

Train a ConvNet!

We now have a generic solver and a bunch of modularized layers. It's time to put it all together, and train a ConvNet to recognize the classes in CIFAR-10. In this notebook we will walk you through training a simple two-layer ConvNet and then set you free to build the best net that you can to perform well on CIFAR-10.

Open up the file `cs231n/classifiers/convnet.py`; you will see that the `two_layer_convnet` function computes the loss and gradients for a two-layer ConvNet. Note that this function uses the "sandwich" layers defined in `cs231n/layer_utils.py`.

```
In [1]: # As usual, a bit of setup

import numpy as np
import matplotlib.pyplot as plt
from cs231n.classifier_trainer import ClassifierTrainer
from cs231n.gradient_check import eval_numerical_gradient
from cs231n.classifiers.convnet import *

%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))))
```

```
In [2]: from cs231n.data_utils import load_CIFAR10

def get_CIFAR10_data(num_training=49000, num_validation=1000, num_test=1000):
    """
    Load the CIFAR-10 dataset from disk and perform preprocessing to prepare
    it for the two-layer neural net classifier. These are the same steps as
    we used for the SVM, but condensed to a single function.
    """
    # Load the raw CIFAR-10 data
    cifar10_dir = 'cs231n/datasets/cifar-10-batches-py'
    X_train, y_train, X_test, y_test = load_CIFAR10(cifar10_dir)

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

    # Normalize the data: subtract the mean image
    mean_image = np.mean(X_train, axis=0)
    X_train -= mean_image
    X_val -= mean_image
    X_test -= mean_image

    # Transpose so that channels come first
    X_train = X_train.transpose(0, 3, 1, 2).copy()
    X_val = X_val.transpose(0, 3, 1, 2).copy()
    X_test = X_test.transpose(0, 3, 1, 2).copy()

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

# Invoke the above function to get our data.
X_train, y_train, X_val, y_val, X_test, y_test = get_CIFAR10_data()
print('Train data shape: ', X_train.shape)
print('Train labels shape: ', y_train.shape)
print('Validation data shape: ', X_val.shape)
print('Validation labels shape: ', y_val.shape)
print('Test data shape: ', X_test.shape)
print('Test labels shape: ', y_test.shape)
```

```
Train data shape: (49000, 3, 32, 32)
Train labels shape: (49000,)
Validation data shape: (1000, 3, 32, 32)
Validation labels shape: (1000,)
Test data shape: (1000, 32, 32, 3)
Test labels shape: (1000,)
```

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 this should go up.

```
In [3]: model = init_two_layer_convnet()

X = np.random.randn(100, 3, 32, 32)
y = np.random.randint(10, size=100)

loss, _ = two_layer_convnet(X, model, y, reg=0)

# Sanity check: Loss should be about log(10) = 2.3026
print('Sanity check loss (no regularization): ', loss)

# Sanity check: Loss should go up when you add regularization
loss, _ = two_layer_convnet(X, model, y, reg=1)
print('Sanity check loss (with regularization): ', loss)

dout (100, 10)
x (100, 32, 16, 16)
w (8192, 10)
Sanity check loss (no regularization): 2.302680787589569
dout (100, 10)
x (100, 32, 16, 16)
w (8192, 10)
Sanity check loss (with regularization): 2.344563384742511
```

Gradient check

After the loss looks reasonable, you should always 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 artificial data and a small number of neurons at each layer.

```
In [5]: num_inputs = 2
input_shape = (3, 16, 16)
reg = 0.0
num_classes = 10
X = np.random.randn(num_inputs, *input_shape)
y = np.random.randint(num_classes, size=num_inputs)

model = init_two_layer_convnet(num_filters=3, filter_size=3, input_shape=input_shape)
loss, grads = two_layer_convnet(X, model, y)
for param_name in sorted(grads):
    f = lambda _: two_layer_convnet(X, model, y)[0]
    param_grad_num = eval_numerical_gradient(f, model[param_name], verbose=False, h=1e-6)
    e = rel_error(param_grad_num, grads[param_name])
    print('%s max relative error: %e' % (param_name, rel_error(param_grad_num, grads[param_name])))

W1 max relative error: 1.462154e-06
W2 max relative error: 1.090814e-05
b1 max relative error: 1.783711e-08
b2 max relative error: 2.063144e-09
```

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.

```
In [6]: # Use a two-layer ConvNet to overfit 50 training examples.

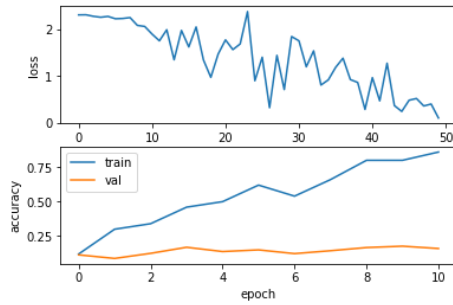
model = init_two_layer_convnet()
trainer = ClassifierTrainer()
best_model, loss_history, train_acc_history, val_acc_history = trainer.train(
    X_train[:50], y_train[:50], X_val, y_val, model, two_layer_convnet,
    reg=0.001, momentum=0.9, learning_rate=0.0001, batch_size=10, num_epochs=10,
    verbose=True)

starting iteration 0
Finished epoch 0 / 10: cost 2.304942, train: 0.120000, val 0.114000, lr 1.000000e-04
Finished epoch 1 / 10: cost 2.272359, train: 0.300000, val 0.088000, lr 9.500000e-05
Finished epoch 2 / 10: cost 2.058033, train: 0.340000, val 0.125000, lr 9.025000e-05
starting iteration 10
Finished epoch 3 / 10: cost 1.972939, train: 0.460000, val 0.169000, lr 8.573750e-05
Finished epoch 4 / 10: cost 1.468262, train: 0.500000, val 0.138000, lr 8.145062e-05
starting iteration 20
Finished epoch 5 / 10: cost 0.899135, train: 0.620000, val 0.150000, lr 7.737809e-05
Finished epoch 6 / 10: cost 1.842718, train: 0.540000, val 0.123000, lr 7.350919e-05
starting iteration 30
Finished epoch 7 / 10: cost 0.917425, train: 0.660000, val 0.144000, lr 6.983373e-05
Finished epoch 8 / 10: cost 0.286941, train: 0.800000, val 0.167000, lr 6.634204e-05
starting iteration 40
Finished epoch 9 / 10: cost 0.243375, train: 0.800000, val 0.177000, lr 6.302494e-05
Finished epoch 10 / 10: cost 0.103600, train: 0.860000, val 0.160000, lr 5.987369e-05
finished optimization. best validation accuracy: 0.177000
```

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

```
In [7]: plt.subplot(2, 1, 1)
plt.plot(loss_history)
plt.xlabel('iteration')
plt.ylabel('loss')

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



Train the net

Once the above works, training the net is the next thing to try. You can set the `acc_frequency` parameter to change the frequency at which the training and validation set accuracies are tested. If your parameters are set properly, you should see the training and validation accuracy start to improve within a hundred iterations, and you should be able to train a reasonable model with just one epoch.

Using the parameters below you should be able to get around 50% accuracy on the validation set.

```
In [8]: model = init_two_layer_convnet(filter_size=7)
        trainer = ClassifierTrainer()
        best_model, loss_history, train_acc_history, val_acc_history = trainer.train(
            X_train, y_train, X_val, y_val, model, two_layer_convnet,
            reg=0.001, momentum=0.9, learning_rate=0.0001, batch_size=50, num_epochs=1,
            acc_frequency=50, verbose=True)
```

```
starting iteration 0
Finished epoch 0 / 1: cost 2.304729, train: 0.157000, val 0.141000, lr 1.000000e-04
starting iteration 10
starting iteration 20
starting iteration 30
starting iteration 40
starting iteration 50
Finished epoch 0 / 1: cost 2.054563, train: 0.324000, val 0.317000, lr 1.000000e-04
starting iteration 60
starting iteration 70
starting iteration 80
starting iteration 90
starting iteration 100
Finished epoch 0 / 1: cost 1.659939, train: 0.398000, val 0.396000, lr 1.000000e-04
starting iteration 110
starting iteration 120
starting iteration 130
starting iteration 140
starting iteration 150
Finished epoch 0 / 1: cost 1.865885, train: 0.399000, val 0.418000, lr 1.000000e-04
starting iteration 160
starting iteration 170
starting iteration 180
starting iteration 190
starting iteration 200
Finished epoch 0 / 1: cost 1.927011, train: 0.408000, val 0.380000, lr 1.000000e-04
starting iteration 210
starting iteration 220
starting iteration 230
starting iteration 240
starting iteration 250
Finished epoch 0 / 1: cost 1.949246, train: 0.420000, val 0.408000, lr 1.000000e-04
starting iteration 260
starting iteration 270
starting iteration 280
starting iteration 290
starting iteration 300
Finished epoch 0 / 1: cost 1.785747, train: 0.446000, val 0.456000, lr 1.000000e-04
starting iteration 310
starting iteration 320
starting iteration 330
starting iteration 340
starting iteration 350
Finished epoch 0 / 1: cost 1.454454, train: 0.471000, val 0.437000, lr 1.000000e-04
starting iteration 360
starting iteration 370
starting iteration 380
starting iteration 390
starting iteration 400
Finished epoch 0 / 1: cost 1.909681, train: 0.465000, val 0.468000, lr 1.000000e-04
starting iteration 410
starting iteration 420
starting iteration 430
starting iteration 440
starting iteration 450
Finished epoch 0 / 1: cost 1.554669, train: 0.476000, val 0.456000, lr 1.000000e-04
starting iteration 460
starting iteration 470
starting iteration 480
starting iteration 490
starting iteration 500
Finished epoch 0 / 1: cost 1.535584, train: 0.452000, val 0.429000, lr 1.000000e-04
starting iteration 510
starting iteration 520
starting iteration 530
starting iteration 540
starting iteration 550
Finished epoch 0 / 1: cost 1.373795, train: 0.494000, val 0.455000, lr 1.000000e-04
starting iteration 560
starting iteration 570
starting iteration 580
starting iteration 590
starting iteration 600
Finished epoch 0 / 1: cost 1.291351, train: 0.406000, val 0.433000, lr 1.000000e-04
starting iteration 610
starting iteration 620
starting iteration 630
starting iteration 640
starting iteration 650
Finished epoch 0 / 1: cost 1.638062, train: 0.432000, val 0.439000, lr 1.000000e-04
starting iteration 660
starting iteration 670
starting iteration 680
starting iteration 690
starting iteration 700
Finished epoch 0 / 1: cost 1.379444, train: 0.455000, val 0.432000, lr 1.000000e-04
starting iteration 710
starting iteration 720
starting iteration 730
starting iteration 740
starting iteration 750
Finished epoch 0 / 1: cost 1.421884, train: 0.524000, val 0.508000, lr 1.000000e-04
starting iteration 760
starting iteration 770
starting iteration 780
starting iteration 790
starting iteration 800
Finished epoch 0 / 1: cost 1.918442, train: 0.449000, val 0.432000, lr 1.000000e-04
starting iteration 810
starting iteration 820
starting iteration 830
starting iteration 840
starting iteration 850
Finished epoch 0 / 1: cost 1.604052, train: 0.453000, val 0.449000, lr 1.000000e-04
```

```
starting iteration 860
starting iteration 870
starting iteration 880
starting iteration 890
starting iteration 900
Finished epoch 0 / 1: cost 1.116873, train: 0.519000, val 0.503000, lr 1.000000e-04
starting iteration 910
starting iteration 920
starting iteration 930
starting iteration 940
starting iteration 950
Finished epoch 0 / 1: cost 1.589487, train: 0.435000, val 0.431000, lr 1.000000e-04
starting iteration 960
starting iteration 970
Finished epoch 1 / 1: cost 1.792701, train: 0.473000, val 0.452000, lr 9.500000e-05
finished optimization. best validation accuracy: 0.508000
```

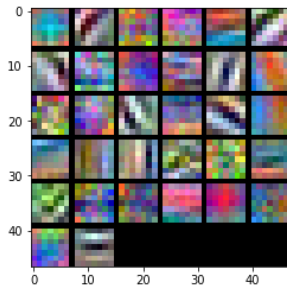
Visualize weights

We can visualize the convolutional weights from the first layer. If everything worked properly, these will usually be edges and blobs of various colors and orientations.

```
In [9]: from cs231n.vis_utils import visualize_grid

grid = visualize_grid(best_model['W1'].transpose(0, 2, 3, 1))
plt.imshow(grid.astype('uint8'))
```

```
Out[9]: <matplotlib.image.AxesImage at 0x1041d8080>
```



```
In [ ]:
```