
Got 618 / 1000 correct (61.80)

Iteration 300, loss = 0.9043
Checking accuracy on validation set
Got 630 / 1000 correct (63.00)

Iteration 400, loss = 0.9315
Checking accuracy on validation set
Got 654 / 1000 correct (65.40)

Iteration 500, loss = 1.0411
Checking accuracy on validation set
Got 696 / 1000 correct (69.60)

Iteration 600, loss = 0.8841
Checking accuracy on validation set
Got 700 / 1000 correct (70.00)

Iteration 700, loss = 0.9131
Checking accuracy on validation set
Got 697 / 1000 correct (69.70)

Iteration 0, loss = 0.8583
Checking accuracy on validation set
```

```
Got 696 / 1000 correct (69.60)

Iteration 100, loss = 0.8494
Checking accuracy on validation set
Got 689 / 1000 correct (68.90)

Iteration 200, loss = 0.7082
Checking accuracy on validation set
Got 684 / 1000 correct (68.40)

Iteration 300, loss = 0.7932
Checking accuracy on validation set
Got 669 / 1000 correct (66.90)

Iteration 400, loss = 0.7573
Checking accuracy on validation set
Got 712 / 1000 correct (71.20)

Iteration 500, loss = 0.7009
Checking accuracy on validation set
Got 703 / 1000 correct (70.30)

Iteration 600, loss = 0.7481
Checking accuracy on validation set
Got 702 / 1000 correct (70.20)

Iteration 700, loss = 0.7792
Checking accuracy on validation set
Got 702 / 1000 correct (70.20)

Iteration 0, loss = 0.6028
Checking accuracy on validation set
Got 698 / 1000 correct (69.80)

Iteration 100, loss = 0.9147
Checking accuracy on validation set
Got 711 / 1000 correct (71.10)

Iteration 200, loss = 0.5429
Checking accuracy on validation set
Got 701 / 1000 correct (70.10)

Iteration 300, loss = 0.7707
Checking accuracy on validation set
Got 716 / 1000 correct (71.60)

Iteration 400, loss = 0.5539
Checking accuracy on validation set
```

```
Got 731 / 1000 correct (73.10)

Iteration 500, loss = 0.6070
Checking accuracy on validation set
Got 723 / 1000 correct (72.30)

Iteration 600, loss = 0.5859
Checking accuracy on validation set
Got 760 / 1000 correct (76.00)

Iteration 700, loss = 0.5875
Checking accuracy on validation set
Got 711 / 1000 correct (71.10)

Iteration 0, loss = 0.6218
Checking accuracy on validation set
Got 620 / 1000 correct (62.00)

Iteration 100, loss = 0.6837
Checking accuracy on validation set
Got 739 / 1000 correct (73.90)

Iteration 200, loss = 0.6331
Checking accuracy on validation set
Got 756 / 1000 correct (75.60)

Iteration 300, loss = 0.4855
Checking accuracy on validation set
Got 746 / 1000 correct (74.60)

Iteration 400, loss = 0.5977
Checking accuracy on validation set
Got 723 / 1000 correct (72.30)

Iteration 500, loss = 0.6267
Checking accuracy on validation set
Got 673 / 1000 correct (67.30)

Iteration 600, loss = 0.8355
Checking accuracy on validation set
Got 764 / 1000 correct (76.40)

Iteration 700, loss = 0.5704
Checking accuracy on validation set
Got 758 / 1000 correct (75.80)

Iteration 0, loss = 0.5165
Checking accuracy on validation set
```

```
Got 742 / 1000 correct (74.20)

Iteration 100, loss = 0.7163
Checking accuracy on validation set
Got 694 / 1000 correct (69.40)

Iteration 200, loss = 0.6612
Checking accuracy on validation set
Got 754 / 1000 correct (75.40)

Iteration 300, loss = 0.4481
Checking accuracy on validation set
Got 759 / 1000 correct (75.90)

Iteration 400, loss = 0.5344
Checking accuracy on validation set
Got 733 / 1000 correct (73.30)

Iteration 500, loss = 0.4210
Checking accuracy on validation set
Got 739 / 1000 correct (73.90)

Iteration 600, loss = 0.3382
Checking accuracy on validation set
Got 752 / 1000 correct (75.20)

Iteration 700, loss = 0.3550
Checking accuracy on validation set
Got 748 / 1000 correct (74.80)

Iteration 0, loss = 0.5073
Checking accuracy on validation set
Got 738 / 1000 correct (73.80)

Iteration 100, loss = 0.5097
Checking accuracy on validation set
Got 744 / 1000 correct (74.40)

Iteration 200, loss = 0.5006
Checking accuracy on validation set
Got 769 / 1000 correct (76.90)

Iteration 300, loss = 0.3290
Checking accuracy on validation set
Got 794 / 1000 correct (79.40)

Iteration 400, loss = 0.7521
Checking accuracy on validation set
```

```
Got 704 / 1000 correct (70.40)

Iteration 500, loss = 0.2776
Checking accuracy on validation set
Got 787 / 1000 correct (78.70)

Iteration 600, loss = 0.3850
Checking accuracy on validation set
Got 774 / 1000 correct (77.40)

Iteration 700, loss = 0.4738
Checking accuracy on validation set
Got 775 / 1000 correct (77.50)

Iteration 0, loss = 0.4381
Checking accuracy on validation set
Got 764 / 1000 correct (76.40)

Iteration 100, loss = 0.5577
Checking accuracy on validation set
Got 794 / 1000 correct (79.40)

Iteration 200, loss = 0.2978
Checking accuracy on validation set
Got 780 / 1000 correct (78.00)

Iteration 300, loss = 0.5042
Checking accuracy on validation set
Got 751 / 1000 correct (75.10)

Iteration 400, loss = 0.3690
Checking accuracy on validation set
Got 776 / 1000 correct (77.60)

Iteration 500, loss = 0.3316
Checking accuracy on validation set
Got 776 / 1000 correct (77.60)

Iteration 600, loss = 0.4091
Checking accuracy on validation set
Got 793 / 1000 correct (79.30)

Iteration 700, loss = 0.3276
Checking accuracy on validation set
Got 752 / 1000 correct (75.20)

Iteration 0, loss = 0.3208
Checking accuracy on validation set
```

```
Got 773 / 1000 correct (77.30)

Iteration 100, loss = 0.2974
Checking accuracy on validation set
Got 789 / 1000 correct (78.90)

Iteration 200, loss = 0.4115
Checking accuracy on validation set
Got 767 / 1000 correct (76.70)

Iteration 300, loss = 0.4908
Checking accuracy on validation set
Got 788 / 1000 correct (78.80)

Iteration 400, loss = 0.4258
Checking accuracy on validation set
Got 762 / 1000 correct (76.20)

Iteration 500, loss = 0.3949
Checking accuracy on validation set
Got 782 / 1000 correct (78.20)

Iteration 600, loss = 0.3194
Checking accuracy on validation set
Got 783 / 1000 correct (78.30)

Iteration 700, loss = 0.3271
Checking accuracy on validation set
Got 778 / 1000 correct (77.80)

Checking accuracy on validation set
Got 726 / 1000 correct (72.60)
Iteration 0, loss = 2.3804
Checking accuracy on validation set
Got 113 / 1000 correct (11.30)

Iteration 100, loss = 1.9679
Checking accuracy on validation set
Got 345 / 1000 correct (34.50)

Iteration 200, loss = 1.6253
Checking accuracy on validation set
Got 372 / 1000 correct (37.20)

Iteration 300, loss = 1.6333
Checking accuracy on validation set
Got 419 / 1000 correct (41.90)
```

```
Iteration 400, loss = 1.5501
Checking accuracy on validation set
Got 379 / 1000 correct (37.90)

Iteration 500, loss = 1.5837
Checking accuracy on validation set
Got 440 / 1000 correct (44.00)

Iteration 600, loss = 1.3862
Checking accuracy on validation set
Got 501 / 1000 correct (50.10)

Iteration 700, loss = 1.3034
Checking accuracy on validation set
Got 473 / 1000 correct (47.30)

Iteration 0, loss = 1.3348
Checking accuracy on validation set
Got 464 / 1000 correct (46.40)

Iteration 100, loss = 1.2608
Checking accuracy on validation set
Got 507 / 1000 correct (50.70)

Iteration 200, loss = 1.4714
Checking accuracy on validation set
Got 499 / 1000 correct (49.90)

Iteration 300, loss = 1.3991
Checking accuracy on validation set
Got 504 / 1000 correct (50.40)

Iteration 400, loss = 1.1654
Checking accuracy on validation set
Got 465 / 1000 correct (46.50)

Iteration 500, loss = 0.8753
Checking accuracy on validation set
Got 521 / 1000 correct (52.10)

Iteration 600, loss = 1.2568
Checking accuracy on validation set
Got 460 / 1000 correct (46.00)

Iteration 700, loss = 1.1855
Checking accuracy on validation set
Got 552 / 1000 correct (55.20)
```

```
Iteration 0, loss = 0.9794
Checking accuracy on validation set
Got 579 / 1000 correct (57.90)

Iteration 100, loss = 1.1384
Checking accuracy on validation set
Got 473 / 1000 correct (47.30)

Iteration 200, loss = 1.5426
Checking accuracy on validation set
Got 473 / 1000 correct (47.30)

Iteration 300, loss = 1.0803
Checking accuracy on validation set
Got 463 / 1000 correct (46.30)

Iteration 400, loss = 1.0393
Checking accuracy on validation set
Got 402 / 1000 correct (40.20)

Iteration 500, loss = 0.8445
Checking accuracy on validation set
Got 550 / 1000 correct (55.00)

Iteration 600, loss = 1.1439
Checking accuracy on validation set
Got 435 / 1000 correct (43.50)

Iteration 700, loss = 0.8594
Checking accuracy on validation set
Got 506 / 1000 correct (50.60)

Iteration 0, loss = 0.8859
Checking accuracy on validation set
Got 457 / 1000 correct (45.70)

Iteration 100, loss = 0.9880
Checking accuracy on validation set
Got 514 / 1000 correct (51.40)

Iteration 200, loss = 0.9987
Checking accuracy on validation set
Got 605 / 1000 correct (60.50)

Iteration 300, loss = 1.0183
Checking accuracy on validation set
Got 509 / 1000 correct (50.90)
```

```
Iteration 400, loss = 0.9364
Checking accuracy on validation set
Got 615 / 1000 correct (61.50)

Iteration 500, loss = 0.8372
Checking accuracy on validation set
Got 570 / 1000 correct (57.00)

Iteration 600, loss = 0.9932
Checking accuracy on validation set
Got 488 / 1000 correct (48.80)

Iteration 700, loss = 1.0572
Checking accuracy on validation set
Got 629 / 1000 correct (62.90)

Iteration 0, loss = 1.0652
Checking accuracy on validation set
Got 571 / 1000 correct (57.10)

Iteration 100, loss = 0.7220
Checking accuracy on validation set
Got 502 / 1000 correct (50.20)

Iteration 200, loss = 0.8702
Checking accuracy on validation set
Got 551 / 1000 correct (55.10)

Iteration 300, loss = 1.0546
Checking accuracy on validation set
Got 543 / 1000 correct (54.30)

Iteration 400, loss = 1.2377
Checking accuracy on validation set
Got 587 / 1000 correct (58.70)

Iteration 500, loss = 0.9627
Checking accuracy on validation set
Got 577 / 1000 correct (57.70)

Iteration 600, loss = 0.9018
Checking accuracy on validation set
Got 656 / 1000 correct (65.60)

Iteration 700, loss = 0.9001
Checking accuracy on validation set
Got 682 / 1000 correct (68.20)
```

```
Iteration 0, loss = 0.8217
Checking accuracy on validation set
Got 624 / 1000 correct (62.40)

Iteration 100, loss = 0.9167
Checking accuracy on validation set
Got 566 / 1000 correct (56.60)

Iteration 200, loss = 0.9245
Checking accuracy on validation set
Got 584 / 1000 correct (58.40)

Iteration 300, loss = 0.8333
Checking accuracy on validation set
Got 592 / 1000 correct (59.20)

Iteration 400, loss = 0.7687
Checking accuracy on validation set
Got 672 / 1000 correct (67.20)

Iteration 500, loss = 0.9230
Checking accuracy on validation set
Got 583 / 1000 correct (58.30)

Iteration 600, loss = 0.8447
Checking accuracy on validation set
Got 659 / 1000 correct (65.90)

Iteration 700, loss = 0.8161
Checking accuracy on validation set
Got 680 / 1000 correct (68.00)

Iteration 0, loss = 0.6592
Checking accuracy on validation set
Got 635 / 1000 correct (63.50)

Iteration 100, loss = 0.6519
Checking accuracy on validation set
Got 619 / 1000 correct (61.90)

Iteration 200, loss = 0.8083
Checking accuracy on validation set
Got 663 / 1000 correct (66.30)

Iteration 300, loss = 0.6792
Checking accuracy on validation set
Got 658 / 1000 correct (65.80)
```

```
Iteration 400, loss = 0.5519
Checking accuracy on validation set
Got 623 / 1000 correct (62.30)

Iteration 500, loss = 0.5859
Checking accuracy on validation set
Got 512 / 1000 correct (51.20)

Iteration 600, loss = 0.9197
Checking accuracy on validation set
Got 633 / 1000 correct (63.30)

Iteration 700, loss = 1.0267
Checking accuracy on validation set
Got 541 / 1000 correct (54.10)

Iteration 0, loss = 0.7763
Checking accuracy on validation set
Got 523 / 1000 correct (52.30)

Iteration 100, loss = 0.7028
Checking accuracy on validation set
Got 568 / 1000 correct (56.80)

Iteration 200, loss = 0.7006
Checking accuracy on validation set
Got 605 / 1000 correct (60.50)

Iteration 300, loss = 0.5790
Checking accuracy on validation set
Got 577 / 1000 correct (57.70)

Iteration 400, loss = 0.5949
Checking accuracy on validation set
Got 630 / 1000 correct (63.00)

Iteration 500, loss = 0.6553
Checking accuracy on validation set
Got 580 / 1000 correct (58.00)

Iteration 600, loss = 0.6042
Checking accuracy on validation set
Got 486 / 1000 correct (48.60)

Iteration 700, loss = 0.8419
Checking accuracy on validation set
Got 549 / 1000 correct (54.90)
```

```
Iteration 0, loss = 0.5329
Checking accuracy on validation set
Got 664 / 1000 correct (66.40)

Iteration 100, loss = 0.6483
Checking accuracy on validation set
Got 703 / 1000 correct (70.30)

Iteration 200, loss = 0.6377
Checking accuracy on validation set
Got 622 / 1000 correct (62.20)

Iteration 300, loss = 0.6414
Checking accuracy on validation set
Got 525 / 1000 correct (52.50)

Iteration 400, loss = 0.6502
Checking accuracy on validation set
Got 649 / 1000 correct (64.90)

Iteration 500, loss = 0.7756
Checking accuracy on validation set
Got 653 / 1000 correct (65.30)

Iteration 600, loss = 0.6251
Checking accuracy on validation set
Got 656 / 1000 correct (65.60)

Iteration 700, loss = 0.6318
Checking accuracy on validation set
Got 648 / 1000 correct (64.80)

Iteration 0, loss = 0.6928
Checking accuracy on validation set
Got 655 / 1000 correct (65.50)

Iteration 100, loss = 0.7962
Checking accuracy on validation set
Got 518 / 1000 correct (51.80)

Iteration 200, loss = 0.5211
Checking accuracy on validation set
Got 682 / 1000 correct (68.20)

Iteration 300, loss = 0.7523
Checking accuracy on validation set
Got 519 / 1000 correct (51.90)
```

```
Iteration 400, loss = 0.6141
Checking accuracy on validation set
Got 541 / 1000 correct (54.10)

Iteration 500, loss = 0.6203
Checking accuracy on validation set
Got 651 / 1000 correct (65.10)

Iteration 600, loss = 0.6152
Checking accuracy on validation set
Got 653 / 1000 correct (65.30)

Iteration 700, loss = 0.5765
Checking accuracy on validation set
Got 656 / 1000 correct (65.60)

Checking accuracy on validation set
Got 622 / 1000 correct (62.20)
Iteration 0, loss = 2.3393
Checking accuracy on validation set
Got 79 / 1000 correct (7.90)

Iteration 100, loss = 1.7153
Checking accuracy on validation set
Got 414 / 1000 correct (41.40)

Iteration 200, loss = 1.2310
Checking accuracy on validation set
Got 440 / 1000 correct (44.00)

Iteration 300, loss = 1.0536
Checking accuracy on validation set
Got 468 / 1000 correct (46.80)

Iteration 400, loss = 1.3219
Checking accuracy on validation set
Got 557 / 1000 correct (55.70)

Iteration 500, loss = 1.1233
Checking accuracy on validation set
Got 597 / 1000 correct (59.70)

Iteration 600, loss = 1.3155
Checking accuracy on validation set
Got 547 / 1000 correct (54.70)

Iteration 700, loss = 0.7934
Checking accuracy on validation set
```

```
Got 635 / 1000 correct (63.50)

Iteration 0, loss = 0.8559
Checking accuracy on validation set
Got 608 / 1000 correct (60.80)

Iteration 100, loss = 0.7534
Checking accuracy on validation set
Got 658 / 1000 correct (65.80)

Iteration 200, loss = 0.9049
Checking accuracy on validation set
Got 579 / 1000 correct (57.90)

Iteration 300, loss = 0.8038
Checking accuracy on validation set
Got 653 / 1000 correct (65.30)

Iteration 400, loss = 0.7172
Checking accuracy on validation set
Got 689 / 1000 correct (68.90)

Iteration 500, loss = 0.9630
Checking accuracy on validation set
Got 631 / 1000 correct (63.10)

Iteration 600, loss = 0.7299
Checking accuracy on validation set
Got 643 / 1000 correct (64.30)

Iteration 700, loss = 0.7294
Checking accuracy on validation set
Got 707 / 1000 correct (70.70)

Iteration 0, loss = 0.6715
Checking accuracy on validation set
Got 638 / 1000 correct (63.80)

Iteration 100, loss = 0.6934
Checking accuracy on validation set
Got 696 / 1000 correct (69.60)

Iteration 200, loss = 0.6923
Checking accuracy on validation set
Got 719 / 1000 correct (71.90)

Iteration 300, loss = 0.6493
Checking accuracy on validation set
```

```
Got 687 / 1000 correct (68.70)

Iteration 400, loss = 0.5244
Checking accuracy on validation set
Got 678 / 1000 correct (67.80)

Iteration 500, loss = 0.9384
Checking accuracy on validation set
Got 714 / 1000 correct (71.40)

Iteration 600, loss = 0.7230
Checking accuracy on validation set
Got 755 / 1000 correct (75.50)

Iteration 700, loss = 0.6184
Checking accuracy on validation set
Got 763 / 1000 correct (76.30)

Iteration 0, loss = 0.6262
Checking accuracy on validation set
Got 718 / 1000 correct (71.80)

Iteration 100, loss = 0.7112
Checking accuracy on validation set
Got 752 / 1000 correct (75.20)

Iteration 200, loss = 0.6322
Checking accuracy on validation set
Got 765 / 1000 correct (76.50)

Iteration 300, loss = 0.5250
Checking accuracy on validation set
Got 746 / 1000 correct (74.60)

Iteration 400, loss = 0.6840
Checking accuracy on validation set
Got 714 / 1000 correct (71.40)

Iteration 500, loss = 0.8304
Checking accuracy on validation set
Got 778 / 1000 correct (77.80)

Iteration 600, loss = 0.5438
Checking accuracy on validation set
Got 760 / 1000 correct (76.00)

Iteration 700, loss = 0.5177
Checking accuracy on validation set
```

```
Got 776 / 1000 correct (77.60)

Iteration 0, loss = 0.5184
Checking accuracy on validation set
Got 782 / 1000 correct (78.20)

Iteration 100, loss = 0.4734
Checking accuracy on validation set
Got 748 / 1000 correct (74.80)

Iteration 200, loss = 0.6123
Checking accuracy on validation set
Got 766 / 1000 correct (76.60)

Iteration 300, loss = 0.4003
Checking accuracy on validation set
Got 775 / 1000 correct (77.50)

Iteration 400, loss = 0.5206
Checking accuracy on validation set
Got 744 / 1000 correct (74.40)

Iteration 500, loss = 0.4467
Checking accuracy on validation set
Got 763 / 1000 correct (76.30)

Iteration 600, loss = 0.4704
Checking accuracy on validation set
Got 786 / 1000 correct (78.60)

Iteration 700, loss = 0.4778
Checking accuracy on validation set
Got 761 / 1000 correct (76.10)

Iteration 0, loss = 0.4275
Checking accuracy on validation set
Got 775 / 1000 correct (77.50)

Iteration 100, loss = 0.3190
Checking accuracy on validation set
Got 771 / 1000 correct (77.10)

Iteration 200, loss = 0.3980
Checking accuracy on validation set
Got 804 / 1000 correct (80.40)

Iteration 300, loss = 0.3942
Checking accuracy on validation set
```

```
Got 737 / 1000 correct (73.70)

Iteration 400, loss = 0.7055
Checking accuracy on validation set
Got 799 / 1000 correct (79.90)

Iteration 500, loss = 0.4338
Checking accuracy on validation set
Got 792 / 1000 correct (79.20)

Iteration 600, loss = 0.6156
Checking accuracy on validation set
Got 781 / 1000 correct (78.10)

Iteration 700, loss = 0.3437
Checking accuracy on validation set
Got 781 / 1000 correct (78.10)

Iteration 0, loss = 0.4350
Checking accuracy on validation set
Got 787 / 1000 correct (78.70)

Iteration 100, loss = 0.4085
Checking accuracy on validation set
Got 801 / 1000 correct (80.10)

Iteration 200, loss = 0.3566
Checking accuracy on validation set
Got 793 / 1000 correct (79.30)

Iteration 300, loss = 0.4244
Checking accuracy on validation set
Got 793 / 1000 correct (79.30)

Iteration 400, loss = 0.2802
Checking accuracy on validation set
Got 818 / 1000 correct (81.80)

Iteration 500, loss = 0.4274
Checking accuracy on validation set
Got 804 / 1000 correct (80.40)

Iteration 600, loss = 0.6678
Checking accuracy on validation set
Got 825 / 1000 correct (82.50)

Iteration 700, loss = 0.2171
Checking accuracy on validation set
```

```
Got 779 / 1000 correct (77.90)

Iteration 0, loss = 0.2385
Checking accuracy on validation set
Got 802 / 1000 correct (80.20)

Iteration 100, loss = 0.2985
Checking accuracy on validation set
Got 801 / 1000 correct (80.10)

Iteration 200, loss = 0.3705
Checking accuracy on validation set
Got 840 / 1000 correct (84.00)

Iteration 300, loss = 0.4440
Checking accuracy on validation set
Got 779 / 1000 correct (77.90)

Iteration 400, loss = 0.4307
Checking accuracy on validation set
Got 819 / 1000 correct (81.90)

Iteration 500, loss = 0.4516
Checking accuracy on validation set
Got 808 / 1000 correct (80.80)

Iteration 600, loss = 0.4707
Checking accuracy on validation set
Got 826 / 1000 correct (82.60)

Iteration 700, loss = 0.4822
Checking accuracy on validation set
Got 817 / 1000 correct (81.70)

Iteration 0, loss = 0.2681
Checking accuracy on validation set
Got 822 / 1000 correct (82.20)

Iteration 100, loss = 0.2593
Checking accuracy on validation set
Got 818 / 1000 correct (81.80)

Iteration 200, loss = 0.3630
Checking accuracy on validation set
Got 806 / 1000 correct (80.60)

Iteration 300, loss = 0.2856
Checking accuracy on validation set
```

```
Got 803 / 1000 correct (80.30)

Iteration 400, loss = 0.4308
Checking accuracy on validation set
Got 826 / 1000 correct (82.60)

Iteration 500, loss = 0.3884
Checking accuracy on validation set
Got 836 / 1000 correct (83.60)

Iteration 600, loss = 0.5477
Checking accuracy on validation set
Got 807 / 1000 correct (80.70)

Iteration 700, loss = 0.3281
Checking accuracy on validation set
Got 801 / 1000 correct (80.10)

Iteration 0, loss = 0.3122
Checking accuracy on validation set
Got 807 / 1000 correct (80.70)

Iteration 100, loss = 0.1820
Checking accuracy on validation set
Got 850 / 1000 correct (85.00)

Iteration 200, loss = 0.2425
Checking accuracy on validation set
Got 830 / 1000 correct (83.00)

Iteration 300, loss = 0.3435
Checking accuracy on validation set
Got 822 / 1000 correct (82.20)

Iteration 400, loss = 0.2657
Checking accuracy on validation set
Got 795 / 1000 correct (79.50)

Iteration 500, loss = 0.4239
Checking accuracy on validation set
Got 829 / 1000 correct (82.90)

Iteration 600, loss = 0.3468
Checking accuracy on validation set
Got 830 / 1000 correct (83.00)

Iteration 700, loss = 0.1951
Checking accuracy on validation set
```

```
Got 825 / 1000 correct (82.50)

Checking accuracy on validation set
Got 816 / 1000 correct (81.60)
you did it Noam, the accuracy is: 0.816
Iteration 0, loss = 2.4026
Checking accuracy on validation set
Got 87 / 1000 correct (8.70)

Iteration 100, loss = 1.6747
Checking accuracy on validation set
Got 356 / 1000 correct (35.60)

Iteration 200, loss = 1.4408
Checking accuracy on validation set
Got 314 / 1000 correct (31.40)

Iteration 300, loss = 1.3263
Checking accuracy on validation set
Got 405 / 1000 correct (40.50)

Iteration 400, loss = 1.1806
Checking accuracy on validation set
Got 454 / 1000 correct (45.40)

Iteration 500, loss = 1.2720
Checking accuracy on validation set
Got 557 / 1000 correct (55.70)

Iteration 600, loss = 0.8844
Checking accuracy on validation set
Got 635 / 1000 correct (63.50)

Iteration 700, loss = 0.9417
Checking accuracy on validation set
Got 634 / 1000 correct (63.40)

Iteration 0, loss = 1.0269
Checking accuracy on validation set
Got 483 / 1000 correct (48.30)

Iteration 100, loss = 1.1192
Checking accuracy on validation set
Got 608 / 1000 correct (60.80)

Iteration 200, loss = 0.9201
Checking accuracy on validation set
Got 628 / 1000 correct (62.80)
```

```
Iteration 300, loss = 0.9230
Checking accuracy on validation set
Got 607 / 1000 correct (60.70)

Iteration 400, loss = 0.8283
Checking accuracy on validation set
Got 538 / 1000 correct (53.80)

Iteration 500, loss = 0.7124
Checking accuracy on validation set
Got 679 / 1000 correct (67.90)

Iteration 600, loss = 0.8092
Checking accuracy on validation set
Got 669 / 1000 correct (66.90)

Iteration 700, loss = 0.7795
Checking accuracy on validation set
Got 670 / 1000 correct (67.00)

Iteration 0, loss = 0.7256
Checking accuracy on validation set
Got 723 / 1000 correct (72.30)

Iteration 100, loss = 0.7766
Checking accuracy on validation set
Got 692 / 1000 correct (69.20)

Iteration 200, loss = 0.5740
Checking accuracy on validation set
Got 649 / 1000 correct (64.90)

Iteration 300, loss = 0.6580
Checking accuracy on validation set
Got 644 / 1000 correct (64.40)

Iteration 400, loss = 0.6753
Checking accuracy on validation set
Got 742 / 1000 correct (74.20)

Iteration 500, loss = 0.7611
Checking accuracy on validation set
Got 700 / 1000 correct (70.00)

Iteration 600, loss = 0.8164
Checking accuracy on validation set
Got 624 / 1000 correct (62.40)
```

```
Iteration 700, loss = 0.5760
Checking accuracy on validation set
Got 746 / 1000 correct (74.60)

Iteration 0, loss = 0.4830
Checking accuracy on validation set
Got 725 / 1000 correct (72.50)

Iteration 100, loss = 0.7291
Checking accuracy on validation set
Got 720 / 1000 correct (72.00)

Iteration 200, loss = 0.5030
Checking accuracy on validation set
Got 728 / 1000 correct (72.80)

Iteration 300, loss = 0.6099
Checking accuracy on validation set
Got 771 / 1000 correct (77.10)

Iteration 400, loss = 0.5757
Checking accuracy on validation set
Got 755 / 1000 correct (75.50)

Iteration 500, loss = 0.6121
Checking accuracy on validation set
Got 764 / 1000 correct (76.40)

Iteration 600, loss = 0.6235
Checking accuracy on validation set
Got 778 / 1000 correct (77.80)

Iteration 700, loss = 0.6058
Checking accuracy on validation set
Got 768 / 1000 correct (76.80)

Iteration 0, loss = 0.3979
Checking accuracy on validation set
Got 754 / 1000 correct (75.40)

Iteration 100, loss = 0.4610
Checking accuracy on validation set
Got 704 / 1000 correct (70.40)

Iteration 200, loss = 0.2944
Checking accuracy on validation set
Got 734 / 1000 correct (73.40)
```

```
Iteration 300, loss = 0.5862
Checking accuracy on validation set
Got 738 / 1000 correct (73.80)

Iteration 400, loss = 0.5473
Checking accuracy on validation set
Got 761 / 1000 correct (76.10)

Iteration 500, loss = 0.5916
Checking accuracy on validation set
Got 726 / 1000 correct (72.60)

Iteration 600, loss = 0.4352
Checking accuracy on validation set
Got 810 / 1000 correct (81.00)

Iteration 700, loss = 0.3217
Checking accuracy on validation set
Got 731 / 1000 correct (73.10)

Iteration 0, loss = 0.4254
Checking accuracy on validation set
Got 782 / 1000 correct (78.20)

Iteration 100, loss = 0.4780
Checking accuracy on validation set
Got 730 / 1000 correct (73.00)

Iteration 200, loss = 0.4991
Checking accuracy on validation set
Got 783 / 1000 correct (78.30)

Iteration 300, loss = 0.5708
Checking accuracy on validation set
Got 779 / 1000 correct (77.90)

Iteration 400, loss = 0.4440
Checking accuracy on validation set
Got 760 / 1000 correct (76.00)

Iteration 500, loss = 0.3683
Checking accuracy on validation set
Got 792 / 1000 correct (79.20)

Iteration 600, loss = 0.5577
Checking accuracy on validation set
Got 792 / 1000 correct (79.20)
```

```
Iteration 700, loss = 0.5759
Checking accuracy on validation set
Got 775 / 1000 correct (77.50)

Iteration 0, loss = 0.3870
Checking accuracy on validation set
Got 799 / 1000 correct (79.90)

Iteration 100, loss = 0.5250
Checking accuracy on validation set
Got 756 / 1000 correct (75.60)

Iteration 200, loss = 0.4783
Checking accuracy on validation set
Got 787 / 1000 correct (78.70)

Iteration 300, loss = 0.4282
Checking accuracy on validation set
Got 793 / 1000 correct (79.30)

Iteration 400, loss = 0.4628
Checking accuracy on validation set
Got 778 / 1000 correct (77.80)

Iteration 500, loss = 0.3494
Checking accuracy on validation set
Got 812 / 1000 correct (81.20)

Iteration 600, loss = 0.5252
Checking accuracy on validation set
Got 803 / 1000 correct (80.30)

Iteration 700, loss = 0.4456
Checking accuracy on validation set
Got 800 / 1000 correct (80.00)

Iteration 0, loss = 0.2540
Checking accuracy on validation set
Got 812 / 1000 correct (81.20)

Iteration 100, loss = 0.2993
Checking accuracy on validation set
Got 806 / 1000 correct (80.60)

Iteration 200, loss = 0.4371
Checking accuracy on validation set
Got 747 / 1000 correct (74.70)
```

```
Iteration 300, loss = 0.3659
Checking accuracy on validation set
Got 711 / 1000 correct (71.10)

Iteration 400, loss = 0.3015
Checking accuracy on validation set
Got 745 / 1000 correct (74.50)

Iteration 500, loss = 0.3900
Checking accuracy on validation set
Got 773 / 1000 correct (77.30)

Iteration 600, loss = 0.2656
Checking accuracy on validation set
Got 813 / 1000 correct (81.30)

Iteration 700, loss = 0.4227
Checking accuracy on validation set
Got 795 / 1000 correct (79.50)

Iteration 0, loss = 0.4233
Checking accuracy on validation set
Got 801 / 1000 correct (80.10)

Iteration 100, loss = 0.4080
Checking accuracy on validation set
Got 792 / 1000 correct (79.20)

Iteration 200, loss = 0.5885
Checking accuracy on validation set
Got 782 / 1000 correct (78.20)

Iteration 300, loss = 0.3174
Checking accuracy on validation set
Got 808 / 1000 correct (80.80)

Iteration 400, loss = 0.6305
Checking accuracy on validation set
Got 793 / 1000 correct (79.30)

Iteration 500, loss = 0.4058
Checking accuracy on validation set
Got 798 / 1000 correct (79.80)

Iteration 600, loss = 0.4663
Checking accuracy on validation set
Got 813 / 1000 correct (81.30)
```

```
Iteration 700, loss = 0.1829
Checking accuracy on validation set
Got 815 / 1000 correct (81.50)

Iteration 0, loss = 0.2856
Checking accuracy on validation set
Got 807 / 1000 correct (80.70)

Iteration 100, loss = 0.2932
Checking accuracy on validation set
Got 817 / 1000 correct (81.70)

Iteration 200, loss = 0.3511
Checking accuracy on validation set
Got 783 / 1000 correct (78.30)

Iteration 300, loss = 0.2448
Checking accuracy on validation set
Got 803 / 1000 correct (80.30)

Iteration 400, loss = 0.2439
Checking accuracy on validation set
Got 789 / 1000 correct (78.90)

Iteration 500, loss = 0.4061
Checking accuracy on validation set
Got 797 / 1000 correct (79.70)

Iteration 600, loss = 0.2574
Checking accuracy on validation set
Got 811 / 1000 correct (81.10)

Iteration 700, loss = 0.2765
Checking accuracy on validation set
Got 816 / 1000 correct (81.60)

Checking accuracy on validation set
Got 835 / 1000 correct (83.50)
you did it Noam, the accuracy is: 0.835
Iteration 0, loss = 2.3553
Checking accuracy on validation set
Got 102 / 1000 correct (10.20)

Iteration 100, loss = 1.7001
Checking accuracy on validation set
Got 212 / 1000 correct (21.20)
```

```
Iteration 200, loss = 1.4500
Checking accuracy on validation set
Got 333 / 1000 correct (33.30)

Iteration 300, loss = 1.3925
Checking accuracy on validation set
Got 410 / 1000 correct (41.00)

Iteration 400, loss = 1.3650
Checking accuracy on validation set
Got 458 / 1000 correct (45.80)

Iteration 500, loss = 1.2375
Checking accuracy on validation set
Got 487 / 1000 correct (48.70)

Iteration 600, loss = 1.1473
Checking accuracy on validation set
Got 568 / 1000 correct (56.80)

Iteration 700, loss = 1.0649
Checking accuracy on validation set
Got 561 / 1000 correct (56.10)

Iteration 0, loss = 1.0806
Checking accuracy on validation set
Got 508 / 1000 correct (50.80)

Iteration 100, loss = 1.0856
Checking accuracy on validation set
Got 495 / 1000 correct (49.50)

Iteration 200, loss = 1.1200
Checking accuracy on validation set
Got 555 / 1000 correct (55.50)

Iteration 300, loss = 1.0733
Checking accuracy on validation set
Got 598 / 1000 correct (59.80)

Iteration 400, loss = 0.7331
Checking accuracy on validation set
Got 638 / 1000 correct (63.80)

Iteration 500, loss = 0.8960
Checking accuracy on validation set
Got 600 / 1000 correct (60.00)
```

```
Iteration 600, loss = 0.9769
Checking accuracy on validation set
Got 611 / 1000 correct (61.10)

Iteration 700, loss = 0.7986
Checking accuracy on validation set
Got 630 / 1000 correct (63.00)

Iteration 0, loss = 0.5917
Checking accuracy on validation set
Got 598 / 1000 correct (59.80)

Iteration 100, loss = 0.6899
Checking accuracy on validation set
Got 620 / 1000 correct (62.00)

Iteration 200, loss = 0.7799
Checking accuracy on validation set
Got 660 / 1000 correct (66.00)

Iteration 300, loss = 0.7256
Checking accuracy on validation set
Got 613 / 1000 correct (61.30)

Iteration 400, loss = 0.6986
Checking accuracy on validation set
Got 718 / 1000 correct (71.80)

Iteration 500, loss = 0.9015
Checking accuracy on validation set
Got 652 / 1000 correct (65.20)

Iteration 600, loss = 0.5081
Checking accuracy on validation set
Got 737 / 1000 correct (73.70)

Iteration 700, loss = 0.4962
Checking accuracy on validation set
Got 746 / 1000 correct (74.60)

Iteration 0, loss = 0.6042
Checking accuracy on validation set
Got 742 / 1000 correct (74.20)

Iteration 100, loss = 0.6836
Checking accuracy on validation set
Got 757 / 1000 correct (75.70)
```

```
Iteration 200, loss = 0.8426
Checking accuracy on validation set
Got 712 / 1000 correct (71.20)

Iteration 300, loss = 0.8060
Checking accuracy on validation set
Got 640 / 1000 correct (64.00)

Iteration 400, loss = 0.8399
Checking accuracy on validation set
Got 722 / 1000 correct (72.20)

Iteration 500, loss = 0.5727
Checking accuracy on validation set
Got 725 / 1000 correct (72.50)

Iteration 600, loss = 0.7197
Checking accuracy on validation set
Got 769 / 1000 correct (76.90)

Iteration 700, loss = 0.6534
Checking accuracy on validation set
Got 760 / 1000 correct (76.00)

Iteration 0, loss = 0.4982
Checking accuracy on validation set
Got 722 / 1000 correct (72.20)

Iteration 100, loss = 0.4603
Checking accuracy on validation set
Got 694 / 1000 correct (69.40)

Iteration 200, loss = 0.6366
Checking accuracy on validation set
Got 764 / 1000 correct (76.40)

Iteration 300, loss = 0.6812
Checking accuracy on validation set
Got 729 / 1000 correct (72.90)

Iteration 400, loss = 0.5961
Checking accuracy on validation set
Got 761 / 1000 correct (76.10)

Iteration 500, loss = 0.6290
Checking accuracy on validation set
Got 737 / 1000 correct (73.70)
```

```
Iteration 600, loss = 0.7320
Checking accuracy on validation set
Got 767 / 1000 correct (76.70)

Iteration 700, loss = 0.6352
Checking accuracy on validation set
Got 730 / 1000 correct (73.00)

Iteration 0, loss = 0.5563
Checking accuracy on validation set
Got 714 / 1000 correct (71.40)

Iteration 100, loss = 0.5170
Checking accuracy on validation set
Got 755 / 1000 correct (75.50)

Iteration 200, loss = 0.4494
Checking accuracy on validation set
Got 760 / 1000 correct (76.00)

Iteration 300, loss = 0.4805
Checking accuracy on validation set
Got 756 / 1000 correct (75.60)

Iteration 400, loss = 0.6070
Checking accuracy on validation set
Got 789 / 1000 correct (78.90)

Iteration 500, loss = 0.4348
Checking accuracy on validation set
Got 687 / 1000 correct (68.70)

Iteration 600, loss = 0.4735
Checking accuracy on validation set
Got 789 / 1000 correct (78.90)

Iteration 700, loss = 0.6405
Checking accuracy on validation set
Got 758 / 1000 correct (75.80)

Iteration 0, loss = 0.4756
Checking accuracy on validation set
Got 754 / 1000 correct (75.40)

Iteration 100, loss = 0.4406
Checking accuracy on validation set
Got 784 / 1000 correct (78.40)
```

```
Iteration 200, loss = 0.4695
Checking accuracy on validation set
Got 793 / 1000 correct (79.30)

Iteration 300, loss = 0.3581
Checking accuracy on validation set
Got 775 / 1000 correct (77.50)

Iteration 400, loss = 0.3723
Checking accuracy on validation set
Got 799 / 1000 correct (79.90)

Iteration 500, loss = 0.3670
Checking accuracy on validation set
Got 785 / 1000 correct (78.50)

Iteration 600, loss = 0.4898
Checking accuracy on validation set
Got 819 / 1000 correct (81.90)

Iteration 700, loss = 0.3984
Checking accuracy on validation set
Got 817 / 1000 correct (81.70)

Iteration 0, loss = 0.3586
Checking accuracy on validation set
Got 775 / 1000 correct (77.50)

Iteration 100, loss = 0.6423
Checking accuracy on validation set
Got 814 / 1000 correct (81.40)

Iteration 200, loss = 0.4188
Checking accuracy on validation set
Got 784 / 1000 correct (78.40)

Iteration 300, loss = 0.3416
Checking accuracy on validation set
Got 811 / 1000 correct (81.10)

Iteration 400, loss = 0.4337
Checking accuracy on validation set
Got 791 / 1000 correct (79.10)

Iteration 500, loss = 0.5732
Checking accuracy on validation set
Got 751 / 1000 correct (75.10)
```

```
Iteration 600, loss = 0.4447
Checking accuracy on validation set
Got 800 / 1000 correct (80.00)

Iteration 700, loss = 0.3345
Checking accuracy on validation set
Got 773 / 1000 correct (77.30)

Iteration 0, loss = 0.5974
Checking accuracy on validation set
Got 813 / 1000 correct (81.30)

Iteration 100, loss = 0.3604
Checking accuracy on validation set
Got 802 / 1000 correct (80.20)

Iteration 200, loss = 0.3357
Checking accuracy on validation set
Got 796 / 1000 correct (79.60)

Iteration 300, loss = 0.6671
Checking accuracy on validation set
Got 798 / 1000 correct (79.80)

Iteration 400, loss = 0.4543
Checking accuracy on validation set
Got 810 / 1000 correct (81.00)

Iteration 500, loss = 0.4090
Checking accuracy on validation set
Got 805 / 1000 correct (80.50)

Iteration 600, loss = 0.2965
Checking accuracy on validation set
Got 804 / 1000 correct (80.40)

Iteration 700, loss = 0.3191
Checking accuracy on validation set
Got 802 / 1000 correct (80.20)

Iteration 0, loss = 0.2218
Checking accuracy on validation set
Got 808 / 1000 correct (80.80)

Iteration 100, loss = 0.3148
Checking accuracy on validation set
Got 796 / 1000 correct (79.60)
```

```
Iteration 200, loss = 0.3161
Checking accuracy on validation set
Got 795 / 1000 correct (79.50)

Iteration 300, loss = 0.3740
Checking accuracy on validation set
Got 805 / 1000 correct (80.50)

Iteration 400, loss = 0.4705
Checking accuracy on validation set
Got 784 / 1000 correct (78.40)

Iteration 500, loss = 0.4266
Checking accuracy on validation set
Got 789 / 1000 correct (78.90)

Iteration 600, loss = 0.3544
Checking accuracy on validation set
Got 805 / 1000 correct (80.50)

Iteration 700, loss = 0.3709
Checking accuracy on validation set
Got 771 / 1000 correct (77.10)

Checking accuracy on validation set
Got 818 / 1000 correct (81.80)
```

8.1 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.

Answer: i did a wide search on the three models that where segested, with the spatial and vanilla norm. i did a search on 4 optimizers (that we have used in the past) and depth of : n = [3, 4, 5],m = [2, 3]. also i used a higher filter size of 64, which is nessecary for this task. I then rand each model for 5 epoch, and took the top 3, and ran them for the full 10 (recreated them - so it woldnt be 5+10). this took over two hours. graphs from this: all the accuracy after 5 epochs of all the models:

the number of conv layer vs accuracy:

affine layer vs accuracy:

optimizer vs accurancy:

model type vs. accuracy:

we can see that Adam was by far the best, and model of type two was also. other wise, the affine layers where quite evenly convolution was a bit more spread, with 5 being a better average, but 4 giving better all togehter

[ ]:
```
est
```

8.2 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.

[40]:
```
best_model = model
check_accuracy_part34(loader_test, best_model)
```

```
Checking accuracy on test set
Got 8156 / 10000 correct (81.56)
```

[40]:
```
0.8156
```

RNN_Captioning_pytorch

January 21, 2026

[ ]:
```
# This mounts your Google Drive to the Colab VM.
from google.colab import drive
drive.mount('/content/drive')

# TODO: Enter the foldername in your Drive where you have saved the unzipped
# assignment folder, e.g. 'icv83551/assignments/assignment2/'
FOLDERNAME = "icv83551/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 COCO dataset to your Drive
# if it doesn't already exist.
%cd /content/drive/My\ Drive/$FOLDERNAME/icv83551/datasets/
!bash get_coco_dataset.sh
%cd /content/drive/My\ Drive/$FOLDERNAME
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
/content/drive/My Drive/icv83551/assignments/assignment2/icv83551/datasets
/content/drive/My Drive/icv83551/assignments/assignment2
```

1 Image Captioning with RNNs

In this exercise, you will implement vanilla Recurrent Neural Networks and use them to train a model that can generate novel captions for images.

[ ]:
```
# Setup cell.
import time, os, json
import numpy as np
import torch
import matplotlib.pyplot as plt
```

```
from icv83551.gradient_check import eval_numerical_gradient,␣
 ↪eval_numerical_gradient_array
from icv83551.rnn_layers_pytorch import *
from icv83551.captioning_solver_pytorch import CaptioningSolverPytorch
from icv83551.classifiers.rnn_pytorch import CaptioningRNN
from icv83551.coco_utils import load_coco_data, sample_coco_minibatch,␣
 ↪decode_captions
from icv83551.image_utils import image_from_url

%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'

#%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 COCO Dataset

For this exercise, we will use the 2014 release of the COCO dataset, a standard testbed for image captioning. The dataset consists of 80,000 training images and 40,000 validation images, each annotated with 5 captions written by workers on Amazon Mechanical Turk.

Image features. We have preprocessed the data and extracted features for you already. For all images, we have extracted features from the fc7 layer of the VGG-16 network pretrained on ImageNet, and these features are stored in the files `train2014_vgg16_fc7.h5` and `val2014_vgg16_fc7.h5`. To cut down on processing time and memory requirements, we have reduced the dimensionality of the features from 4096 to 512 using Principal Component Analysis (PCA), and these features are stored in the files `train2014_vgg16_fc7_pca.h5` and `val2014_vgg16_fc7_pca.h5`. The raw images take up nearly 20GB of space so we have not included them in the download. Since all images are taken from Flickr, we have stored the URLs of the training and validation images in the files `train2014_urls.txt` and `val2014_urls.txt`. This allows you to download images on-the-fly for visualization.

Captions. Dealing with strings is inefficient, so we will work with an encoded version of the captions. Each word is assigned an integer ID, allowing us to represent a caption by a sequence of integers. The mapping between integer IDs and words is in the file `coco2014_vocab.json`, and you can use the function `decode_captions` from the file `icv83551/coco_utils.py` to convert NumPy arrays of integer IDs back into strings.

Tokens. There are a couple special tokens that we add to the vocabulary, and we have taken care of all implementation details around special tokens for you. We prepend a special `<START>` token and append an `<END>` token to the beginning and end of each caption respectively. Rare words are replaced with a special `<UNK>` token (for "unknown"). In addition, since we want to train with

minibatches containing captions of different lengths, we pad short captions with a special <NULL> token after the <END> token and don't compute loss or gradient for <NULL> tokens.

You can load all of the COCO data (captions, features, URLs, and vocabulary) using the load_coco_data function from the file icv83551/coco_utils.py. Run the following cell to do so:

[ ]:
```
# Load COCO data from disk into a dictionary.
# We'll work with dimensionality-reduced features for the remainder of this␣
 ↪assignment,
# but you can also experiment with the original features on your own by␣
 ↪changing the flag below.
data = load_coco_data(pca_features=True)

# Print out all the keys and values from the data dictionary.
for k, v in data.items():
    if type(v) == np.ndarray:
        print(k, type(v), v.shape, v.dtype)
    else:
        print(k, type(v), len(v))
```

```
base dir  /content/drive/My
Drive/icv83551/assignments/assignment2/icv83551/datasets/coco_captioning
train_captions <class 'numpy.ndarray'> (400135, 17) int32
train_image_idxs <class 'numpy.ndarray'> (400135,) int32
val_captions <class 'numpy.ndarray'> (195954, 17) int32
val_image_idxs <class 'numpy.ndarray'> (195954,) int32
train_features <class 'numpy.ndarray'> (82783, 512) float32
val_features <class 'numpy.ndarray'> (40504, 512) float32
idx_to_word <class 'list'> 1004
word_to_idx <class 'dict'> 1004
train_urls <class 'numpy.ndarray'> (82783,) <U63
val_urls <class 'numpy.ndarray'> (40504,) <U63
```

2.1 Inspect the Data

It is always a good idea to look at examples from the dataset before working with it.

You can use the sample_coco_minibatch function from the file icv83551/coco_utils.py to sample minibatches of data from the data structure returned from load_coco_data. Run the following to sample a small minibatch of training data and show the images and their captions. Running it multiple times and looking at the results helps you to get a sense of the dataset.

[ ]:
```
# Sample a minibatch and show the images and captions.
# If you get an error, the URL just no longer exists, so don't worry!
# You can re-sample as many times as you want.
#batch_size = 3

#captions, features, urls = sample_coco_minibatch(data, batch_size=batch_size)
```

```
#for i, (caption, url) in enumerate(zip(captions, urls)):
    #plt.imshow(image_from_url(url))
    #plt.axis('off')
    #caption_str = decode_captions(caption, data['idx_to_word'])
    #plt.title(caption_str)
    #plt.show()
```

3 Recurrent Neural Network

As discussed in lecture, we will use Recurrent Neural Network (RNN) language models for image captioning. The file `icv83551/rnn_layers_pytorch.py` contains implementations of different layer types that are needed for recurrent neural networks, and the file `icv83551/classifiers/rnn_pytorch.py` uses these layers to implement an image captioning model.

We will first implement different types of RNN layers in `icv83551/rnn_layers_pytorch.py`.

4 Vanilla RNN: Step Forward

Open the file `icv83551/rnn_layers_pytorch.py`. This file implements the forward passes for different types of layers that are commonly used in recurrent neural networks. Note that since we use pytorch, the backward pass will be handled by pytorch's autograd.

First implement the function `rnn_step_forward` which implements the forward pass for a single timestep of a vanilla recurrent neural network. After doing so run the following to check your implementation. You should see errors on the order of e-8 or less.

[ ]:
```
N, D, H = 3, 10, 4

x = torch.from_numpy(np.linspace(-0.4, 0.7, num=N*D).reshape(N, D))
prev_h = torch.from_numpy(np.linspace(-0.2, 0.5, num=N*H).reshape(N, H))
Wx = torch.from_numpy(np.linspace(-0.1, 0.9, num=D*H).reshape(D, H))
Wh = torch.from_numpy(np.linspace(-0.3, 0.7, num=H*H).reshape(H, H))
b = torch.from_numpy(np.linspace(-0.2, 0.4, num=H))

next_h = rnn_step_forward(x, prev_h, Wx, Wh, b).numpy()
expected_next_h = np.asarray([
  [-0.58172089, -0.50182032, -0.41232771, -0.31410098],
  [ 0.66854692,  0.79562378,  0.87755553,  0.92795967],
  [ 0.97934501,  0.99144213,  0.99646691,  0.99854353]])

print('next_h error: ', rel_error(expected_next_h, next_h))
```

```
next_h error:  6.292421426471037e-09
```

5 Vanilla RNN: Step Backward

Since we implemented `rnn_step_forward` with pytorch, we do NOT have to implement `rnn_step_backward`. We can verify pytorch autograd backward pass using our numerical gradient checker.

However, if you are feeling adventurous, you can try to implement `rnn_step_backward` yourself. It is not required in this assignment though.

[ ]:
```
from icv83551.rnn_layers_pytorch import rnn_step_forward

# Create test inputs
np.random.seed(231)
N, D, H = 4, 5, 6
x = torch.from_numpy(np.random.randn(N, D))
h = torch.from_numpy(np.random.randn(N, H))
Wx = torch.from_numpy(np.random.randn(D, H))
Wh = torch.from_numpy(np.random.randn(H, H))
b = torch.from_numpy(np.random.randn(H))

# Enable gradient tracking and do rnn forward pass
for tensor in [x, h, Wx, Wh, b]:
  tensor.requires_grad_()
next_h = rnn_step_forward(x, h, Wx, Wh, b)

# Simulate random upstream gradients and do a backward pass using pytorch's
# autograd.
dnext_h = torch.from_numpy(np.random.randn(*next_h.shape))
next_h.backward(dnext_h)

# Collect gradient in separate numpy arrays
dx = x.grad.detach().numpy()
dh = h.grad.detach().numpy()
dWx = Wx.grad.detach().numpy()
dWh = Wh.grad.detach().numpy()
db = b.grad.detach().numpy()
dnext_h = dnext_h.detach().numpy()

# Also convert test inputs to numpy arrays
x =  x.detach().numpy()
h =  h.detach().numpy()
Wx = Wx.detach().numpy()
Wh = Wh.detach().numpy()
b =  b.detach().numpy()

# Wrap our forward pass to support numpy array input and output. We use
# `torch.no_grad()` to explicitly disable gradient tracking.
def rnn_step_forward_numpy(x, h, Wx, Wh, b):
```

```
  with torch.no_grad():
    return rnn_step_forward(
        torch.from_numpy(x),
        torch.from_numpy(h),
        torch.from_numpy(Wx),
        torch.from_numpy(Wh),
        torch.from_numpy(b),
    ).numpy()

# Compute numerical gradients and compare.
fx = lambda x: rnn_step_forward_numpy(x, h, Wx, Wh, b)
fh = lambda h: rnn_step_forward_numpy(x, h, Wx, Wh, b)
fWx = lambda Wx: rnn_step_forward_numpy(x, h, Wx, Wh, b)
fWh = lambda Wh: rnn_step_forward_numpy(x, h, Wx, Wh, b)
fb = lambda b: rnn_step_forward_numpy(x, h, Wx, Wh, b)

dx_num = eval_numerical_gradient_array(fx, x, dnext_h)
dh_num = eval_numerical_gradient_array(fh, h, dnext_h)
dWx_num = eval_numerical_gradient_array(fWx, Wx, dnext_h)
dWh_num = eval_numerical_gradient_array(fWh, Wh, dnext_h)
db_num = eval_numerical_gradient_array(fb, b, dnext_h)

# You should see errors on the order of 1e-9 or less
print('dx error: ', rel_error(dx_num, dx))
print('dh error: ', rel_error(dh_num, dh))
print('dWx error: ', rel_error(dWx_num, dWx))
print('dWh error: ', rel_error(dWh_num, dWh))
print('db error: ', rel_error(db_num, db))
```

```
dx error:  2.319932372313319e-10
dh error:  2.682833932515051e-10
dWx error:  8.820301273669344e-10
dWh error:  4.703191244726939e-10
db error:  1.5956895526227225e-11
```

6 Vanilla RNN: Forward

Now that you have implemented the forward for a single timestep of a vanilla RNN, you will use it to implement a RNN that processes an entire sequence of data.

In the file `icv83551/rnn_layers_pytorch.py`, implement the function `rnn_forward`. This should be implemented using the `rnn_step_forward` function that you defined above. After doing so run the following to check your implementation. You should see errors on the order of `e-7` or less.

[ ]:
```
from icv83551.rnn_layers_pytorch import rnn_forward

N, T, D, H = 2, 3, 4, 5
```

```
x = torch.from_numpy(np.linspace(-0.1, 0.3, num=N*T*D).reshape(N, T, D))
h0 = torch.from_numpy(np.linspace(-0.3, 0.1, num=N*H).reshape(N, H))
Wx = torch.from_numpy(np.linspace(-0.2, 0.4, num=D*H).reshape(D, H))
Wh = torch.from_numpy(np.linspace(-0.4, 0.1, num=H*H).reshape(H, H))
b = torch.from_numpy(np.linspace(-0.7, 0.1, num=H))

h = rnn_forward(x, h0, Wx, Wh, b).numpy()
expected_h = np.asarray([
  [
    [-0.42070749, -0.27279261, -0.11074945,  0.05740409,  0.22236251],
    [-0.39525808, -0.22554661, -0.0409454,   0.14649412,  0.32397316],
    [-0.42305111, -0.24223728, -0.04287027,  0.15997045,  0.35014525],
  ],
  [
    [-0.55857474, -0.39065825, -0.19198182,  0.02378408,  0.23735671],
    [-0.27150199, -0.07088804,  0.13562939,  0.33099728,  0.50158768],
    [-0.51014825, -0.30524429, -0.06755202,  0.17806392,  0.40333043]]])
print('h error: ', rel_error(expected_h, h))
```

```
h error:  7.728466180186066e-08
```

7 Vanilla RNN: Backward

As before, we can verify pytorch autograd backward pass using our numerical gradient checker. You can also you can try to implement `rnn_step_backward` yourself if you want. It is not required in this assignment though.

[ ]:
```
from icv83551.rnn_layers_pytorch import rnn_forward

# Create test inputs
np.random.seed(231)
N, D, T, H = 2, 3, 10, 5
x = torch.from_numpy(np.random.randn(N, T, D))
h0 = torch.from_numpy(np.random.randn(N, H))
Wx = torch.from_numpy(np.random.randn(D, H))
Wh = torch.from_numpy(np.random.randn(H, H))
b = torch.from_numpy(np.random.randn(H))

# Enable gradient tracking and do forward pass
for tensor in [x, h0, Wx, Wh, b]:
  tensor.requires_grad_()
h = rnn_forward(x, h0, Wx, Wh, b)

# Simulate random upstream gradients and do a backward pass using pytorch's
# autograd.
dh = torch.from_numpy(np.random.randn(*h.shape))
```

```
h.backward(dh)

# Collect gradient in separate numpy arrays
dx = x.grad.detach().numpy()
dh0 = h0.grad.detach().numpy()
dWx = Wx.grad.detach().numpy()
dWh = Wh.grad.detach().numpy()
db = b.grad.detach().numpy()
dh = dh.detach().numpy()

# Also convert test inputs to numpy arrays
x =  x.detach().numpy()
h0 =  h0.detach().numpy()
Wx = Wx.detach().numpy()
Wh = Wh.detach().numpy()
b =  b.detach().numpy()

# Wrap our forward pass to support numpy array input and output. We use
# `torch.no_grad()` to explicitly disable gradient tracking.
def rnn_forward_numpy(x, h0, Wx, Wh, b):
  with torch.no_grad():
    return rnn_forward(
        torch.from_numpy(x),
        torch.from_numpy(h0),
        torch.from_numpy(Wx),
        torch.from_numpy(Wh),
        torch.from_numpy(b),
    ).numpy()


fx = lambda x: rnn_forward_numpy(x, h0, Wx, Wh, b)
fh0 = lambda h0: rnn_forward_numpy(x, h0, Wx, Wh, b)
fWx = lambda Wx: rnn_forward_numpy(x, h0, Wx, Wh, b)
fWh = lambda Wh: rnn_forward_numpy(x, h0, Wx, Wh, b)
fb = lambda b: rnn_forward_numpy(x, h0, Wx, Wh, b)

dx_num = eval_numerical_gradient_array(fx, x, dh)
dh0_num = eval_numerical_gradient_array(fh0, h0, dh)
dWx_num = eval_numerical_gradient_array(fWx, Wx, dh)
dWh_num = eval_numerical_gradient_array(fWh, Wh, dh)
db_num = eval_numerical_gradient_array(fb, b, dh)

# You should see errors on the order of 1e-6 or less
print('dx error: ', rel_error(dx_num, dx))
print('dh0 error: ', rel_error(dh0_num, dh0))
print('dWx error: ', rel_error(dWx_num, dWx))
print('dWh error: ', rel_error(dWh_num, dWh))
```

```
print('db error: ', rel_error(db_num, db))
```

```
dx error:  2.4180845082048113e-09
dh0 error:  3.3811400640982614e-09
dWx error:  7.221725933416746e-09
dWh error:  1.282124717752663e-07
db error:  4.676348457243789e-10
```

8 Word Embedding: Forward

In deep learning systems, we commonly represent words using vectors. Each word of the vocabulary will be associated with a vector, and these vectors will be learned jointly with the rest of the system.

In the file `icv83551/rnn_layers_pytorch.py`, implement the function `word_embedding_forward` to convert words (represented by integers) into vectors. Run the following to check your implementation. You should see an error on the order of `e-8` or less.

[ ]:
```
N, T, V, D = 2, 4, 5, 3

x = torch.from_numpy(np.asarray([[0, 3, 1, 2], [2, 1, 0, 3]]))
W = torch.from_numpy(np.linspace(0, 1, num=V*D).reshape(V, D))

out = word_embedding_forward(x, W).numpy()
expected_out = np.asarray([
 [[ 0.,          0.07142857,  0.14285714],
  [ 0.64285714,  0.71428571,  0.78571429],
  [ 0.21428571,  0.28571429,  0.35714286],
  [ 0.42857143,  0.5,         0.57142857]],
 [[ 0.42857143,  0.5,         0.57142857],
  [ 0.21428571,  0.28571429,  0.35714286],
  [ 0.,          0.07142857,  0.14285714],
  [ 0.64285714,  0.71428571,  0.78571429]]])

print('out error: ', rel_error(expected_out, out))
```

```
out error:  1.0000000094736443e-08
```

9 Word Embedding: Backward

As before, we can verify pytorch autograd backward pass using our numerical gradient checker. You can also you can try to implement `word_embedding_backward` yourself if you want. It is not required in this assignment though.

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

N, T, V, D = 50, 3, 5, 6
x = torch.from_numpy(np.random.randint(V, size=(N, T)))
W = torch.from_numpy(np.random.randn(V, D))
```

```
W.requires_grad_()

out = word_embedding_forward(x, W)
dout = torch.from_numpy(np.random.randn(*out.shape))
out.backward(dout)

dW = W.grad.detach().numpy()
x = x.detach().numpy()
W = W.detach().numpy()
dout = dout.detach().numpy()

def word_embedding_forward_numpy(x, W):
  return word_embedding_forward(
      torch.from_numpy(x),
      torch.from_numpy(W),
  ).numpy()

f = lambda W: word_embedding_forward_numpy(x, W)
dW_num = eval_numerical_gradient_array(f, W, dout)

# You should see an error on the order of 1e-11 or less
print('dW error: ', rel_error(dW, dW_num))
```

```
dW error:  3.2774595693100364e-12
```

10 Temporal Affine Layer

At every timestep we use an affine function to transform the RNN hidden vector at that timestep into scores for each word in the vocabulary. Because this is very similar to the affine layer that you implemented in assignment 2, we have provided this function for you in the `temporal_affine_forward`. Run the following to perform numeric gradient checking on the implementation. You should see errors on the order of `e-9` or less.

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

# Gradient check for temporal affine layer
N, T, D, M = 2, 3, 4, 5
x = torch.from_numpy(np.random.randn(N, T, D))
w = torch.from_numpy(np.random.randn(D, M))
b = torch.from_numpy(np.random.randn(M))

for tensor in [x, w, b]:
  tensor.requires_grad_()
out = temporal_affine_forward(x, w, b)
dout = torch.from_numpy(np.random.randn(*out.shape))
out.backward(dout)
```

```
dx = x.grad.detach().numpy()
dw = w.grad.detach().numpy()
db = b.grad.detach().numpy()

x = x.detach().numpy()
w = w.detach().numpy()
b = b.detach().numpy()
dout = dout.detach().numpy()

def temporal_affine_forward_numpy(x, w, b):
  return temporal_affine_forward(
      torch.from_numpy(x),
      torch.from_numpy(w),
      torch.from_numpy(b),
  ).numpy()

fx = lambda x: temporal_affine_forward_numpy(x, w, b)
fw = lambda w: temporal_affine_forward_numpy(x, w, b)
fb = lambda b: temporal_affine_forward_numpy(x, w, b)

dx_num = eval_numerical_gradient_array(fx, x, dout)
dw_num = eval_numerical_gradient_array(fw, w, dout)
db_num = eval_numerical_gradient_array(fb, b, dout)

print('dx error: ', rel_error(dx_num, dx))
print('dw error: ', rel_error(dw_num, dw))
print('db error: ', rel_error(db_num, db))
```

```
dx error:  2.9215854231394017e-10
dw error:  1.5772088618663602e-10
db error:  3.252209560097257e-11
```

11 Temporal Softmax Loss

In an RNN language model, at every timestep we produce a score for each word in the vocabulary. We know the ground-truth word at each timestep, so we use a softmax loss function to compute loss and gradient at each timestep. We sum the losses over time and average them over the minibatch.

However there is one wrinkle: since we operate over minibatches and different captions may have different lengths, we append `<NULL>` tokens to the end of each caption so they all have the same length. We don't want these `<NULL>` tokens to count toward the loss or gradient, so in addition to scores and ground-truth labels our loss function also accepts a `mask` array that tells it which elements of the scores count towards the loss.

Since this is very similar to the softmax loss function you implemented in assignment 1, we have implemented this loss function for you; look at the `temporal_softmax_loss` function in the file `icv83551/rnn_layers_pytorch.py`.

Run the following cell to sanity check the loss and perform numeric gradient checking on the

function. You should see an error for dx on the order of `e-7` or less.

[ ]:
```
# Sanity check for temporal softmax loss
from icv83551.rnn_layers_pytorch import temporal_softmax_loss

N, T, V = 100, 1, 10

def check_loss(N, T, V, p):
    x = 0.001 * torch.from_numpy(np.random.randn(N, T, V))
    y = torch.from_numpy(np.random.randint(V, size=(N, T)))
    mask = torch.from_numpy(np.random.rand(N, T)) <= p
    print(temporal_softmax_loss(x, y, mask).item())

check_loss(100, 1, 10, 1.0)   # Should be about 2.3
check_loss(100, 10, 10, 1.0)  # Should be about 23
check_loss(5000, 10, 10, 0.1) # Should be within 2.2-2.4

# Gradient check for temporal softmax loss
np.random.seed(231231)
N, T, V = 7, 8, 9

x = torch.from_numpy(np.random.randn(N, T, V))
y = torch.from_numpy(np.random.randint(V, size=(N, T)))
mask = torch.from_numpy(np.random.rand(N, T) > 0.5)

x.requires_grad_()
loss = temporal_softmax_loss(x, y, mask, verbose=False)
loss.backward()
dx = x.grad.detach().numpy()
x = x.detach().numpy()
dx_num = eval_numerical_gradient(
    lambda x: temporal_softmax_loss(torch.from_numpy(x), y, mask), x,␣
 ↪verbose=False)

print('dx error: ', rel_error(dx, dx_num))
```

```
2.3027781774290146
23.02598595312723
2.2643611790293394
dx error:  5.5228696963589426e-08
```

12 RNN for Image Captioning

Now that you have implemented the necessary layers, you can combine them to build an image captioning model. Open the file `icv83551/classifiers/rnn_pytorch.py` and look at the `CaptioningRNN` class.

Implement the forward pass of the model in the `loss` function. For now you only need to implement

the case where `cell_type='rnn'` for vanilla RNNs; you will implement the LSTM case later. After doing so, run the following to check your forward pass using a small test case; you should see error on the order of `e-10` or less.

[ ]:
```
N, D, W, H = 10, 20, 30, 40
word_to_idx = {'<NULL>': 0, 'cat': 2, 'dog': 3}
V = len(word_to_idx)
T = 13

model = CaptioningRNN(
    word_to_idx,
    input_dim=D,
    wordvec_dim=W,
    hidden_dim=H,
    cell_type='rnn',
    dtype=torch.float64
)

# Set all model parameters to fixed values
for k, v in model.params.items():
    model.params[k] = torch.from_numpy(
        np.linspace(-1.4, 1.3, num=v.numel()).reshape(*v.shape))

features = torch.from_numpy(np.linspace(-1.5, 0.3, num=(N * D)).reshape(N, D))
captions = torch.from_numpy((np.arange(N * T) % V).reshape(N, T))

loss = model.loss(features, captions).item()
expected_loss = 9.83235591003

print('loss: ', loss)
print('expected loss: ', expected_loss)
print('difference: ', abs(loss - expected_loss))
```

```
loss:  9.83235591002739
expected loss:  9.83235591003
difference:  2.609468197078968e-12
```

Run the following cell to perform numeric gradient checking on the `CaptioningRNN` class; you should see errors around the order of `e-6` or less.

[ ]:
```
np.random.seed(231)
torch.manual_seed(231)

batch_size = 2
timesteps = 3
input_dim = 4
wordvec_dim = 5
hidden_dim = 6
word_to_idx = {'<NULL>': 0, 'cat': 2, 'dog': 3}
```

```
vocab_size = len(word_to_idx)

captions = torch.from_numpy(np.random.randint(vocab_size, size=(batch_size,␣
 ↪timesteps)))
features = torch.from_numpy(np.random.randn(batch_size, input_dim))

model = CaptioningRNN(
    word_to_idx,
    input_dim=input_dim,
    wordvec_dim=wordvec_dim,
    hidden_dim=hidden_dim,
    cell_type='rnn',
    dtype=torch.float64,
)

for k, v in model.params.items():
  v.requires_grad_()
loss = model.loss(features, captions)
loss.backward()
grads = {k: v.grad.detach().numpy() for k, v in model.params.items()}
for k, v in model.params.items():
  v.requires_grad_(False)

for param_name in sorted(grads.keys()):
    def fn(val):
      model.params[param_name] = torch.from_numpy(val)
      ret = model.loss(features, captions).numpy()
      return ret

    param_grad_num = eval_numerical_gradient(
        fn, model.params[param_name].numpy(), verbose=False, h=1e-6)

    e = rel_error(param_grad_num, grads[param_name])
    print('%s relative error: %e' % (param_name, e))
```

```
W_embed relative error: 2.630824e-09
W_proj relative error: 5.778112e-08
W_vocab relative error: 1.309392e-08
Wh relative error: 1.762622e-09
Wx relative error: 8.072585e-06
b relative error: 8.450890e-10
b_proj relative error: 3.580123e-10
b_vocab relative error: 5.193917e-09
```

13 Overfit RNN Captioning Model on Small Data

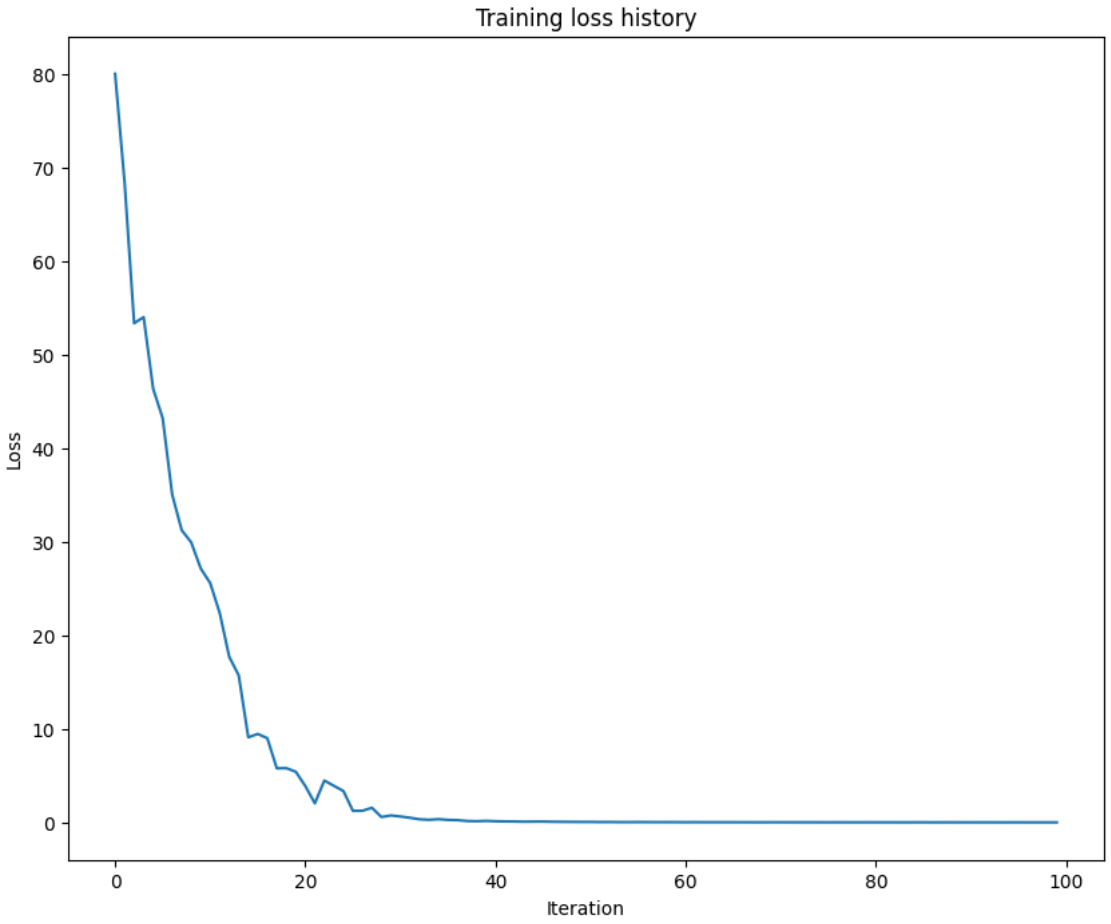
Similar to the `Solver` class that we used to train image classification models on the previous assignment, on this assignment we use a `CaptioningSolverPytorch` class to train image captioning models. Open the file `icv83551/captioning_solver_pytorch.py` and read through the `CaptioningSolverPytorch` class; it should look very familiar.

Once you have familiarized yourself with the API, run the following to make sure your model overfits a small sample of 100 training examples. You should see a final loss of less than 0.1.

[ ]:
```
np.random.seed(231)
torch.manual_seed(231)

small_data = load_coco_data(max_train=50)

small_rnn_model = CaptioningRNN(
    cell_type='rnn',
    word_to_idx=data['word_to_idx'],
    input_dim=data['train_features'].shape[1],
    hidden_dim=512,
    wordvec_dim=256,
)

small_rnn_solver = CaptioningSolverPytorch(
    small_rnn_model, small_data,
    num_epochs=50,
    batch_size=25,
    learning_rate=5e-3,
    verbose=True, print_every=10,
)

small_rnn_solver.train()

# Plot the training losses.
plt.plot(small_rnn_solver.loss_history)
plt.xlabel('Iteration')
plt.ylabel('Loss')
plt.title('Training loss history')
plt.show()
```

```
base dir  /content/drive/My
Drive/icv83551/assignments/assignment2/icv83551/datasets/coco_captioning
(Iteration 1 / 100) loss: 80.027161
(Iteration 11 / 100) loss: 25.581013
(Iteration 21 / 100) loss: 3.890443
(Iteration 31 / 100) loss: 0.641122
(Iteration 41 / 100) loss: 0.133215
(Iteration 51 / 100) loss: 0.057625
(Iteration 61 / 100) loss: 0.028611
```

```
(Iteration 71 / 100) loss: 0.022358
(Iteration 81 / 100) loss: 0.018526
(Iteration 91 / 100) loss: 0.016731
```



Print final training loss. You should see a final loss of less than 0.1.

[ ]:
```
print('Final loss: ', small_rnn_solver.loss_history[-1])
```

```
Final loss:  0.013372515
```

14 RNN Sampling at Test Time

Unlike classification models, image captioning models behave very differently at training time vs. at test time. At training time, we have access to the ground-truth caption, so we feed ground-truth words as input to the RNN at each timestep. At test time, we sample from the distribution over the vocabulary at each timestep and feed the sample as input to the RNN at the next timestep.

In the file `icv83551/classifiers/rnn_pytorch.py`, implement the `sample` method for test-time sampling. After doing so, run the following to sample from your overfitted model on both training

and validation data. The samples on training data should be very good. The samples on validation data, however, probably won't make sense.

[ ]:
```
# If you get an error, the URL just no longer exists, so don't worry!
# You can re-sample as many times as you want.
for split in ['train', 'val']:
    minibatch = sample_coco_minibatch(small_data, split=split, batch_size=2)
    gt_captions, features, urls = minibatch
    gt_captions = decode_captions(gt_captions, data['idx_to_word'])

    sample_captions = small_rnn_model.sample(torch.from_numpy(features)).numpy()
    sample_captions = decode_captions(sample_captions, data['idx_to_word'])

    for gt_caption, sample_caption, url in zip(gt_captions, sample_captions,␣
 ↪urls):
        img = image_from_url(url)
        # Skip missing URLs.
        if img is None: continue
        plt.imshow(img)
        plt.title('%s\n%s\nGT:%s' % (split, sample_caption, gt_caption))
        plt.axis('off')
        plt.show()
```

train

GT:<START> a living room with <UNK> of <UNK> <UNK> <END>

train

GT:<START> a group of people that are sitting near train tracks <END>

val

GT:<START> a man riding in the back of a white and red boat <END>

URL Error: Gone http://farm8.staticflickr.com/7185/6958105247_8e397d24c0_z.jpg

15 Inline Question 1

In our current image captioning setup, our RNN language model produces a word at every timestep as its output. However, an alternate way to pose the problem is to train the network to operate over *characters* (e.g. 'a', 'b', etc.) as opposed to words, so that at it every timestep, it receives the previous character as input and tries to predict the next character in the sequence. For example, the network might generate a caption like

'A', ' ', 'c', 'a', 't', ' ', 'o', 'n', ' ', 'a', ' ', 'b', 'e', 'd'

Can you describe one advantage of an image-captioning model that uses a character-level RNN? Can you also describe one disadvantage? HINT: there are several valid answers, but it might be useful to compare the parameter space of word-level and character-level models.

Your Answer: 1. vocabulary size, for words we have a massive vocabluary (and therefore emmbedding), and as we want to be more exact, we need a bigger embedding space. and for rare words, we can miss (we cannot hold all the words that exist) 2. the character vocabulary is very small (a,b,c plus some characters). meaning the embedding is magnitudes smaller. also - we can generate any

words. 3. in character space, we have to do many more steps, as it is character space and not word space. this is computationally expensive.

[ ]: