FullyConnectedNets

May 3, 2022

[21]:
```
# 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. 'cs231n/assignments/assignment2/'
FOLDERNAME = 'Colab_Notebooks/cs231n/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/$FOLDERNAME/cs231n/datasets/
!bash get_datasets.sh
%cd /content/drive/My\ Drive/$FOLDERNAME
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
/content/drive/My
Drive/Colab_Notebooks/cs231n/assignments/assignment2/cs231n/datasets
/content/drive/My Drive/Colab_Notebooks/cs231n/assignments/assignment2
```

1 Multi-Layer Fully Connected Network

In this exercise, you will implement a fully connected network with an arbitrary number of hidden layers.

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

Implement the network initialization, forward pass, and backward pass. Throughout this assignment, you will be implementing layers in `cs231n/layers.py`. You can re-use your implementations for `affine_forward`, `affine_backward`, `relu_forward`, `relu_backward`, and `softmax_loss` from

Assignment 1. For right now, don't worry about implementing dropout or batch/layer normalization yet, as you will add those features later.

[22]:
```
# Setup cell.
import time
import numpy as np
import matplotlib.pyplot as plt
from cs231n.classifiers.fc_net import *
from cs231n.data_utils import get_CIFAR10_data
from cs231n.gradient_check import eval_numerical_gradient,␣
↪eval_numerical_gradient_array
from cs231n.solver import Solver

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

%load_ext autoreload
%autoreload 2

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

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

[23]:
```
# 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,)
```

1.1 Initial Loss and Gradient Check

As a sanity check, run the following to check the initial loss and to gradient check the network both with and without regularization. This is a good way to see if the initial losses seem reasonable.

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

[24]:
```
np.random.seed(231)
N, D, H1, H2, C = 2, 15, 20, 30, 10
X = np.random.randn(N, D)
y = np.random.randint(C, size=(N,))

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

    # Most of the errors should be on the order of e-7 or smaller.
    # NOTE: It is fine however to see an error for W2 on the order of e-5
    # for the check when reg = 0.0

    for name in sorted(grads):
        f = lambda _: model.loss(X, y)[0]
        grad_num = eval_numerical_gradient(f, model.params[name],␣
↪verbose=False, h=1e-5)
        print(f"{name} relative error: {rel_error(grad_num, grads[name])}")
```

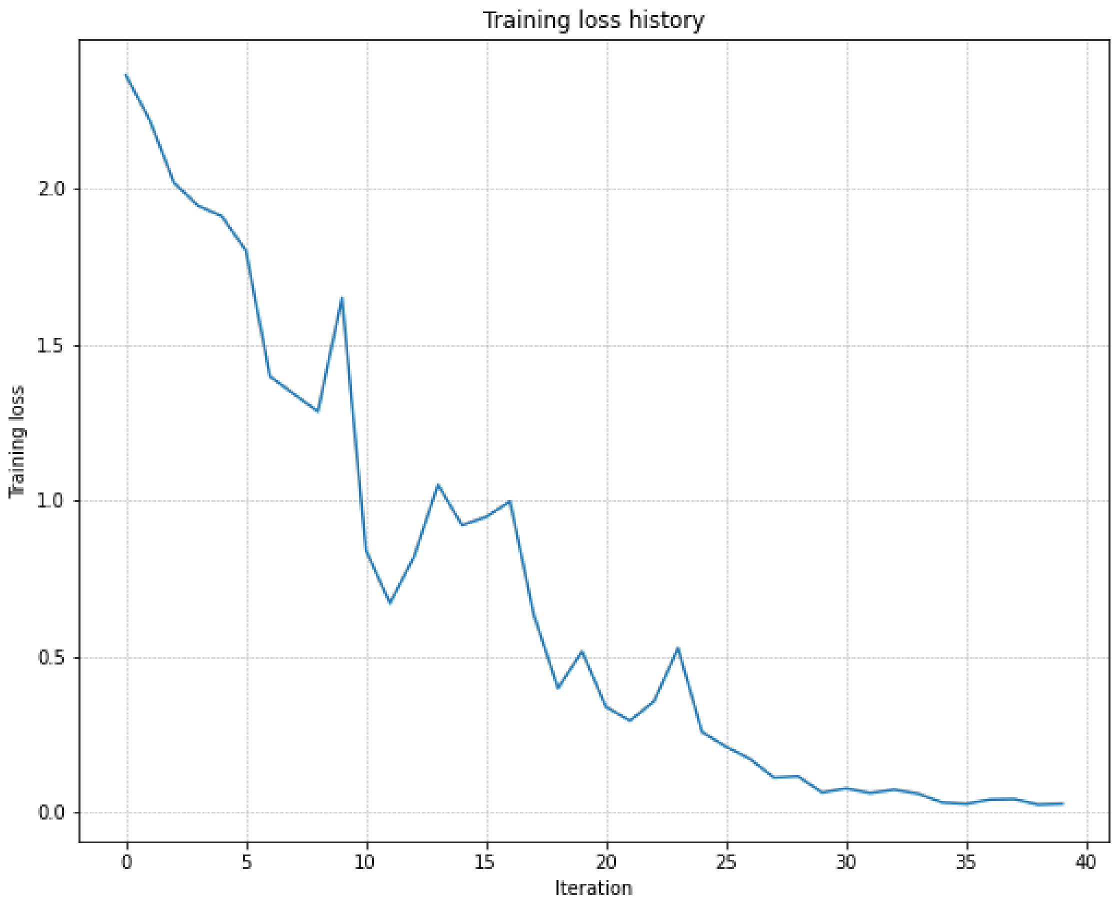
```
Running check with reg =  0
Initial loss:  2.3004790897684924
W1 relative error: 1.4839894098713283e-07
W2 relative error: 2.21204793107852e-05
W3 relative error: 3.527252851540647e-07
b1 relative error: 5.376386228531692e-09
b2 relative error: 2.085654200257447e-09
b3 relative error: 5.7957243458479405e-11
Running check with reg =  3.14
Initial loss:  7.052114776533016
W1 relative error: 7.355058816898759e-09
W2 relative error: 6.86942277940646e-08
W3 relative error: 3.483989247437803e-08
b1 relative error: 1.4752428222134868e-08
b2 relative error: 1.7223750761525226e-09
b3 relative error: 1.801765144951982e-10
```

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

[25]:
```
# TODO: Use a three-layer Net to overfit 50 training examples by
# tweaking just the learning rate and initialization scale.

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

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

plt.plot(solver.loss_history)
plt.title("Training loss history")
plt.xlabel("Iteration")
plt.ylabel("Training loss")
plt.grid(linestyle='--', linewidth=0.5)
plt.show()
```

```
(Iteration 1 / 40) loss: 2.363364
(Epoch 0 / 20) train acc: 0.180000; val_acc: 0.108000
(Epoch 1 / 20) train acc: 0.320000; val_acc: 0.127000
(Epoch 2 / 20) train acc: 0.440000; val_acc: 0.172000
(Epoch 3 / 20) train acc: 0.500000; val_acc: 0.184000
(Epoch 4 / 20) train acc: 0.540000; val_acc: 0.181000
(Epoch 5 / 20) train acc: 0.740000; val_acc: 0.190000
(Iteration 11 / 40) loss: 0.839976
(Epoch 6 / 20) train acc: 0.740000; val_acc: 0.187000
(Epoch 7 / 20) train acc: 0.740000; val_acc: 0.183000
```

```
(Epoch 8 / 20) train acc: 0.820000; val_acc: 0.177000
(Epoch 9 / 20) train acc: 0.860000; val_acc: 0.200000
(Epoch 10 / 20) train acc: 0.920000; val_acc: 0.191000
(Iteration 21 / 40) loss: 0.337174
(Epoch 11 / 20) train acc: 0.960000; val_acc: 0.189000
(Epoch 12 / 20) train acc: 0.940000; val_acc: 0.180000
(Epoch 13 / 20) train acc: 1.000000; val_acc: 0.199000
(Epoch 14 / 20) train acc: 1.000000; val_acc: 0.199000
(Epoch 15 / 20) train acc: 1.000000; val_acc: 0.195000
(Iteration 31 / 40) loss: 0.075911
(Epoch 16 / 20) train acc: 1.000000; val_acc: 0.182000
(Epoch 17 / 20) train acc: 1.000000; val_acc: 0.201000
(Epoch 18 / 20) train acc: 1.000000; val_acc: 0.207000
(Epoch 19 / 20) train acc: 1.000000; val_acc: 0.185000
(Epoch 20 / 20) train acc: 1.000000; val_acc: 0.192000
```



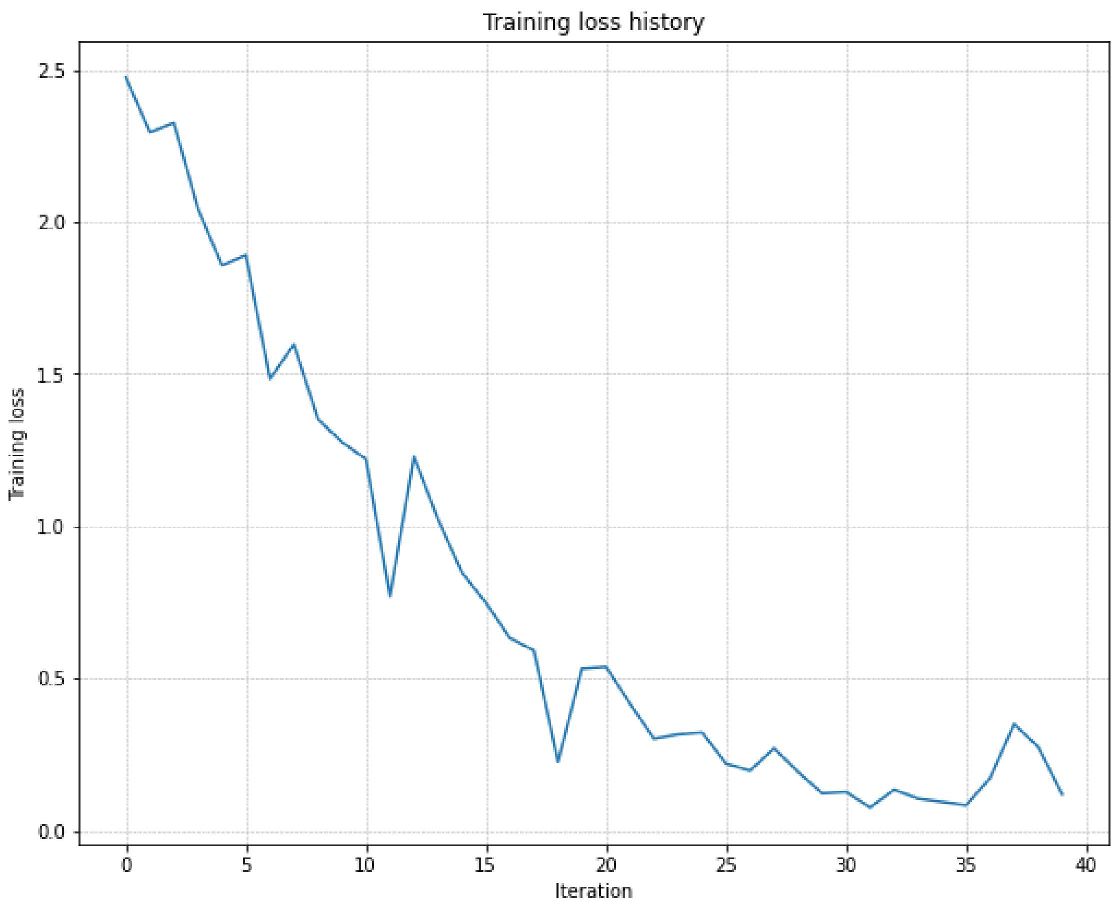
Now, try to use a five-layer network with 100 units on each layer to overfit on 50 training examples. Again, you will have to adjust the learning rate and weight initialization scale, but you should be able to achieve 100% training accuracy within 20 epochs.

[26]:

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

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

learning_rate = 2e-2  # Experiment with this!
weight_scale = 3.5e-2   # Experiment with this!
model = FullyConnectedNet(
    [100, 100, 100, 100],
    weight_scale=weight_scale,
    dtype=np.float64
)
solver = Solver(
    model,
    small_data,
    print_every=10,
    num_epochs=20,
    batch_size=25,
    update_rule='sgd',
    optim_config={'learning_rate': learning_rate},
)
solver.train()

plt.plot(solver.loss_history)
plt.title('Training loss history')
plt.xlabel('Iteration')
plt.ylabel('Training loss')
plt.grid(linestyle='--', linewidth=0.5)
plt.show()
```

```
(Iteration 1 / 40) loss: 2.475208
(Epoch 0 / 20) train acc: 0.340000; val_acc: 0.114000
(Epoch 1 / 20) train acc: 0.180000; val_acc: 0.081000
(Epoch 2 / 20) train acc: 0.540000; val_acc: 0.129000
(Epoch 3 / 20) train acc: 0.400000; val_acc: 0.121000
(Epoch 4 / 20) train acc: 0.640000; val_acc: 0.171000
(Epoch 5 / 20) train acc: 0.580000; val_acc: 0.128000
(Iteration 11 / 40) loss: 1.220311
(Epoch 6 / 20) train acc: 0.740000; val_acc: 0.173000
(Epoch 7 / 20) train acc: 0.800000; val_acc: 0.171000
(Epoch 8 / 20) train acc: 0.920000; val_acc: 0.188000
```

```
(Epoch 9 / 20) train acc: 0.900000; val_acc: 0.180000
(Epoch 10 / 20) train acc: 0.820000; val_acc: 0.171000
(Iteration 21 / 40) loss: 0.538297
(Epoch 11 / 20) train acc: 0.980000; val_acc: 0.179000
(Epoch 12 / 20) train acc: 0.980000; val_acc: 0.196000
(Epoch 13 / 20) train acc: 0.940000; val_acc: 0.187000
(Epoch 14 / 20) train acc: 0.940000; val_acc: 0.173000
(Epoch 15 / 20) train acc: 0.980000; val_acc: 0.197000
(Iteration 31 / 40) loss: 0.127319
(Epoch 16 / 20) train acc: 1.000000; val_acc: 0.188000
(Epoch 17 / 20) train acc: 1.000000; val_acc: 0.196000
(Epoch 18 / 20) train acc: 0.960000; val_acc: 0.202000
(Epoch 19 / 20) train acc: 0.940000; val_acc: 0.186000
(Epoch 20 / 20) train acc: 0.980000; val_acc: 0.177000
```



1.2 Inline Question 1:

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

1.3 Answer:

Claim: \ 5 layer FC neural network is more sensitive to initialization scale for weights than 3 layer FC neural network. \

Reason: \ This is because, as we initialize weights between 0 and 1 for each layers and as the activations get multiplied over number of layers, output tends to become closer to 0 and hence variance of the activation map in deeper layers become smaller and smaller. Therefor, small change in weight scale has high impact in the distribution of activation maps in deeper network than shallow layers.

2 Update rules

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

2.1 SGD+Momentum

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

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

[27]:
```
from cs231n.optim import sgd_momentum

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

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

expected_next_w = np.asarray([
  [ 0.1406,      0.20738947,  0.27417895,  0.34096842,  0.40775789],
  [ 0.47454737,  0.54133684,  0.60812632,  0.67491579,  0.74170526],
```

```
  [ 0.80849474,  0.87528421,  0.94207368,  1.00886316,  1.07565263],
  [ 1.14244211,  1.20923158,  1.27602105,  1.34281053,  1.4096    ]])
expected_velocity = np.asarray([
  [ 0.5406,      0.55475789,  0.56891579, 0.58307368,  0.59723158],
  [ 0.61138947,  0.62554737,  0.63970526,  0.65386316,  0.66802105],
  [ 0.68217895,  0.69633684,  0.71049474,  0.72465263,  0.73881053],
  [ 0.75296842,  0.76712632,  0.78128421,  0.79544211,  0.8096    ]])

# Should see relative errors around e-8 or less
print("next_w error: ", rel_error(next_w, expected_next_w))
print("velocity error: ", rel_error(expected_velocity, config["velocity"]))
```

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

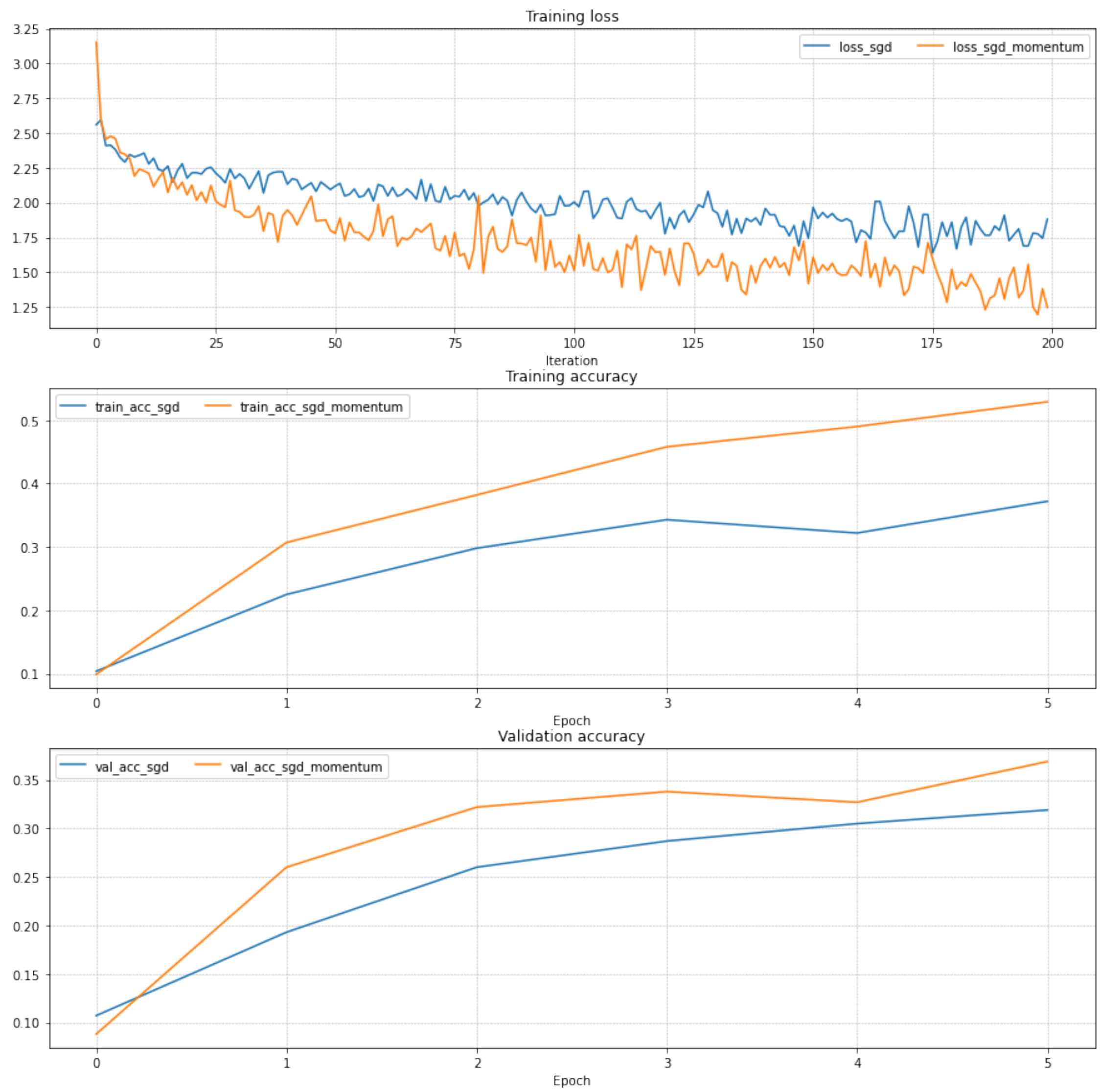
Once you have done so, run the following to train a six-layer network with both SGD and SGD+momentum. You should see the SGD+momentum update rule converge faster.

[28]:
```
num_train = 4000
small_data = {
  'X_train': data['X_train'][:num_train],
  'y_train': data['y_train'][:num_train],
  'X_val': data['X_val'],
  'y_val': data['y_val'],
}

solvers = {}

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

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

fig, axes = plt.subplots(3, 1, figsize=(15, 15))
```

```python
axes[0].set_title('Training loss')
axes[0].set_xlabel('Iteration')
axes[1].set_title('Training accuracy')
axes[1].set_xlabel('Epoch')
axes[2].set_title('Validation accuracy')
axes[2].set_xlabel('Epoch')

for update_rule, solver in solvers.items():
    axes[0].plot(solver.loss_history, label=f"loss_{update_rule}")
    axes[1].plot(solver.train_acc_history, label=f"train_acc_{update_rule}")
    axes[2].plot(solver.val_acc_history, label=f"val_acc_{update_rule}")

for ax in axes:
    ax.legend(loc="best", ncol=4)
    ax.grid(linestyle='--', linewidth=0.5)

plt.show()
```

```
Running with  sgd
(Iteration 1 / 200) loss: 2.559978
(Epoch 0 / 5) train acc: 0.104000; val_acc: 0.107000
(Iteration 11 / 200) loss: 2.356069
(Iteration 21 / 200) loss: 2.214091
(Iteration 31 / 200) loss: 2.205928
(Epoch 1 / 5) train acc: 0.225000; val_acc: 0.193000
(Iteration 41 / 200) loss: 2.132095
(Iteration 51 / 200) loss: 2.118950
(Iteration 61 / 200) loss: 2.116443
(Iteration 71 / 200) loss: 2.132549
(Epoch 2 / 5) train acc: 0.298000; val_acc: 0.260000
(Iteration 81 / 200) loss: 1.977227
(Iteration 91 / 200) loss: 2.007528
(Iteration 101 / 200) loss: 2.004762
(Iteration 111 / 200) loss: 1.885342
(Epoch 3 / 5) train acc: 0.343000; val_acc: 0.287000
(Iteration 121 / 200) loss: 1.891517
(Iteration 131 / 200) loss: 1.923677
(Iteration 141 / 200) loss: 1.957743
(Iteration 151 / 200) loss: 1.966736
(Epoch 4 / 5) train acc: 0.322000; val_acc: 0.305000
(Iteration 161 / 200) loss: 1.801483
(Iteration 171 / 200) loss: 1.973780
(Iteration 181 / 200) loss: 1.666572
(Iteration 191 / 200) loss: 1.909494
(Epoch 5 / 5) train acc: 0.372000; val_acc: 0.319000
Running with  sgd_momentum
```

```
(Iteration 1 / 200) loss: 3.153778
(Epoch 0 / 5) train acc: 0.099000; val_acc: 0.088000
(Iteration 11 / 200) loss: 2.227203
(Iteration 21 / 200) loss: 2.125706
(Iteration 31 / 200) loss: 1.932695
(Epoch 1 / 5) train acc: 0.307000; val_acc: 0.260000
(Iteration 41 / 200) loss: 1.946488
(Iteration 51 / 200) loss: 1.778584
(Iteration 61 / 200) loss: 1.758119
(Iteration 71 / 200) loss: 1.849137
(Epoch 2 / 5) train acc: 0.382000; val_acc: 0.322000
(Iteration 81 / 200) loss: 2.048671
(Iteration 91 / 200) loss: 1.693223
(Iteration 101 / 200) loss: 1.511693
(Iteration 111 / 200) loss: 1.390754
(Epoch 3 / 5) train acc: 0.458000; val_acc: 0.338000
(Iteration 121 / 200) loss: 1.670614
(Iteration 131 / 200) loss: 1.540271
(Iteration 141 / 200) loss: 1.597365
(Iteration 151 / 200) loss: 1.609851
(Epoch 4 / 5) train acc: 0.490000; val_acc: 0.327000
(Iteration 161 / 200) loss: 1.472687
(Iteration 171 / 200) loss: 1.378620
(Iteration 181 / 200) loss: 1.378175
(Iteration 191 / 200) loss: 1.306439
(Epoch 5 / 5) train acc: 0.529000; val_acc: 0.369000
```



2.2 RMSProp and Adam

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

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

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

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

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

[29]:
```
# Test RMSProp implementation
from cs231n.optim import rmsprop

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

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

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

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

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

[30]:
```
# Test Adam implementation
from cs231n.optim import adam

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

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

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

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

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

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

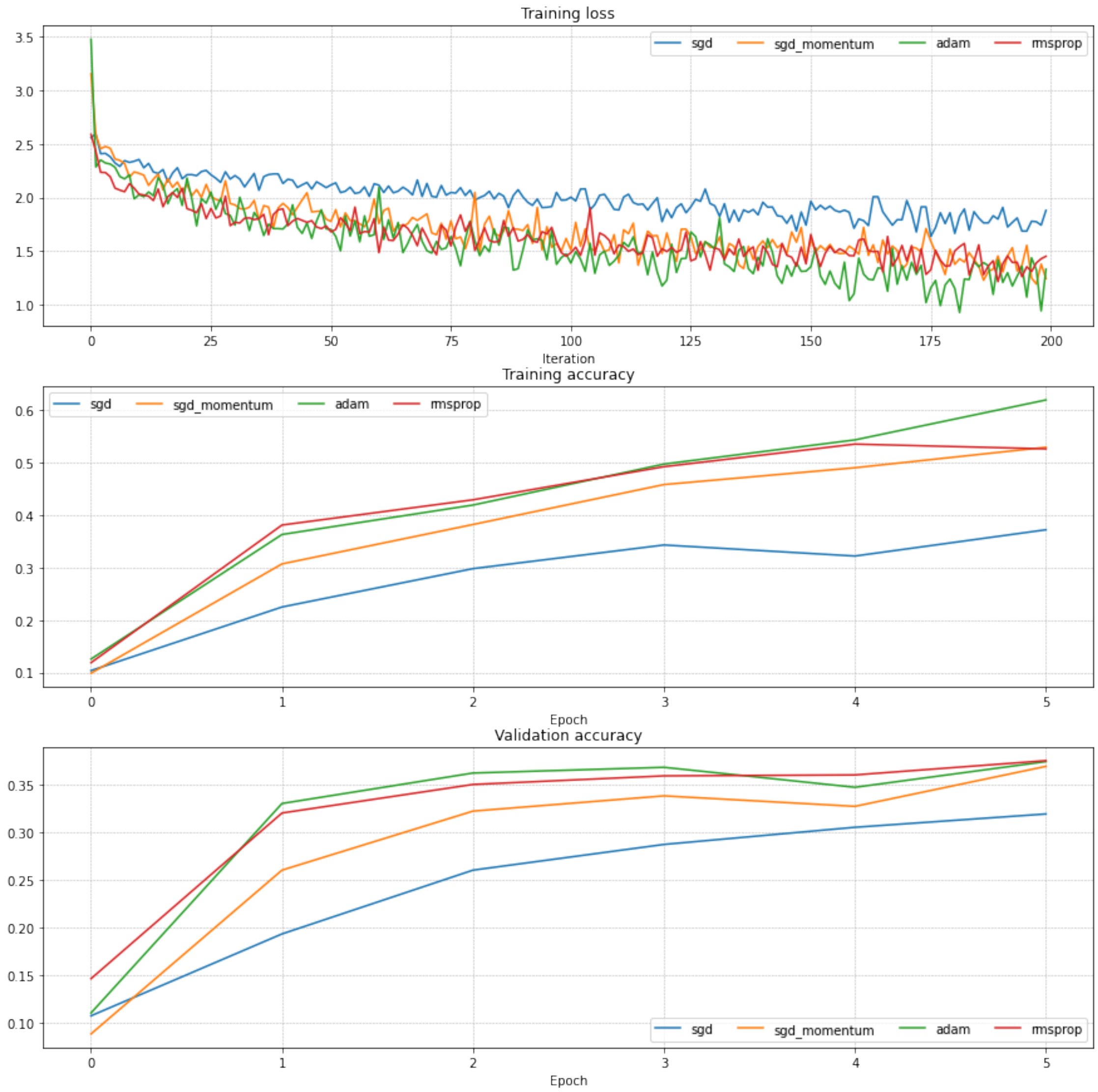
Once you have debugged your RMSProp and Adam implementations, run the following to train a pair of deep networks using these new update rules:

[31]:
```
learning_rates = {'rmsprop': 1e-4, 'adam': 1e-3}
for update_rule in ['adam', 'rmsprop']:
    print('Running with ', update_rule)
    model = FullyConnectedNet(
        [100, 100, 100, 100, 100],
        weight_scale=5e-2
    )
    solver = Solver(
        model,
        small_data,
        num_epochs=5,
        batch_size=100,
        update_rule=update_rule,
        optim_config={'learning_rate': learning_rates[update_rule]},
        verbose=True
    )
    solvers[update_rule] = solver
    solver.train()
    print()

fig, axes = plt.subplots(3, 1, figsize=(15, 15))

axes[0].set_title('Training loss')
axes[0].set_xlabel('Iteration')
axes[1].set_title('Training accuracy')
```

```python
axes[1].set_xlabel('Epoch')
axes[2].set_title('Validation accuracy')
axes[2].set_xlabel('Epoch')

for update_rule, solver in solvers.items():
    axes[0].plot(solver.loss_history, label=f"{update_rule}")
    axes[1].plot(solver.train_acc_history, label=f"{update_rule}")
    axes[2].plot(solver.val_acc_history, label=f"{update_rule}")

for ax in axes:
    ax.legend(loc='best', ncol=4)
    ax.grid(linestyle='--', linewidth=0.5)

plt.show()
```

```
Running with  adam
(Iteration 1 / 200) loss: 3.476928
(Epoch 0 / 5) train acc: 0.126000; val_acc: 0.110000
(Iteration 11 / 200) loss: 2.027712
(Iteration 21 / 200) loss: 2.183358
(Iteration 31 / 200) loss: 1.744257
(Epoch 1 / 5) train acc: 0.363000; val_acc: 0.330000
(Iteration 41 / 200) loss: 1.707951
(Iteration 51 / 200) loss: 1.703835
(Iteration 61 / 200) loss: 2.094758
(Iteration 71 / 200) loss: 1.505557
(Epoch 2 / 5) train acc: 0.419000; val_acc: 0.362000
(Iteration 81 / 200) loss: 1.594431
(Iteration 91 / 200) loss: 1.511452
(Iteration 101 / 200) loss: 1.389237
(Iteration 111 / 200) loss: 1.463575
(Epoch 3 / 5) train acc: 0.497000; val_acc: 0.368000
(Iteration 121 / 200) loss: 1.231313
(Iteration 131 / 200) loss: 1.520199
(Iteration 141 / 200) loss: 1.363221
(Iteration 151 / 200) loss: 1.355143
(Epoch 4 / 5) train acc: 0.543000; val_acc: 0.347000
(Iteration 161 / 200) loss: 1.436402
(Iteration 171 / 200) loss: 1.231426
(Iteration 181 / 200) loss: 1.153575
(Iteration 191 / 200) loss: 1.209479
(Epoch 5 / 5) train acc: 0.619000; val_acc: 0.374000

Running with  rmsprop
(Iteration 1 / 200) loss: 2.589166
(Epoch 0 / 5) train acc: 0.119000; val_acc: 0.146000
(Iteration 11 / 200) loss: 2.032921
```

```
(Iteration 21 / 200) loss: 1.897278
(Iteration 31 / 200) loss: 1.770793
(Epoch 1 / 5) train acc: 0.381000; val_acc: 0.320000
(Iteration 41 / 200) loss: 1.895731
(Iteration 51 / 200) loss: 1.681091
(Iteration 61 / 200) loss: 1.487204
(Iteration 71 / 200) loss: 1.629973
(Epoch 2 / 5) train acc: 0.429000; val_acc: 0.350000
(Iteration 81 / 200) loss: 1.506686
(Iteration 91 / 200) loss: 1.610742
(Iteration 101 / 200) loss: 1.486124
(Iteration 111 / 200) loss: 1.559454
(Epoch 3 / 5) train acc: 0.492000; val_acc: 0.359000
(Iteration 121 / 200) loss: 1.496860
(Iteration 131 / 200) loss: 1.531552
(Iteration 141 / 200) loss: 1.550195
(Iteration 151 / 200) loss: 1.657568
(Epoch 4 / 5) train acc: 0.535000; val_acc: 0.360000
(Iteration 161 / 200) loss: 1.605275
(Iteration 171 / 200) loss: 1.409442
(Iteration 181 / 200) loss: 1.503289
(Iteration 191 / 200) loss: 1.383692
(Epoch 5 / 5) train acc: 0.526000; val_acc: 0.375000
```



2.3 Inline Question 2:

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

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

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

2.4 Answer:

In AdaGrad, `cache` accumulates `dw**2` as we train the model for large number of iternations. Hence the parameter update or learning process will slow down as the value of cache increases, this is the reason for decrease in the learning process. \ However in Adams optimizer: `first_moment` (keeping tracking of gradient velocity) and `second_moment` (keeping track of squared gradient) includes decay rate `beta1` (~0.9) and `beta2` (~0.999) respectively, which prevents values becoming too large as the number of iteration increases. \ In addition, during initial learning stage (low iteration value) `first_unbias` and `second_unbias` prevents overshooting of `inverse second_moment`. Hence, adams optimization rule is highly robust as compared to adagrad.

3 Train a Good Model!

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

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

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

[35]:
```
best_model = None
best_val_acc = 0

################################################################################
# TODO: Train the best FullyConnectedNet that you can on CIFAR-10. You might   #
# find batch/layer normalization and dropout useful. Store your best model in  #
# the best_model variable.                                                     #
################################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

for reg in [1e-2]:
  for dropout_keep_ratio in [1]:
    for weight_scale in [1.2e-2]:

      print("Reg:", reg, ", dropout keep ratio:", dropout_keep_ratio, ",␣
↪weight_scale:", weight_scale)
      model = FullyConnectedNet(
          [128, 128, 128],
          weight_scale=weight_scale,
          normalization=None,
          dropout_keep_ratio=dropout_keep_ratio,
          reg = reg
```

```python
      )
      solver = Solver(
          model,
          small_data,
          num_epochs=20,
          batch_size=100,
          update_rule='adam',
          optim_config={'learning_rate': 1.2e-4},
          verbose=True
      )
      solvers[update_rule] = solver
      solver.train()
      val_acc = solver.check_accuracy(small_data["X_val"], small_data["y_val"])
      print(val_acc)
      if (val_acc > best_val_acc):
        best_val_acc = val_acc
        best_model = model
      print()
print("Best validation accuracy: ", best_val_acc)


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

```
Reg: 0.01 , dropout keep ratio: 1 , weight_scale: 0.012
(Iteration 1 / 800) loss: 2.614779
(Epoch 0 / 20) train acc: 0.130000; val_acc: 0.155000
(Iteration 11 / 800) loss: 2.504502
(Iteration 21 / 800) loss: 2.422891
(Iteration 31 / 800) loss: 2.309123
(Epoch 1 / 20) train acc: 0.328000; val_acc: 0.293000
(Iteration 41 / 800) loss: 2.262267
(Iteration 51 / 800) loss: 2.246867
(Iteration 61 / 800) loss: 2.080733
(Iteration 71 / 800) loss: 2.103133
(Epoch 2 / 20) train acc: 0.368000; val_acc: 0.344000
(Iteration 81 / 800) loss: 1.984752
(Iteration 91 / 800) loss: 2.063155
(Iteration 101 / 800) loss: 1.901240
(Iteration 111 / 800) loss: 2.010740
(Epoch 3 / 20) train acc: 0.407000; val_acc: 0.380000
(Iteration 121 / 800) loss: 1.858783
(Iteration 131 / 800) loss: 1.866430
(Iteration 141 / 800) loss: 1.971631
(Iteration 151 / 800) loss: 1.839881
```

```
(Epoch 4 / 20) train acc: 0.446000; val_acc: 0.396000
(Iteration 161 / 800) loss: 1.869957
(Iteration 171 / 800) loss: 1.743806
(Iteration 181 / 800) loss: 1.785095
(Iteration 191 / 800) loss: 1.701415
(Epoch 5 / 20) train acc: 0.458000; val_acc: 0.393000
(Iteration 201 / 800) loss: 1.714681
(Iteration 211 / 800) loss: 1.647959
(Iteration 221 / 800) loss: 1.704180
(Iteration 231 / 800) loss: 1.570353
(Epoch 6 / 20) train acc: 0.504000; val_acc: 0.417000
(Iteration 241 / 800) loss: 1.730055
(Iteration 251 / 800) loss: 1.529468
(Iteration 261 / 800) loss: 1.585484
(Iteration 271 / 800) loss: 1.384368
(Epoch 7 / 20) train acc: 0.525000; val_acc: 0.408000
(Iteration 281 / 800) loss: 1.378343
(Iteration 291 / 800) loss: 1.645529
(Iteration 301 / 800) loss: 1.586298
(Iteration 311 / 800) loss: 1.455270
(Epoch 8 / 20) train acc: 0.569000; val_acc: 0.397000
(Iteration 321 / 800) loss: 1.397930
(Iteration 331 / 800) loss: 1.477359
(Iteration 341 / 800) loss: 1.304978
(Iteration 351 / 800) loss: 1.240641
(Epoch 9 / 20) train acc: 0.570000; val_acc: 0.402000
(Iteration 361 / 800) loss: 1.356890
(Iteration 371 / 800) loss: 1.374359
(Iteration 381 / 800) loss: 1.295855
(Iteration 391 / 800) loss: 1.300168
(Epoch 10 / 20) train acc: 0.654000; val_acc: 0.414000
(Iteration 401 / 800) loss: 1.184765
(Iteration 411 / 800) loss: 1.384557
(Iteration 421 / 800) loss: 1.332594
(Iteration 431 / 800) loss: 1.278177
(Epoch 11 / 20) train acc: 0.675000; val_acc: 0.409000
(Iteration 441 / 800) loss: 1.089584
(Iteration 451 / 800) loss: 1.228212
(Iteration 461 / 800) loss: 1.227328
(Iteration 471 / 800) loss: 1.103301
(Epoch 12 / 20) train acc: 0.685000; val_acc: 0.391000
(Iteration 481 / 800) loss: 0.990814
(Iteration 491 / 800) loss: 1.201670
(Iteration 501 / 800) loss: 1.162523
(Iteration 511 / 800) loss: 1.076397
(Epoch 13 / 20) train acc: 0.720000; val_acc: 0.437000
(Iteration 521 / 800) loss: 1.126484
(Iteration 531 / 800) loss: 1.029462
```

```
(Iteration 541 / 800) loss: 1.045696
(Iteration 551 / 800) loss: 1.055930
(Epoch 14 / 20) train acc: 0.721000; val_acc: 0.430000
(Iteration 561 / 800) loss: 0.977323
(Iteration 571 / 800) loss: 0.819238
(Iteration 581 / 800) loss: 1.005773
(Iteration 591 / 800) loss: 0.872906
(Epoch 15 / 20) train acc: 0.753000; val_acc: 0.418000
(Iteration 601 / 800) loss: 1.107147
(Iteration 611 / 800) loss: 1.098544
(Iteration 621 / 800) loss: 0.906941
(Iteration 631 / 800) loss: 1.042574
(Epoch 16 / 20) train acc: 0.805000; val_acc: 0.413000
(Iteration 641 / 800) loss: 0.860500
(Iteration 651 / 800) loss: 0.905821
(Iteration 661 / 800) loss: 0.948025
(Iteration 671 / 800) loss: 0.855804
(Epoch 17 / 20) train acc: 0.791000; val_acc: 0.415000
(Iteration 681 / 800) loss: 0.959099
(Iteration 691 / 800) loss: 0.882246
(Iteration 701 / 800) loss: 0.687256
(Iteration 711 / 800) loss: 0.916421
(Epoch 18 / 20) train acc: 0.814000; val_acc: 0.402000
(Iteration 721 / 800) loss: 0.903756
(Iteration 731 / 800) loss: 0.821997
(Iteration 741 / 800) loss: 0.723944
(Iteration 751 / 800) loss: 0.809238
(Epoch 19 / 20) train acc: 0.862000; val_acc: 0.413000
(Iteration 761 / 800) loss: 0.645673
(Iteration 771 / 800) loss: 0.677218
(Iteration 781 / 800) loss: 0.755318
(Iteration 791 / 800) loss: 0.640551
(Epoch 20 / 20) train acc: 0.867000; val_acc: 0.396000
0.437

Best validation accuracy:  0.437
```

4 Test Your Model!

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

[36]:
```python
y_test_pred = np.argmax(best_model.loss(data['X_test']), axis=1)
y_val_pred = np.argmax(best_model.loss(data['X_val']), axis=1)
print('Validation set accuracy: ', (y_val_pred == data['y_val']).mean())
print('Test set accuracy: ', (y_test_pred == data['y_test']).mean())
```

```
Validation set accuracy:  0.437
Test set accuracy:  0.414
```

BatchNormalization

May 3, 2022

[ ]:
```
# 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. 'cs231n/assignments/assignment2/'
FOLDERNAME = 'Colab_Notebooks/cs231n/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/$FOLDERNAME/cs231n/datasets/
!bash get_datasets.sh
%cd /content/drive/My\ Drive/$FOLDERNAME
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
/content/drive/My
Drive/Colab_Notebooks/cs231n/assignments/assignment2/cs231n/datasets
/content/drive/My Drive/Colab_Notebooks/cs231n/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.](https://arxiv.org/abs/1502.03167)

[ ]:
```
# Setup cell.
import time
import numpy as np
import matplotlib.pyplot as plt
from cs231n.classifiers.fc_net import *
from cs231n.data_utils import get_CIFAR10_data
from cs231n.gradient_check import eval_numerical_gradient,␣
↪eval_numerical_gradient_array
from cs231n.solver import Solver

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

%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")
```

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

[ ]:
```
# 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 `cs231n/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!

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

```python
# 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.

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

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

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

dx_num = eval_numerical_gradient_array(fx, x, dout)
da_num = eval_numerical_gradient_array(fg, gamma.copy(), dout)
db_num = eval_numerical_gradient_array(fb, beta.copy(), dout)
#print(dx_num)
_, cache = batchnorm_forward(x, gamma, beta, bn_param)
dx, dgamma, dbeta = batchnorm_backward(dout, cache)
#print(dx)
# 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:  1.7029985226865764e-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).

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

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

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:  2.486886815906992e-11
dgamma difference:  0.0
dbeta difference:  0.0
speedup: 1.12x
```

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 `cs231n/classifiers/fc_net.py`. Modify your implementation to add batch normalization.

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

Hint: You might find it useful to define an additional helper layer similar to those in the file `cs231n/layer_utils.py`.

[ ]:
```
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: 2.85e-06
W3 relative error: 4.05e-10
b1 relative error: 2.22e-08
b2 relative error: 2.22e-08
b3 relative error: 1.01e-10
beta1 relative error: 7.33e-09
beta2 relative error: 1.89e-09
gamma1 relative error: 6.96e-09
gamma2 relative error: 1.96e-09

Running check with reg =  3.14
Initial loss:  6.996533220108303
W1 relative error: 1.98e-06
W2 relative error: 2.28e-06
W3 relative error: 1.11e-08
b1 relative error: 5.55e-09
b2 relative error: 2.22e-08
b3 relative error: 2.10e-10
beta1 relative error: 6.65e-09
beta2 relative error: 4.23e-09
gamma1 relative error: 6.27e-09
gamma2 relative error: 5.28e-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)
```

```python
# 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()
```

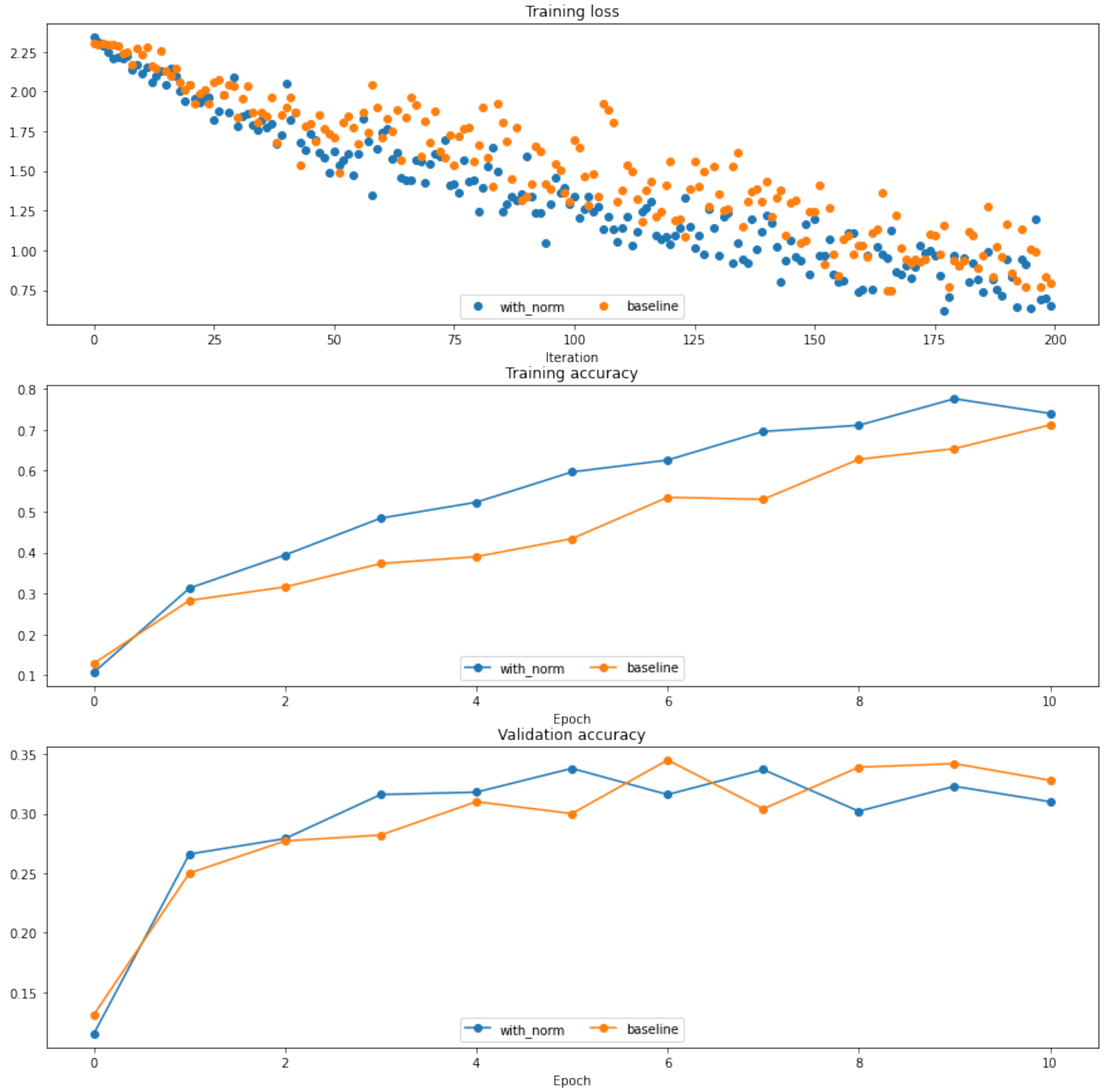
```
Solver with batch norm:
(Iteration 1 / 200) loss: 2.340974
(Epoch 0 / 10) train acc: 0.107000; val_acc: 0.115000
(Epoch 1 / 10) train acc: 0.313000; val_acc: 0.266000
(Iteration 21 / 200) loss: 2.039345
(Epoch 2 / 10) train acc: 0.394000; val_acc: 0.279000
(Iteration 41 / 200) loss: 2.047471
(Epoch 3 / 10) train acc: 0.484000; val_acc: 0.316000
(Iteration 61 / 200) loss: 1.739554
(Epoch 4 / 10) train acc: 0.523000; val_acc: 0.318000
```

```
(Iteration 81 / 200) loss: 1.247064
(Epoch 5 / 10) train acc: 0.597000; val_acc: 0.338000
(Iteration 101 / 200) loss: 1.335661
(Epoch 6 / 10) train acc: 0.626000; val_acc: 0.316000
(Iteration 121 / 200) loss: 1.040250
(Epoch 7 / 10) train acc: 0.696000; val_acc: 0.337000
(Iteration 141 / 200) loss: 1.221896
(Epoch 8 / 10) train acc: 0.711000; val_acc: 0.302000
(Iteration 161 / 200) loss: 0.756157
(Epoch 9 / 10) train acc: 0.776000; val_acc: 0.323000
(Iteration 181 / 200) loss: 0.903611
(Epoch 10 / 10) train acc: 0.740000; val_acc: 0.310000

Solver without batch norm:
(Iteration 1 / 200) loss: 2.302332
(Epoch 0 / 10) train acc: 0.129000; val_acc: 0.131000
(Epoch 1 / 10) train acc: 0.283000; val_acc: 0.250000
(Iteration 21 / 200) loss: 2.041970
(Epoch 2 / 10) train acc: 0.316000; val_acc: 0.277000
(Iteration 41 / 200) loss: 1.900473
(Epoch 3 / 10) train acc: 0.373000; val_acc: 0.282000
(Iteration 61 / 200) loss: 1.713156
(Epoch 4 / 10) train acc: 0.390000; val_acc: 0.310000
(Iteration 81 / 200) loss: 1.662209
(Epoch 5 / 10) train acc: 0.434000; val_acc: 0.300000
(Iteration 101 / 200) loss: 1.696059
(Epoch 6 / 10) train acc: 0.535000; val_acc: 0.345000
(Iteration 121 / 200) loss: 1.557987
(Epoch 7 / 10) train acc: 0.530000; val_acc: 0.304000
(Iteration 141 / 200) loss: 1.432189
(Epoch 8 / 10) train acc: 0.628000; val_acc: 0.339000
(Iteration 161 / 200) loss: 1.034116
(Epoch 9 / 10) train acc: 0.654000; val_acc: 0.342000
(Iteration 181 / 200) loss: 0.905795
(Epoch 10 / 10) train acc: 0.712000; val_acc: 0.328000
```

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.

[ ]:
```python
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.
```

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

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

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

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

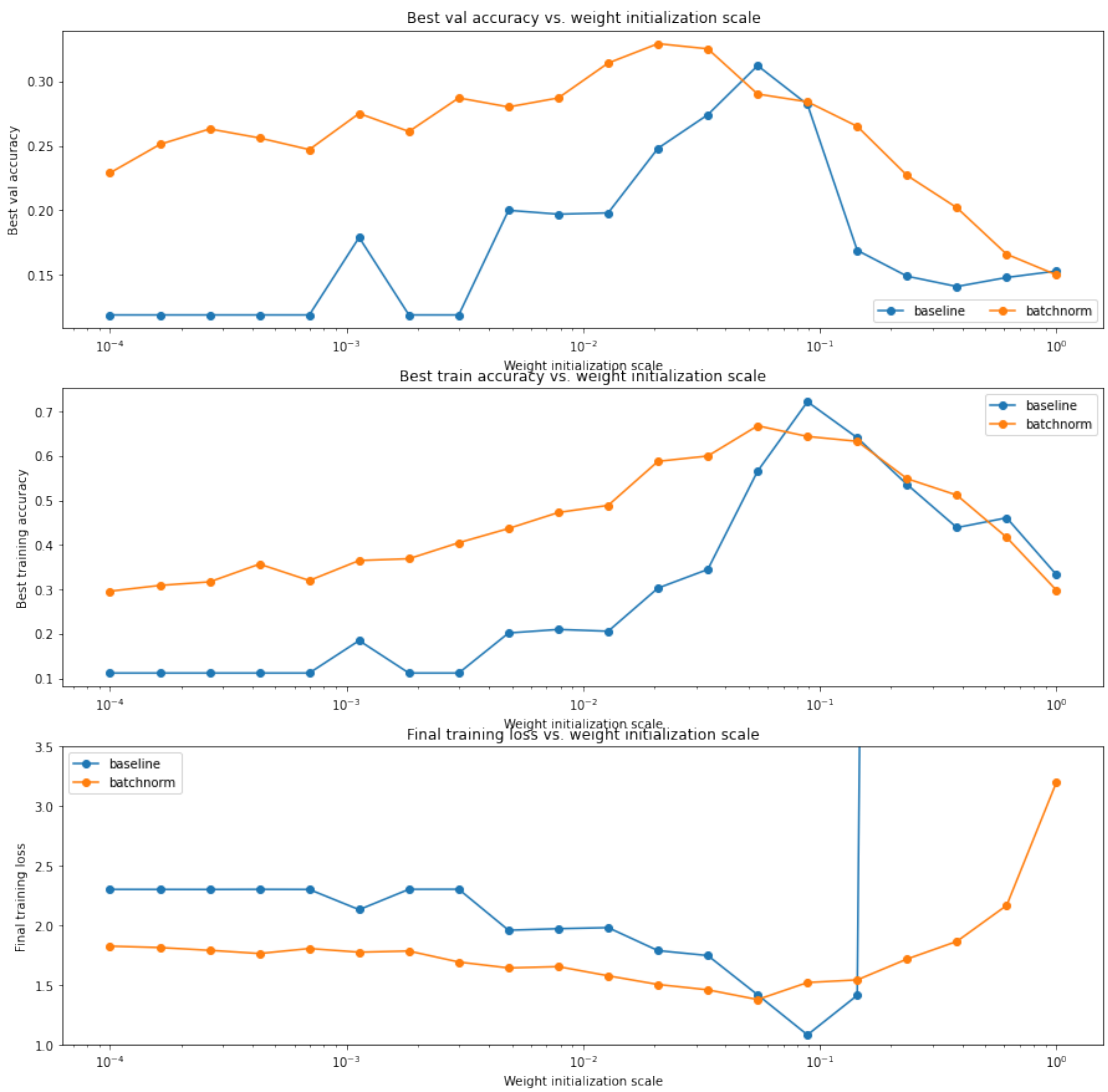
```
Running weight scale 1 / 20
Running weight scale 2 / 20
Running weight scale 3 / 20
Running weight scale 4 / 20
Running weight scale 5 / 20
Running weight scale 6 / 20
Running weight scale 7 / 20
Running weight scale 8 / 20
```

```
Running weight scale 9 / 20
Running weight scale 10 / 20
Running weight scale 11 / 20
Running weight scale 12 / 20
Running weight scale 13 / 20
Running weight scale 14 / 20
Running weight scale 15 / 20
Running weight scale 16 / 20
Running weight scale 17 / 20
Running weight scale 18 / 20
Running weight scale 19 / 20
Running weight scale 20 / 20
```

[ ]:

```
# 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?

7.2 Answer:

Observation: \ `With BN`, weight initialization (in range of 10^-3 to 10^-1) we observe comparable best validation accuracy (~0.325) as opposed to `without BN` where weight initialization only near to 10^-1 yield higher best validation accuracy (~0.32). Hence, BN is found to be robust to different weight initialization scale. \

Reason: \ When using BN, every input layer is normalized to 0 mean and unit variance before applying non-linear activations, this makes the model less sensitive to changes in weights and hence easier to optimize. Using BN, we solve the problem of internal covariant shift which takes places between layers which is very crucial to ensure numerical stability in deep layers (more in DeepStability research paper: https://arxiv.org/pdf/2202.03493.pdf). During training, BN makes model more robust to variation in weight scale initialization and not much variation is observed in final activation.

8 Batch Normalization and Batch Size

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

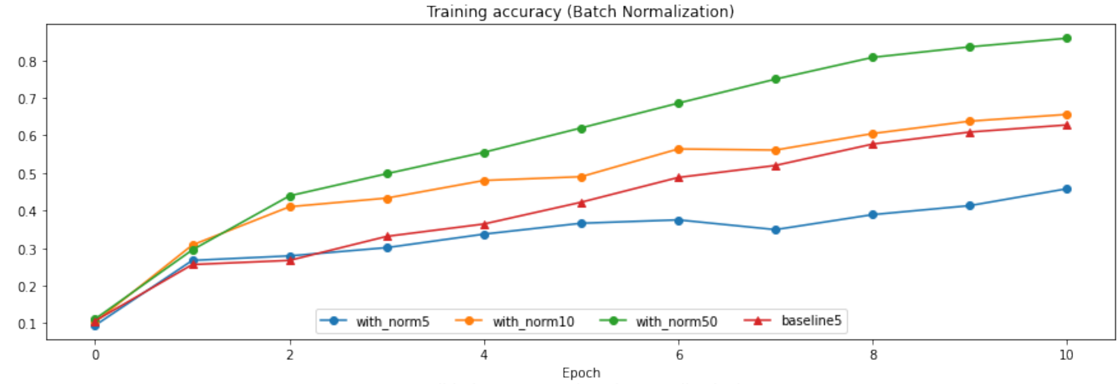
The first cell will train 6-layer networks both with and without batch normalization using different batch sizes. The second layer will plot training accuracy and validation set accuracy over time.

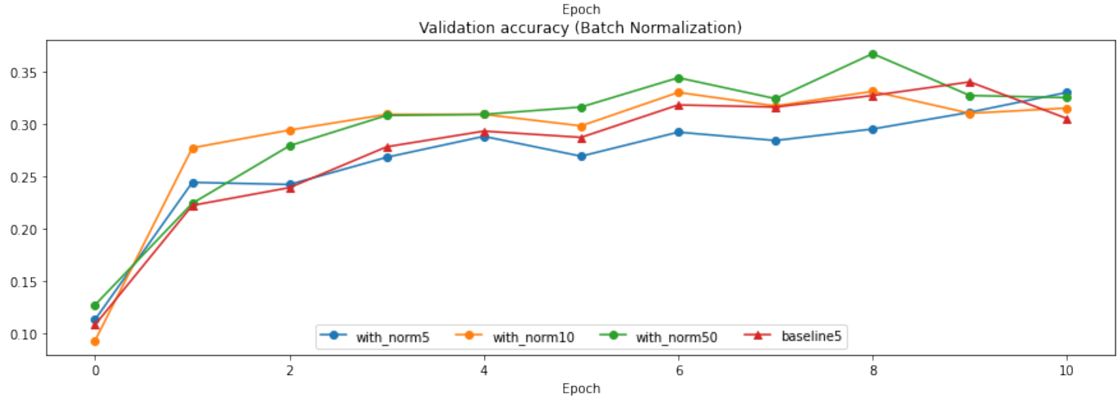
[ ]:
```
def run_batchsize_experiments(normalization_mode):
    np.random.seed(231)

    # 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:

Observation: \ With increase in batch size, BN's validation accuracy increases i.e. `with_norm50` has ~0.35 best val accuracy and `with_norm5` has ~0.3 best val accuracy. \

Reason: \ With increased batch size, computed mean and variance is near to actual total input training data's mean and variance. Hence, normalized input mini-batch data (with large mini batch size) will correspondingly be near to actual normalized training data. This is the reason for improved best val accuracy for higher mini batch size. \ Comparing best val accuracy for with and without (baseline) batchnorm: we find that when BN is implemented it makes model training robust to weight scale initializaiton and also model's final output does not diverge much when BN is implemented.

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.](https://arxiv.org/pdf/1607.06450.pdf)

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:

1. Layer Normalization \ Reason: Considering each row of the `H X W` image as different training examples and if we scale an image such that RGB channel for each row adds to one, we are essentially performing layer normalization across each channel and column dimensions. Hence this is analagous to layer normalization where instead of individual training example, we are considering individual rows. Hence this is not exactly layer normalization, but similar (or analagous) behavior can be extended.

2. Layer Normalization \ Reason: Since we are normalizing all channels and spatial diemensions for each of the image, this is same as layer normalization.

3. Batch Normalization \ Reason: By substracting the mean image of the dataset, we are essentially computing `x_i - mu`, meaning: we are centering the input data to 0 mean for each of the channel dimensions. This is similarly done in BN for mean and variance computed for mini batch of the input data.

4. None \ Reason: This is similar to neither of the Batch Normalization or Layer normalization, as qualifying a dimension as 0 or 1 will not help normalize the input data.

More on this ed post: https://edstem.org/us/courses/21177/discussion/1467914

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 `cs231n/layers.py`, implement the forward pass for layer normalization in the function `layernorm_forward`.

Run the cell below to check your results. * In `cs231n/layers.py`, implement the backward pass for layer normalization in the function `layernorm_backward`.

Run the second cell below to check your results. * Modify `cs231n/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))
```

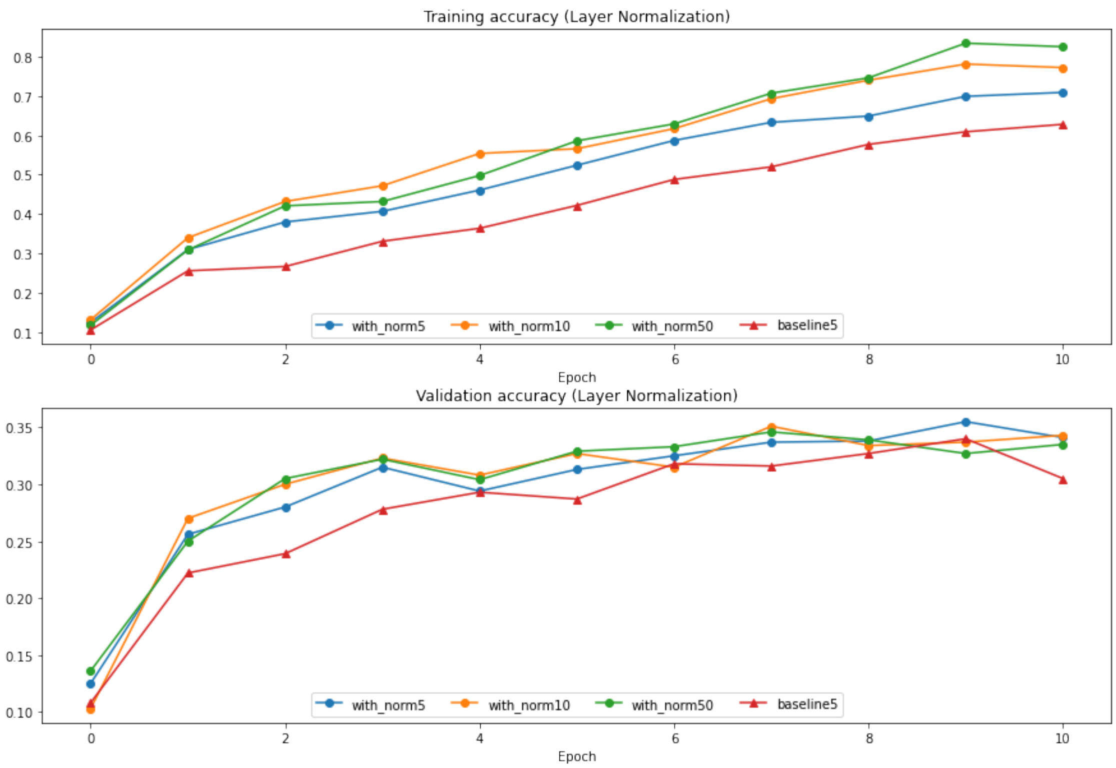
```
dx error:  1.433615146847572e-09
dgamma error:  4.519489546032799e-12
dbeta error:  2.276445013433725e-12
```

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:

Layer Normalization (LN) is likely to NOT work well for:

1. Using LN in deep network would ensure data points to be normalized across all channels and spatial dimension for each of the training example. Implementing LN in deep network would help model to be robust to changes in the input.

2. Small feature dimension: since in LN, we compute mean and variance across all the features and spatial dimensions. Hence, if we were to have very feature dimension,layer normalized efficacy would be less as compared to when we would have large number of feature dimension.

3. With high regularization, LN will have similar effect as done without regularization. \

Dropout

May 3, 2022

```
[ ]: inli# 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. 'cs231n/assignments/assignment2/'
FOLDERNAME = 'Colab_Notebooks/cs231n/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/$FOLDERNAME/cs231n/datasets/
!bash get_datasets.sh
%cd /content/drive/My\ Drive/$FOLDERNAME
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
/content/drive/My
Drive/Colab_Notebooks/cs231n/assignments/assignment2/cs231n/datasets
/content/drive/My Drive/Colab_Notebooks/cs231n/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](https://arxiv.org/abs/1207.0580)

[ ]:
```
# Setup cell.
import time
import numpy as np
import matplotlib.pyplot as plt
from cs231n.classifiers.fc_net import *
from cs231n.data_utils import get_CIFAR10_data
from cs231n.gradient_check import eval_numerical_gradient,␣
↪eval_numerical_gradient_array
from cs231n.solver import Solver

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

%load_ext autoreload
%autoreload 2

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

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

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

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

[ ]:
```
np.random.seed(231)
x = np.random.randn(500, 500) + 10
```

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

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

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

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

Running tests with p =  0.7
Mean of input:  10.000207878477502
Mean of train-time output:  9.987811912159426
Mean of test-time output:  10.000207878477502
Fraction of train-time output set to zero:  0.30074
Fraction of test-time output set to zero:  0.0
```

3 Dropout: Backward Pass

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

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

dropout_param = {'mode': 'train', 'p': 0.2, 'seed': 123}
out, cache = dropout_forward(x, dropout_param)
dx = dropout_backward(dout, cache)
```

```
dx_num = eval_numerical_gradient_array(lambda xx: dropout_forward(xx,␣
↪dropout_param)[0], x, dout)

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

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

3.1 Inline Question 1:

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 do not divide the values being passed through the inverse dropout layer by 'p' in the dropout layer, we see a mismatch between the neuron output values in the train and test phase which might hamper the overall output / performance of the model. This is because while we implement dropout in the training mode, the neuron outputs become px + (1-p)0 and during the test mode, the neuron outputs are simply x, thus leading to weightage mismatch.

4 Fully Connected Networks with Dropout

In the file `cs231n/classifiers/fc_net.py`, modify your implementation to use dropout. Specifically, if the constructor of the network receives a value that is not 1 for the `dropout_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
    )
```

```python
    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:  2.3004790897684924
W1 relative error: 1.48e-07
W2 relative error: 2.21e-05
W3 relative error: 3.53e-07
b1 relative error: 5.38e-09
b2 relative error: 2.09e-09
b3 relative error: 5.80e-11

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

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

5 Regularization Experiment

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

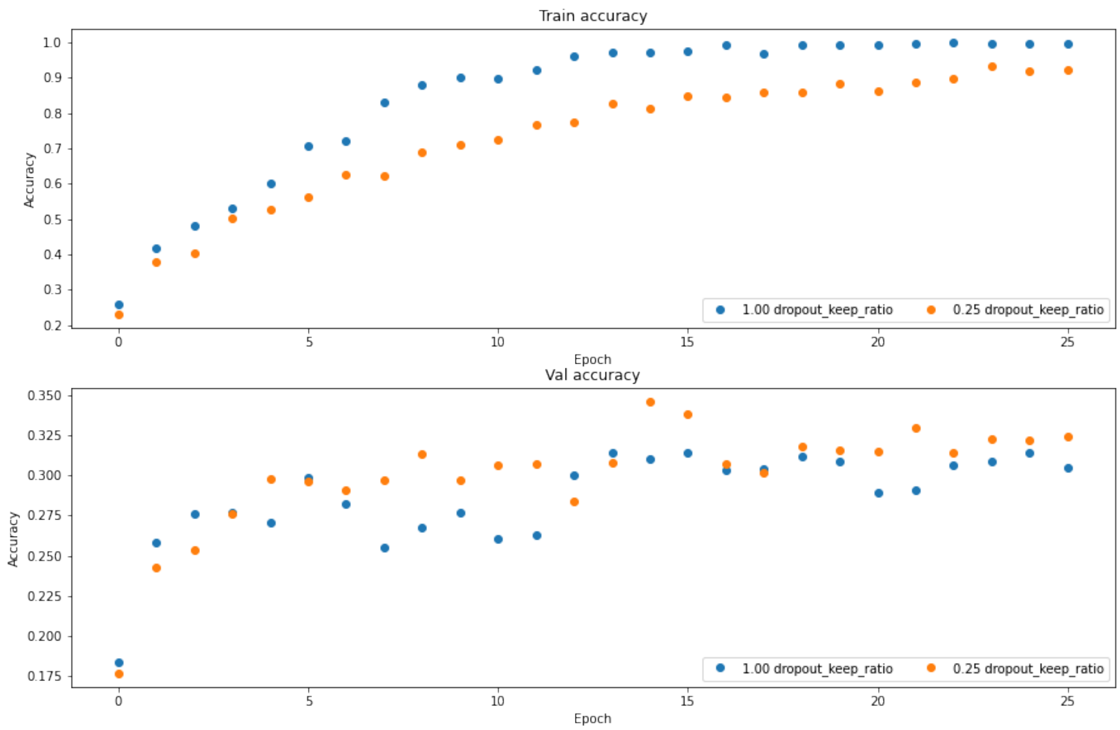
[ ]:
```
# Train two identical nets, one with dropout and one without.
np.random.seed(231)
num_train = 500
small_data = {
    'X_train': data['X_train'][:num_train],
    'y_train': data['y_train'][:num_train],
    'X_val': data['X_val'],
    'y_val': data['y_val'],
}

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: 7.856643
(Epoch 0 / 25) train acc: 0.260000; val_acc: 0.184000
(Epoch 1 / 25) train acc: 0.416000; val_acc: 0.258000
(Epoch 2 / 25) train acc: 0.482000; val_acc: 0.276000
(Epoch 3 / 25) train acc: 0.532000; val_acc: 0.277000
(Epoch 4 / 25) train acc: 0.600000; val_acc: 0.271000
(Epoch 5 / 25) train acc: 0.708000; val_acc: 0.299000
(Epoch 6 / 25) train acc: 0.722000; val_acc: 0.282000
(Epoch 7 / 25) train acc: 0.832000; val_acc: 0.255000
(Epoch 8 / 25) train acc: 0.880000; val_acc: 0.268000
(Epoch 9 / 25) train acc: 0.902000; val_acc: 0.277000
(Epoch 10 / 25) train acc: 0.898000; val_acc: 0.261000
```

```
(Epoch 11 / 25) train acc: 0.924000; val_acc: 0.263000
(Epoch 12 / 25) train acc: 0.960000; val_acc: 0.300000
(Epoch 13 / 25) train acc: 0.972000; val_acc: 0.314000
(Epoch 14 / 25) train acc: 0.972000; val_acc: 0.310000
(Epoch 15 / 25) train acc: 0.974000; val_acc: 0.314000
(Epoch 16 / 25) train acc: 0.994000; val_acc: 0.303000
(Epoch 17 / 25) train acc: 0.970000; val_acc: 0.304000
(Epoch 18 / 25) train acc: 0.992000; val_acc: 0.312000
(Epoch 19 / 25) train acc: 0.992000; val_acc: 0.309000
(Epoch 20 / 25) train acc: 0.992000; val_acc: 0.289000
(Iteration 101 / 125) loss: 0.001969
(Epoch 21 / 25) train acc: 0.996000; val_acc: 0.291000
(Epoch 22 / 25) train acc: 1.000000; val_acc: 0.306000
(Epoch 23 / 25) train acc: 0.996000; val_acc: 0.309000
(Epoch 24 / 25) train acc: 0.998000; val_acc: 0.314000
(Epoch 25 / 25) train acc: 0.998000; val_acc: 0.305000

0.25
(Iteration 1 / 125) loss: 17.318478
(Epoch 0 / 25) train acc: 0.230000; val_acc: 0.177000
(Epoch 1 / 25) train acc: 0.378000; val_acc: 0.243000
(Epoch 2 / 25) train acc: 0.402000; val_acc: 0.254000
(Epoch 3 / 25) train acc: 0.502000; val_acc: 0.276000
(Epoch 4 / 25) train acc: 0.528000; val_acc: 0.298000
(Epoch 5 / 25) train acc: 0.562000; val_acc: 0.296000
(Epoch 6 / 25) train acc: 0.626000; val_acc: 0.291000
(Epoch 7 / 25) train acc: 0.622000; val_acc: 0.297000
(Epoch 8 / 25) train acc: 0.688000; val_acc: 0.313000
(Epoch 9 / 25) train acc: 0.712000; val_acc: 0.297000
(Epoch 10 / 25) train acc: 0.724000; val_acc: 0.306000
(Epoch 11 / 25) train acc: 0.768000; val_acc: 0.307000
(Epoch 12 / 25) train acc: 0.774000; val_acc: 0.284000
(Epoch 13 / 25) train acc: 0.828000; val_acc: 0.308000
(Epoch 14 / 25) train acc: 0.812000; val_acc: 0.346000
(Epoch 15 / 25) train acc: 0.850000; val_acc: 0.338000
(Epoch 16 / 25) train acc: 0.844000; val_acc: 0.307000
(Epoch 17 / 25) train acc: 0.858000; val_acc: 0.302000
(Epoch 18 / 25) train acc: 0.860000; val_acc: 0.318000
(Epoch 19 / 25) train acc: 0.884000; val_acc: 0.316000
(Epoch 20 / 25) train acc: 0.862000; val_acc: 0.315000
(Iteration 101 / 125) loss: 4.293572
(Epoch 21 / 25) train acc: 0.886000; val_acc: 0.330000
(Epoch 22 / 25) train acc: 0.898000; val_acc: 0.314000
(Epoch 23 / 25) train acc: 0.934000; val_acc: 0.323000
(Epoch 24 / 25) train acc: 0.918000; val_acc: 0.322000
(Epoch 25 / 25) train acc: 0.922000; val_acc: 0.324000
```

[ ]:

```python
# 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:

While training accuracy is lower when using dropout, validation accuracy is observed to be higher when using dropout. This results suggest that dropout (i.e. one form of regularizer) helps generalizes the model parameters and prevents overfiting to training data and improves the performance on validation (unseen) data which comes from the similar distribution as training data.

ConvolutionalNetworks

May 3, 2022

```
[ ]: # 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. 'cs231n/assignments/assignment2/'
FOLDERNAME = 'Colab_Notebooks/cs231n/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/$FOLDERNAME/cs231n/datasets/
!bash get_datasets.sh
%cd /content/drive/My\ Drive/$FOLDERNAME
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
/content/drive/My
Drive/Colab_Notebooks/cs231n/assignments/assignment2/cs231n/datasets
/content/drive/My Drive/Colab_Notebooks/cs231n/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.

[ ]:
```python
# Setup cell.
import numpy as np
import matplotlib.pyplot as plt
from cs231n.classifiers.cnn import *
from cs231n.data_utils import get_CIFAR10_data
from cs231n.gradient_check import eval_numerical_gradient_array,␣
 ↪eval_numerical_gradient
from cs231n.layers import *
from cs231n.fast_layers import *
from cs231n.solver import Solver

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

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

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

[ ]:
```python
# Load the (preprocessed) 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 `cs231n/layers.py`, implement the forward pass for the convolution layer in the function `conv_forward_naive`.

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

You can test your implementation by running the following:

[ ]:
```
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
```

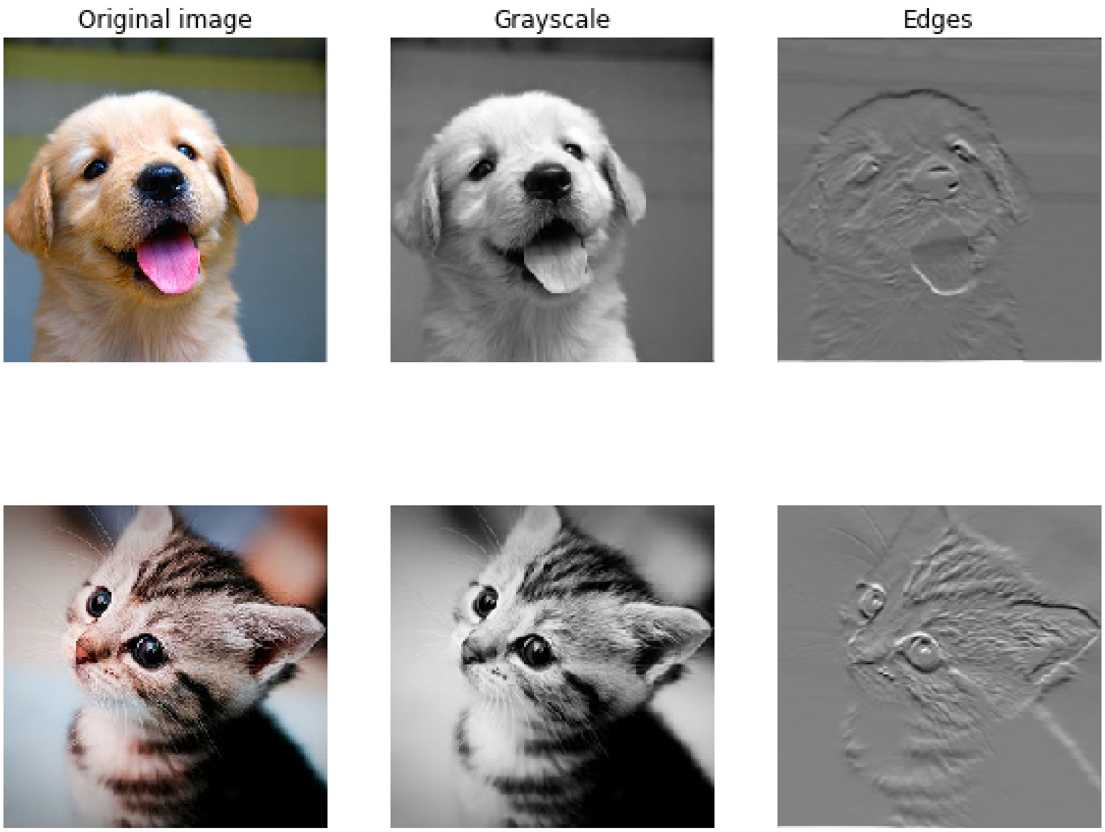
2.1 Aside: Image Processing via Convolutions

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.

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

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

img_size = 200   # Make this smaller if it runs too slow
resized_puppy = np.array(Image.fromarray(puppy).resize((img_size, img_size)))
```

```
resized_kitten = np.array(Image.fromarray(kitten_cropped).resize((img_size,
 ↪img_size)))
x = np.zeros((2, 3, img_size, img_size))
x[0, :, :, :] = resized_puppy.transpose((2, 0, 1))
x[1, :, :, :] = resized_kitten.transpose((2, 0, 1))

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

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

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

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

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

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

# Show the original images and the results of the conv operation
plt.subplot(2, 3, 1)
imshow_no_ax(puppy, normalize=False)
plt.title('Original image')
plt.subplot(2, 3, 2)
imshow_no_ax(out[0, 0])
plt.title('Grayscale')
plt.subplot(2, 3, 3)
imshow_no_ax(out[0, 1])
plt.title('Edges')
plt.subplot(2, 3, 4)
imshow_no_ax(kitten_cropped, normalize=False)
```

```
plt.subplot(2, 3, 5)
imshow_no_ax(out[1, 0])
plt.subplot(2, 3, 6)
imshow_no_ax(out[1, 1])
plt.show()
```



3 Convolution: Naive Backward Pass

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

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

[ ]:
```
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 `cs231n/layers.py`. Again, don't worry too much about computational efficiency.

Check your implementation by running the following:

[ ]:
```
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 `cs231n/layers.py`. You don't need to worry about computational efficiency.

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

[ ]:
```
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 `cs231n/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.

[ ]:
```
# Remember to restart the runtime after executing this cell!
%cd /content/drive/My\ Drive/$FOLDERNAME/cs231n/
!python setup.py build_ext --inplace
%cd /content/drive/My\ Drive/$FOLDERNAME/
```

```
/content/drive/My Drive/Colab_Notebooks/cs231n/assignments/assignment2/cs231n
running build_ext
/content/drive/My Drive/Colab_Notebooks/cs231n/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:

[ ]:
```
# Rel errors should be around e-9 or less.
from cs231n.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: 5.329089s
Fast: 0.013901s
Speedup: 383.353686x
Difference:  4.926407851494105e-11

Testing conv_backward_fast:
Naive: 8.289638s
Fast: 0.018491s
Speedup: 448.300137x
dx difference:  1.949764775345631e-11
dw difference:  3.681156828004736e-13
db difference:  3.481354613192702e-14
```

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

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

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

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

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

```
Testing pool_forward_fast:
Naive: 0.404023s
fast: 0.006713s
speedup: 60.185999x
difference:  0.0

Testing pool_backward_fast:
Naive: 1.190462s
fast: 0.014262s
speedup: 83.472550x
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 `cs231n/layer_utils.py` you will find sandwich layers that implement a few commonly used patterns for convolutional networks. Run the cells below to sanity check their usage.

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

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

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

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

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

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

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

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

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

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

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

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

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.

[ ]:
```
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.

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

model = ThreeLayerConvNet(
```

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

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

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.

[ ]:
```
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: 3.102925
(Epoch 1 / 15) train acc: 0.140000; val_acc: 0.087000
(Iteration 3 / 30) loss: 2.270330
(Iteration 4 / 30) loss: 2.096705
(Epoch 2 / 15) train acc: 0.240000; val_acc: 0.094000
(Iteration 5 / 30) loss: 1.838880
(Iteration 6 / 30) loss: 1.934188
(Epoch 3 / 15) train acc: 0.510000; val_acc: 0.173000
(Iteration 7 / 30) loss: 1.827912
(Iteration 8 / 30) loss: 1.639574
(Epoch 4 / 15) train acc: 0.520000; val_acc: 0.188000
(Iteration 9 / 30) loss: 1.330082
(Iteration 10 / 30) loss: 1.756115
(Epoch 5 / 15) train acc: 0.630000; val_acc: 0.167000
(Iteration 11 / 30) loss: 1.024162
(Iteration 12 / 30) loss: 1.041826
(Epoch 6 / 15) train acc: 0.750000; val_acc: 0.229000
(Iteration 13 / 30) loss: 1.142777
(Iteration 14 / 30) loss: 0.835706
(Epoch 7 / 15) train acc: 0.790000; val_acc: 0.247000
(Iteration 15 / 30) loss: 0.587786
(Iteration 16 / 30) loss: 0.645509
(Epoch 8 / 15) train acc: 0.820000; val_acc: 0.252000
(Iteration 17 / 30) loss: 0.786844
(Iteration 18 / 30) loss: 0.467054
(Epoch 9 / 15) train acc: 0.820000; val_acc: 0.178000
(Iteration 19 / 30) loss: 0.429880
(Iteration 20 / 30) loss: 0.635498
(Epoch 10 / 15) train acc: 0.900000; val_acc: 0.206000
(Iteration 21 / 30) loss: 0.365807
(Iteration 22 / 30) loss: 0.284220
(Epoch 11 / 15) train acc: 0.820000; val_acc: 0.201000
(Iteration 23 / 30) loss: 0.469343
(Iteration 24 / 30) loss: 0.509369
(Epoch 12 / 15) train acc: 0.920000; val_acc: 0.211000
(Iteration 25 / 30) loss: 0.111638
(Iteration 26 / 30) loss: 0.145388
(Epoch 13 / 15) train acc: 0.930000; val_acc: 0.213000
```

```
(Iteration 27 / 30) loss: 0.155575
(Iteration 28 / 30) loss: 0.143398
(Epoch 14 / 15) train acc: 0.960000; val_acc: 0.212000
(Iteration 29 / 30) loss: 0.158160
(Iteration 30 / 30) loss: 0.118934
(Epoch 15 / 15) train acc: 0.990000; val_acc: 0.220000
```

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

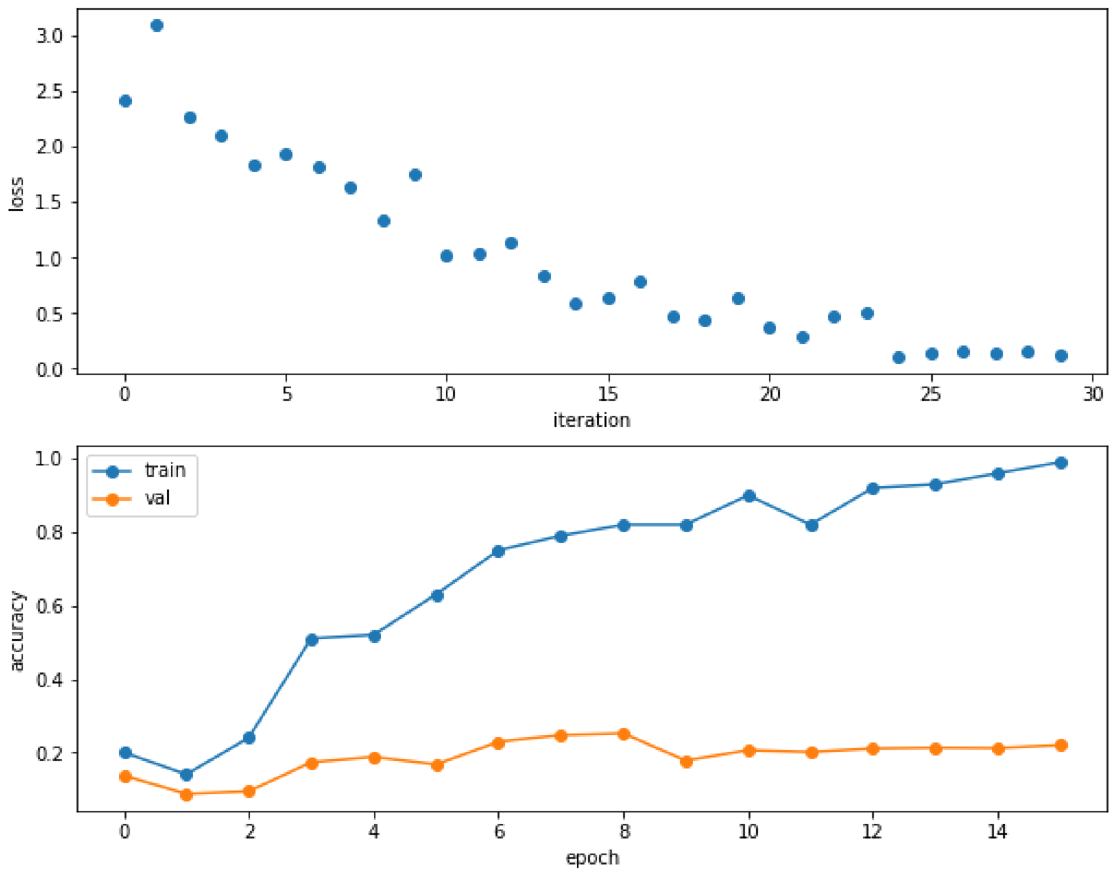
```
Small data training accuracy: 0.82
```

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

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

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

[ ]:
```
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:

[ ]:
```
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: 2.098229
(Iteration 41 / 980) loss: 1.949788
(Iteration 61 / 980) loss: 1.888398
(Iteration 81 / 980) loss: 1.877093
(Iteration 101 / 980) loss: 1.851877
(Iteration 121 / 980) loss: 1.859353
(Iteration 141 / 980) loss: 1.800181
(Iteration 161 / 980) loss: 2.143292
(Iteration 181 / 980) loss: 1.830573
(Iteration 201 / 980) loss: 2.037280
(Iteration 221 / 980) loss: 2.020304
(Iteration 241 / 980) loss: 1.823728
(Iteration 261 / 980) loss: 1.692679
(Iteration 281 / 980) loss: 1.882594
(Iteration 301 / 980) loss: 1.798261
(Iteration 321 / 980) loss: 1.851960
(Iteration 341 / 980) loss: 1.716323
(Iteration 361 / 980) loss: 1.897655
(Iteration 381 / 980) loss: 1.319744
(Iteration 401 / 980) loss: 1.738790
(Iteration 421 / 980) loss: 1.488866
(Iteration 441 / 980) loss: 1.718409
(Iteration 461 / 980) loss: 1.744440
(Iteration 481 / 980) loss: 1.605460
(Iteration 501 / 980) loss: 1.494847
(Iteration 521 / 980) loss: 1.835179
(Iteration 541 / 980) loss: 1.483923
(Iteration 561 / 980) loss: 1.676871
(Iteration 581 / 980) loss: 1.438325
(Iteration 601 / 980) loss: 1.443469
(Iteration 621 / 980) loss: 1.529369
(Iteration 641 / 980) loss: 1.763475
(Iteration 661 / 980) loss: 1.790329
(Iteration 681 / 980) loss: 1.693343
(Iteration 701 / 980) loss: 1.637078
(Iteration 721 / 980) loss: 1.644564
(Iteration 741 / 980) loss: 1.708919
(Iteration 761 / 980) loss: 1.494252
(Iteration 781 / 980) loss: 1.901751
(Iteration 801 / 980) loss: 1.898991
(Iteration 821 / 980) loss: 1.489988
(Iteration 841 / 980) loss: 1.377615
(Iteration 861 / 980) loss: 1.763751
(Iteration 881 / 980) loss: 1.540284
(Iteration 901 / 980) loss: 1.525582
(Iteration 921 / 980) loss: 1.674166
```

```
(Iteration 941 / 980) loss: 1.714316
(Iteration 961 / 980) loss: 1.534668
(Epoch 1 / 1) train acc: 0.504000; val_acc: 0.499000
```

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

```
Full data training accuracy: 0.47618367346938778
```

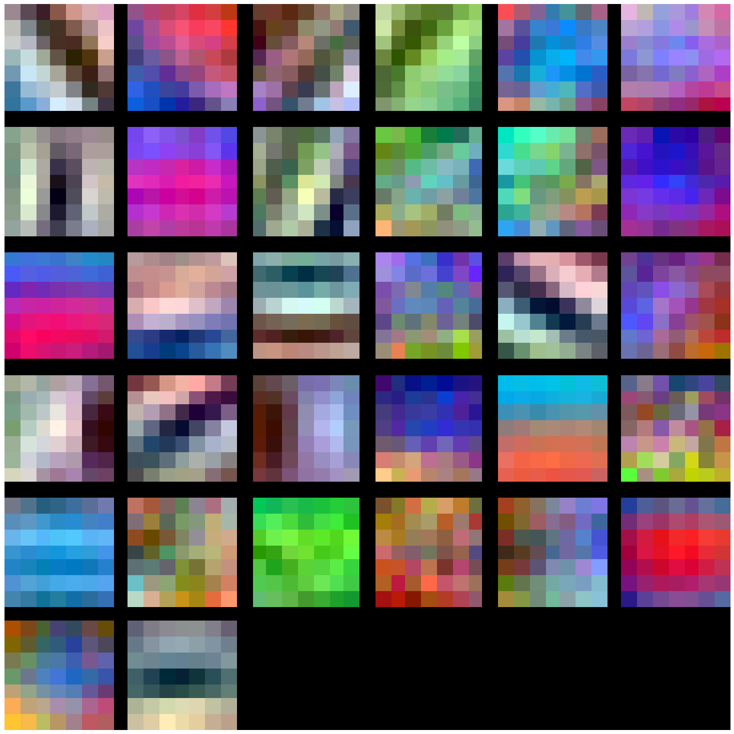
[ ]:
```
# Print final validation accuracy.
print(
    "Full data validation accuracy:",
    solver.check_accuracy(data['X_val'], data['y_val'])
)
```

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

8.5 Visualize Filters

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

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

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



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.](https://arxiv.org/abs/1502.03167)

10 Spatial Batch Normalization: Forward Pass

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

[ ]:
```python
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]
```

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

[ ]:
```python
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]
```

```python
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:  2.786648197756335e-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.](https://arxiv.org/pdf/1607.06450.pdf)

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

[4] [N. Dalal and B. Triggs. Histograms of oriented gradients for human detection. In Computer Vision and Pattern Recognition (CVPR), 2005.](https://ieeexplore.ieee.org/abstract/document/1467360/)

13 Spatial Group Normalization: Forward Pass

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

[ ]:
```
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))
#gamma = np.arange(C).reshape((1, -1, 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 `cs231n/layers.py`, implement the backward pass for spatial batch normalization in the function `spatial_groupnorm_backward`. Run the following to check your implementation using a numeric gradient check:

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

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

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

_, cache = spatial_groupnorm_forward(x, gamma, beta, G, gn_param)
dx, dgamma, dbeta = spatial_groupnorm_backward(dout, cache)

# You should expect errors of magnitudes between 1e-12 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:  7.413109437563619e-08
dgamma error:  9.468195772749234e-12
dbeta error:  3.35440867127888e-12
```

PyTorch

May 3, 2022

[ ]:
```
# 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. 'cs231n/assignments/assignment2/'
FOLDERNAME = 'Colab_Notebooks/cs231n/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/$FOLDERNAME/cs231n/datasets/
!bash get_datasets.sh
%cd /content/drive/My\ Drive/$FOLDERNAME
```

```
Mounted at /content/drive
/content/drive/My
Drive/Colab_Notebooks/cs231n/assignments/assignment2/cs231n/datasets
/content/drive/My Drive/Colab_Notebooks/cs231n/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 (or TensorFlow, if you choose to work with that notebook).

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 or TensorFlow you can harness the power of the GPU for your own custom neural network architectures without having to write CUDA code directly (which is beyond the scope of this class).
- 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! TensorFlow and PyTorch are both excellent frameworks that will make your lives a lot easier, and now that you understand their guts, you are free to use them :)
- 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
`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.

[ ]:
```python
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.

```
[ ]: NUM_TRAIN = 49000

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

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

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

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

```
Files already downloaded and verified
Files already downloaded and verified
Files already downloaded and verified
```

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).

[ ]:
```python
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.

[ ]:
```
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!

[ ]:
```
def three_layer_convnet(x, params):
    """
    Performs the forward pass of a three-layer convolutional network with the
```

```
    architecture defined above.

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

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

    # # Input dimensions
    # N, C_in, H_in, W_in = x.shape

    # # Conv 1 dimensions
    # C_1, C_in, KH1, KW1 = conv_w1.shape
    # p_1 = 2

    # # Conv 2 dimensions
    # C_2, C_1, KH2, KW2 = conv_w2.shape
    # p_2 = 1
```

```
    #print(x.size())

    # H_1 = int(1 + (H_in + 2 * p_1 - KH1) / 1)
    # W_1 = int(1 + (W_in + 2 * p_1 - KW1) / 1)

    # H_2 = int(1 + (H_1 + 2 * p_2 - KH2) / 1)
    # W_2 = int(1 + (W_1 + 2 * p_2 - KW2) / 1)

    conv1 = F.relu(F.conv2d(x, weight=conv_w1, bias=conv_b1, stride=1,␣
↪padding=2))
    #print(conv1.size())
    conv2 = F.relu(F.conv2d(conv1, weight=conv_w2, bias=conv_b2, stride=1,␣
↪padding=1))
    #out_2_shape = (N, C_2, H_2, W_2)
    conv2 = flatten(conv2)
    scores = conv2.mm(fc_w) + fc_b



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

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

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

```
[ ]: 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

[ ]:
```
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))
```

[ ]:
```
tensor([[-1.8247, -1.6969,  1.8271,  0.0347, -0.1772],
        [ 0.0402,  1.1608,  0.0359, -0.3799,  0.2216],
```

```
 [ 0.3913, -0.9264,  0.7843, -1.0049,  0.6021]], 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.

```
[ ]: 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.

```
[ ]: 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.

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

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

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

```
Iteration 0, loss = 3.7104
Checking accuracy on the val set
Got 171 / 1000 correct (17.10%)

Iteration 100, loss = 2.4368
Checking accuracy on the val set
Got 302 / 1000 correct (30.20%)

Iteration 200, loss = 2.4716
Checking accuracy on the val set
Got 367 / 1000 correct (36.70%)

Iteration 300, loss = 1.8843
Checking accuracy on the val set
Got 391 / 1000 correct (39.10%)

Iteration 400, loss = 1.7115
Checking accuracy on the val set
Got 369 / 1000 correct (36.90%)

Iteration 500, loss = 2.0888
Checking accuracy on the val set
Got 415 / 1000 correct (41.50%)

Iteration 600, loss = 1.6811
```

```
Checking accuracy on the val set
Got 418 / 1000 correct (41.80%)

Iteration 700, loss = 1.6243
Checking accuracy on the val set
Got 442 / 1000 correct (44.20%)
```

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.

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

channel_1 = 32
channel_2 = 16

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

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

# initialization
conv_w1 = random_weight((32, 3, 5, 5))
conv_b1 = zero_weight((32,))
conv_w2 = random_weight((16, 32, 3, 3))
conv_b2 = zero_weight((16,))
fc_w = random_weight((16*32*32, 10))
```

```python
fc_b = zero_weight((10,))

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

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

```
Iteration 0, loss = 3.3488
Checking accuracy on the val set
Got 92 / 1000 correct (9.20%)

Iteration 100, loss = 1.8062
Checking accuracy on the val set
Got 329 / 1000 correct (32.90%)

Iteration 200, loss = 1.7550
Checking accuracy on the val set
Got 417 / 1000 correct (41.70%)

Iteration 300, loss = 1.6560
Checking accuracy on the val set
Got 415 / 1000 correct (41.50%)

Iteration 400, loss = 1.6503
Checking accuracy on the val set
Got 437 / 1000 correct (43.70%)

Iteration 500, loss = 1.5987
Checking accuracy on the val set
Got 450 / 1000 correct (45.00%)

Iteration 600, loss = 1.3495
Checking accuracy on the val set
Got 471 / 1000 correct (47.10%)

Iteration 700, loss = 1.2857
Checking accuracy on the val set
Got 486 / 1000 correct (48.60%)
```

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:

[ ]:
```
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.

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

        self.conv1 = nn.Conv2d(in_channel, channel_1, kernel_size=5, stride=1,␣
↪padding=2, bias=True)
        nn.init.kaiming_normal_(self.conv1.weight)

        self.conv2 = nn.Conv2d(channel_1, channel_2, kernel_size=3, stride=1,␣
↪padding=1, bias=True)
        nn.init.kaiming_normal_(self.conv2.weight)
```

```
        self.fc = nn.Linear(channel_2* 32 * 32, num_classes)
        nn.init.kaiming_normal_(self.fc.weight)


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

    def forward(self, x):
        scores = None
        ########################################################################
        # TODO: Implement the forward function for a 3-layer ConvNet. you      #
        # should use the layers you defined in __init__ and specify the        #
        # connectivity of those layers in forward()                            #
        ########################################################################
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
        out_1 = F.relu(self.conv1(x))
        out_2 = F.relu(self.conv2(out_1))

        out_2 = flatten(out_2)
        scores = self.fc(out_2)

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


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

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

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.

```
[ ]: 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))
```

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.

```
[ ]: 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.

[ ]:
```
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 = 3.4000
Checking accuracy on validation set
Got 118 / 1000 correct (11.80)

Iteration 100, loss = 1.8604
Checking accuracy on validation set
```

```
Got 336 / 1000 correct (33.60)

Iteration 200, loss = 1.9647
Checking accuracy on validation set
Got 390 / 1000 correct (39.00)

Iteration 300, loss = 1.9463
Checking accuracy on validation set
Got 420 / 1000 correct (42.00)

Iteration 400, loss = 2.3990
Checking accuracy on validation set
Got 408 / 1000 correct (40.80)

Iteration 500, loss = 1.4288
Checking accuracy on validation set
Got 450 / 1000 correct (45.00)

Iteration 600, loss = 1.9272
Checking accuracy on validation set
Got 428 / 1000 correct (42.80)

Iteration 700, loss = 1.7052
Checking accuracy on validation set
Got 436 / 1000 correct (43.60)
```

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.

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

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

model = ThreeLayerConvNet(3, channel_1, channel_2, 10)
```

```python
optimizer = optim.SGD(model.parameters(), lr=learning_rate)

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

train_part34(model, optimizer)
```

```
Iteration 0, loss = 3.9835
Checking accuracy on validation set
Got 110 / 1000 correct (11.00)

Iteration 100, loss = 1.8703
Checking accuracy on validation set
Got 344 / 1000 correct (34.40)

Iteration 200, loss = 1.9556
Checking accuracy on validation set
Got 382 / 1000 correct (38.20)

Iteration 300, loss = 1.7935
Checking accuracy on validation set
Got 409 / 1000 correct (40.90)

Iteration 400, loss = 1.5658
Checking accuracy on validation set
Got 436 / 1000 correct (43.60)

Iteration 500, loss = 1.7068
Checking accuracy on validation set
Got 452 / 1000 correct (45.20)

Iteration 600, loss = 1.2964
Checking accuracy on validation set
Got 468 / 1000 correct (46.80)

Iteration 700, loss = 1.4977
Checking accuracy on validation set
Got 479 / 1000 correct (47.90)
```

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.

[ ]:
```
# 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 = 2.3419
Checking accuracy on validation set
Got 156 / 1000 correct (15.60)

Iteration 100, loss = 1.9498
Checking accuracy on validation set
Got 387 / 1000 correct (38.70)

Iteration 200, loss = 2.0810
Checking accuracy on validation set
```

```
Got 402 / 1000 correct (40.20)

Iteration 300, loss = 1.9610
Checking accuracy on validation set
Got 418 / 1000 correct (41.80)

Iteration 400, loss = 1.7210
Checking accuracy on validation set
Got 464 / 1000 correct (46.40)

Iteration 500, loss = 1.9825
Checking accuracy on validation set
Got 432 / 1000 correct (43.20)

Iteration 600, loss = 1.8446
Checking accuracy on validation set
Got 428 / 1000 correct (42.80)

Iteration 700, loss = 1.9725
Checking accuracy on validation set
Got 427 / 1000 correct (42.70)
```

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.

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

model = None
optimizer = None

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

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

model = nn.Sequential(nn.Conv2d(3, channel_1, kernel_size=5, stride=1,␣
 ↪padding=2, bias=True),
                      nn.ReLU(),
                      nn.Conv2d(channel_1, channel_2, kernel_size=3, stride=1,␣
 ↪padding=1, bias=True),
                      nn.ReLU(),
                      Flatten(),
                      nn.Linear(channel_2* 32 * 32, 10))

# you can use Nesterov momentum in optim.SGD
optimizer = optim.SGD(model.parameters(), lr=learning_rate,
                     momentum=0.9, nesterov=True)
# *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
################################################################################
#                                 END OF YOUR CODE                             #
################################################################################

train_part34(model, optimizer)
```

```
Iteration 0, loss = 2.3205
Checking accuracy on validation set
Got 135 / 1000 correct (13.50)

Iteration 100, loss = 1.5741
Checking accuracy on validation set
Got 453 / 1000 correct (45.30)

Iteration 200, loss = 1.4510
Checking accuracy on validation set
Got 462 / 1000 correct (46.20)

Iteration 300, loss = 1.4496
Checking accuracy on validation set
Got 501 / 1000 correct (50.10)

Iteration 400, loss = 1.1901
Checking accuracy on validation set
Got 524 / 1000 correct (52.40)

Iteration 500, loss = 1.2832
Checking accuracy on validation set
Got 543 / 1000 correct (54.30)
```

```
Iteration 600, loss = 1.2528
Checking accuracy on validation set
Got 581 / 1000 correct (58.10)

Iteration 700, loss = 1.4405
Checking accuracy on validation set
Got 581 / 1000 correct (58.10)
```

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!

[ ]:
```
################################################################################
# TODO:                                                                        
 ↪#
# Experiment with any architectures, optimizers, and hyperparameters.          #
# Achieve AT LEAST 70% accuracy on the *validation set* within 10 epochs.      #
#                                                                              #
# Note that you can use the check_accuracy function to evaluate on either      #
# the test set or the validation set, by passing either loader_test or         #
# loader_val as the second argument to check_accuracy. You should not touch    #
# the test set until you have finished your architecture and  hyperparameter   #
# tuning, and only run the test set once at the end to report a final value.   #
################################################################################
model = None
optimizer = None
```

```
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
best_model = None

# Hyper-parameters
epochs = 10
learning_rate = 1e-2

# Conv layer 1
channel_1 = 32
kernel_size_1 = 3
stride_1 = 1
padding_1 = 1

# Conv layer 2
channel_2 = 32
kernel_size_2 = 3
stride_2 = 1
padding_2 = 1

# Conv layer 3
channel_3 = 64
kernel_size_3 = 3
stride_3 = 1
padding_3 = 1

model = nn.Sequential(
                      # (Conv-ReLU)x2 - Max_Pool #1
                      nn.Conv2d(3, channel_1, kernel_size=kernel_size_1,␣
 ↪stride=stride_1, padding=padding_1, bias=True),
                      nn.BatchNorm2d(channel_1, eps=1e-05, momentum=0.1,␣
 ↪affine=True, track_running_stats=True),
                      nn.ReLU(),

                      nn.Conv2d(channel_1, channel_2,␣
 ↪kernel_size=kernel_size_2, stride=stride_2, padding=padding_2, bias=True),
                      nn.BatchNorm2d(channel_2, eps=1e-05, momentum=0.1,␣
 ↪affine=True, track_running_stats=True),
                      nn.ReLU(),

                      nn.MaxPool2d(2, stride=2),

                      # (Conv-ReLU)x2 - Max_Pool #2
                      nn.Conv2d(channel_2, channel_3,␣
 ↪kernel_size=kernel_size_3, stride=stride_3, padding=padding_3, bias=True),
                      nn.BatchNorm2d(channel_3, eps=1e-05, momentum=0.1,␣
 ↪affine=True, track_running_stats=True),
```

```
                        nn.ReLU(),

                        nn.Conv2d(channel_3, channel_3,␣
↪kernel_size=kernel_size_3, stride=stride_3, padding=padding_3, bias=True),
                        nn.BatchNorm2d(channel_3, eps=1e-05, momentum=0.1,␣
↪affine=True, track_running_stats=True),
                        nn.ReLU(),

                        nn.MaxPool2d(2, stride=2),

                        #
                        Flatten(),
                        nn.Linear(channel_3* 8 * 8, 10))

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

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

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

```
Iteration 0, loss = 2.3196
Checking accuracy on validation set
Got 99 / 1000 correct (9.90)

Iteration 100, loss = 1.6668
Checking accuracy on validation set
Got 398 / 1000 correct (39.80)

Iteration 200, loss = 1.6291
Checking accuracy on validation set
Got 439 / 1000 correct (43.90)

Iteration 300, loss = 1.4622
Checking accuracy on validation set
Got 524 / 1000 correct (52.40)

Iteration 400, loss = 1.2400
Checking accuracy on validation set
Got 544 / 1000 correct (54.40)

Iteration 500, loss = 1.0605
```

```
Checking accuracy on validation set
Got 567 / 1000 correct (56.70)

Iteration 600, loss = 0.9833
Checking accuracy on validation set
Got 602 / 1000 correct (60.20)

Iteration 700, loss = 0.9769
Checking accuracy on validation set
Got 583 / 1000 correct (58.30)

Iteration 0, loss = 1.2387
Checking accuracy on validation set
Got 599 / 1000 correct (59.90)

Iteration 100, loss = 0.9433
Checking accuracy on validation set
Got 670 / 1000 correct (67.00)

Iteration 200, loss = 0.8229
Checking accuracy on validation set
Got 663 / 1000 correct (66.30)

Iteration 300, loss = 0.8558
Checking accuracy on validation set
Got 666 / 1000 correct (66.60)

Iteration 400, loss = 0.8262
Checking accuracy on validation set
Got 676 / 1000 correct (67.60)

Iteration 500, loss = 0.9398
Checking accuracy on validation set
Got 682 / 1000 correct (68.20)

Iteration 600, loss = 0.6701
Checking accuracy on validation set
Got 690 / 1000 correct (69.00)

Iteration 700, loss = 0.6975
Checking accuracy on validation set
Got 667 / 1000 correct (66.70)

Iteration 0, loss = 0.7604
Checking accuracy on validation set
Got 702 / 1000 correct (70.20)

Iteration 100, loss = 0.6514
```

```
Checking accuracy on validation set
Got 693 / 1000 correct (69.30)

Iteration 200, loss = 0.7274
Checking accuracy on validation set
Got 702 / 1000 correct (70.20)

Iteration 300, loss = 1.0445
Checking accuracy on validation set
Got 695 / 1000 correct (69.50)

Iteration 400, loss = 0.6027
Checking accuracy on validation set
Got 729 / 1000 correct (72.90)

Iteration 500, loss = 0.8768
Checking accuracy on validation set
Got 750 / 1000 correct (75.00)

Iteration 600, loss = 0.8867
Checking accuracy on validation set
Got 718 / 1000 correct (71.80)

Iteration 700, loss = 0.6305
Checking accuracy on validation set
Got 736 / 1000 correct (73.60)

Iteration 0, loss = 0.6804
Checking accuracy on validation set
Got 720 / 1000 correct (72.00)

Iteration 100, loss = 0.6432
Checking accuracy on validation set
Got 714 / 1000 correct (71.40)

Iteration 200, loss = 0.5546
Checking accuracy on validation set
Got 738 / 1000 correct (73.80)

Iteration 300, loss = 0.7702
Checking accuracy on validation set
Got 735 / 1000 correct (73.50)

Iteration 400, loss = 0.4654
Checking accuracy on validation set
Got 727 / 1000 correct (72.70)

Iteration 500, loss = 0.4748
```

```
Checking accuracy on validation set
Got 739 / 1000 correct (73.90)

Iteration 600, loss = 0.4550
Checking accuracy on validation set
Got 759 / 1000 correct (75.90)

Iteration 700, loss = 0.5298
Checking accuracy on validation set
Got 756 / 1000 correct (75.60)

Iteration 0, loss = 0.6567
Checking accuracy on validation set
Got 760 / 1000 correct (76.00)

Iteration 100, loss = 0.3886
Checking accuracy on validation set
Got 761 / 1000 correct (76.10)

Iteration 200, loss = 0.5007
Checking accuracy on validation set
Got 747 / 1000 correct (74.70)

Iteration 300, loss = 0.5719
Checking accuracy on validation set
Got 760 / 1000 correct (76.00)

Iteration 400, loss = 0.4079
Checking accuracy on validation set
Got 752 / 1000 correct (75.20)

Iteration 500, loss = 0.5743
Checking accuracy on validation set
Got 732 / 1000 correct (73.20)

Iteration 600, loss = 0.7093
Checking accuracy on validation set
Got 784 / 1000 correct (78.40)

Iteration 700, loss = 0.6181
Checking accuracy on validation set
Got 748 / 1000 correct (74.80)

Iteration 0, loss = 0.5429
Checking accuracy on validation set
Got 761 / 1000 correct (76.10)

Iteration 100, loss = 0.4118
```

```
Checking accuracy on validation set
Got 777 / 1000 correct (77.70)

Iteration 200, loss = 0.3850
Checking accuracy on validation set
Got 772 / 1000 correct (77.20)

Iteration 300, loss = 0.2867
Checking accuracy on validation set
Got 770 / 1000 correct (77.00)

Iteration 400, loss = 0.5307
Checking accuracy on validation set
Got 789 / 1000 correct (78.90)

Iteration 500, loss = 0.5349
Checking accuracy on validation set
Got 774 / 1000 correct (77.40)

Iteration 600, loss = 0.4039
Checking accuracy on validation set
Got 782 / 1000 correct (78.20)

Iteration 700, loss = 0.3747
Checking accuracy on validation set
Got 769 / 1000 correct (76.90)

Iteration 0, loss = 0.3165
Checking accuracy on validation set
Got 760 / 1000 correct (76.00)

Iteration 100, loss = 0.3850
Checking accuracy on validation set
Got 757 / 1000 correct (75.70)

Iteration 200, loss = 0.4360
Checking accuracy on validation set
Got 766 / 1000 correct (76.60)

Iteration 300, loss = 0.2691
Checking accuracy on validation set
Got 757 / 1000 correct (75.70)

Iteration 400, loss = 0.3567
Checking accuracy on validation set
Got 767 / 1000 correct (76.70)

Iteration 500, loss = 0.6219
```

```
Checking accuracy on validation set
Got 762 / 1000 correct (76.20)

Iteration 600, loss = 0.3942
Checking accuracy on validation set
Got 763 / 1000 correct (76.30)

Iteration 700, loss = 0.4748
Checking accuracy on validation set
Got 760 / 1000 correct (76.00)

Iteration 0, loss = 0.2411
Checking accuracy on validation set
Got 756 / 1000 correct (75.60)

Iteration 100, loss = 0.3177
Checking accuracy on validation set
Got 770 / 1000 correct (77.00)

Iteration 200, loss = 0.2486
Checking accuracy on validation set
Got 773 / 1000 correct (77.30)

Iteration 300, loss = 0.3423
Checking accuracy on validation set
Got 778 / 1000 correct (77.80)

Iteration 400, loss = 0.5612
Checking accuracy on validation set
Got 772 / 1000 correct (77.20)

Iteration 500, loss = 0.2395
Checking accuracy on validation set
Got 775 / 1000 correct (77.50)

Iteration 600, loss = 0.3797
Checking accuracy on validation set
Got 776 / 1000 correct (77.60)

Iteration 700, loss = 0.2263
Checking accuracy on validation set
Got 782 / 1000 correct (78.20)

Iteration 0, loss = 0.2200
Checking accuracy on validation set
Got 776 / 1000 correct (77.60)

Iteration 100, loss = 0.1912
```

```
Checking accuracy on validation set
Got 780 / 1000 correct (78.00)

Iteration 200, loss = 0.4438
Checking accuracy on validation set
Got 786 / 1000 correct (78.60)

Iteration 300, loss = 0.3350
Checking accuracy on validation set
Got 783 / 1000 correct (78.30)

Iteration 400, loss = 0.4147
Checking accuracy on validation set
Got 777 / 1000 correct (77.70)

Iteration 500, loss = 0.2661
Checking accuracy on validation set
Got 776 / 1000 correct (77.60)

Iteration 600, loss = 0.3471
Checking accuracy on validation set
Got 788 / 1000 correct (78.80)

Iteration 700, loss = 0.3272
Checking accuracy on validation set
Got 778 / 1000 correct (77.80)

Iteration 0, loss = 0.2736
Checking accuracy on validation set
Got 790 / 1000 correct (79.00)

Iteration 100, loss = 0.3456
Checking accuracy on validation set
Got 802 / 1000 correct (80.20)

Iteration 200, loss = 0.4689
Checking accuracy on validation set
Got 788 / 1000 correct (78.80)

Iteration 300, loss = 0.4483
Checking accuracy on validation set
Got 785 / 1000 correct (78.50)

Iteration 400, loss = 0.3922
Checking accuracy on validation set
Got 780 / 1000 correct (78.00)

Iteration 500, loss = 0.2443
```

```
Checking accuracy on validation set
Got 778 / 1000 correct (77.80)

Iteration 600, loss = 0.4158
Checking accuracy on validation set
Got 787 / 1000 correct (78.70)

Iteration 700, loss = 0.3847
Checking accuracy on validation set
Got 782 / 1000 correct (78.20)
```

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 tweaked around the CNN model architecture and included nestrov SGD momentum for optimizer. \

In my final CNN model architecture, I have: \ ((Conv-BN-ReLU)x2 - MaxPOOL) x2 - Fully Connected layer.

I found including BN in the intermediate layers to be helpful as it normalizes the input data and makes the model robust to slight changes in the weight initialization. \

In addition, I have `same convolution` with `filter size 3`, `padding 1` and `stride 1` to have consistent spatial dimension, and followed by maxpool with `filter size 2` and `stride 2` for downsampling spatial dimension.

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.

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

```
Checking accuracy on test set
Got 7776 / 10000 correct (77.76)
```

Network_Visualization

May 3, 2022

[2]:
```
# 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. 'cs231n/assignments/assignment2/'
FOLDERNAME = 'Colab_Notebooks/cs231n/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/$FOLDERNAME/cs231n/datasets/
!bash get_datasets.sh
%cd /content/drive/My\ Drive/$FOLDERNAME
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
/content/drive/My
Drive/Colab_Notebooks/cs231n/assignments/assignment2/cs231n/datasets
/content/drive/My Drive/Colab_Notebooks/cs231n/assignments/assignment2
```

1 Network Visualization

In this notebook, we will explore the use of *image gradients* for generating new images.

When training a model, we define a loss function which measures our current unhappiness with the model's performance. We then use backpropagation to compute the gradient of the loss with respect to the model parameters and perform gradient descent on the model parameters to minimize the loss.

Here we will do something slightly different. We will start from a CNN model which has been pretrained to perform image classification on the ImageNet dataset. We will use this model to define a loss function which quantifies our current unhappiness with our image. Then we will use backpropagation to compute the gradient of this loss with respect to the pixels of the image. We will then keep the model fixed and perform gradient descent *on the image* to synthesize a new image which minimizes the loss.

We will explore three techniques for image generation.

Saliency Maps. We can use saliency maps to tell which part of the image influenced the classification decision made by the network.

Fooling Images. We can perturb an input image so that it appears the same to humans but will be misclassified by the pretrained network.

Class Visualization. We can synthesize an image to maximize the classification score of a particular class; this can give us some sense of what the network is looking for when it classifies images of that class.

[3]:
```
# Setup cell.
import torch
import torchvision
import numpy as np
import random
import matplotlib.pyplot as plt
from PIL import Image
from cs231n.image_utils import SQUEEZENET_MEAN, SQUEEZENET_STD
from cs231n.net_visualization_pytorch 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'

%load_ext autoreload
%autoreload 2
```

2 Pretrained Model

For all of our image generation experiments, we will start with a convolutional neural network which was pretrained to perform image classification on ImageNet. We can use any model here, but for the purposes of this assignment we will use SqueezeNet [1], which achieves accuracies comparable to AlexNet but with a significantly reduced parameter count and computational complexity.

Using SqueezeNet rather than AlexNet or VGG or ResNet means that we can easily perform all image generation experiments on CPU.

[1] Iandola et al, "SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and < 0.5MB model size", arXiv 2016

[4]:
```
# Download and load the pretrained SqueezeNet model.
model = torchvision.models.squeezenet1_1(pretrained=True)

# We don't want to train the model, so tell PyTorch not to compute gradients
# with respect to model parameters.
for param in model.parameters():
    param.requires_grad = False
```

```
Downloading: "https://download.pytorch.org/models/squeezenet1_1-b8a52dc0.pth" to
/root/.cache/torch/hub/checkpoints/squeezenet1_1-b8a52dc0.pth

  0%|          | 0.00/4.73M [00:00<?, ?B/s]
```

2.1 Loading ImageNet Validation Images

We have provided a few example images from the validation set of the ImageNet ILSVRC 2012 Classification dataset. Since they come from the validation set, our pretrained model did not see these images during training. Run the following cell to visualize some of these images along with their ground-truth labels.

[5]:
```
from cs231n.data_utils import load_imagenet_val
X, y, class_names = load_imagenet_val(num=5)

plt.figure(figsize=(12, 6))
for i in range(5):
    plt.subplot(1, 5, i + 1)
    plt.imshow(X[i])
    plt.title(class_names[y[i]])
    plt.axis('off')
plt.gcf().tight_layout()
```

3 Saliency Maps

Using this pretrained model, we will compute class saliency maps as described in Section 3.1 of [2].

A **saliency map** tells us the degree to which each pixel in the image affects the classification score for that image. To compute it, we compute the gradient of the unnormalized score corresponding to the correct class (which is a scalar) with respect to the pixels of the image. If the image has shape (3, H, W) then this gradient will also have shape (3, H, W); for each pixel in the image, this gradient tells us the amount by which the classification score will change if the pixel changes by a small amount. To compute the saliency map, we take the absolute value of this gradient, then take the maximum value over the 3 input channels; the final saliency map thus has shape (H, W) and all entries are nonnegative.

[2] Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman. "Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps", ICLR Workshop 2014.

3.0.1 Hint: PyTorch `gather` method

Recall in Assignment 1 you needed to select one element from each row of a matrix; if `s` is an numpy array of shape `(N, C)` and `y` is a numpy array of shape `(N,)` containing integers `0 <= y[i] < C`, then `s[np.arange(N), y]` is a numpy array of shape `(N,)` which selects one element from each element in `s` using the indices in `y`.

In PyTorch you can perform the same operation using the `gather()` method. If `s` is a PyTorch Tensor of shape `(N, C)` and `y` is a PyTorch Tensor of shape `(N,)` containing longs in the range `0 <= y[i] < C`, then

`s.gather(1, y.view(-1, 1)).squeeze()`

will be a PyTorch Tensor of shape `(N,)` containing one entry from each row of `s`, selected according to the indices in `y`.

run the following cell to see an example.

You can also read the documentation for the gather method and the squeeze method.

[6]:
```python
# Example of using gather to select one entry from each row in PyTorch
def gather_example():
    N, C = 4, 5
    s = torch.randn(N, C)
    y = torch.LongTensor([1, 2, 1, 3])
    print(s)
    print(y)
    print(s.gather(1, y.view(-1, 1)).squeeze())
gather_example()
```

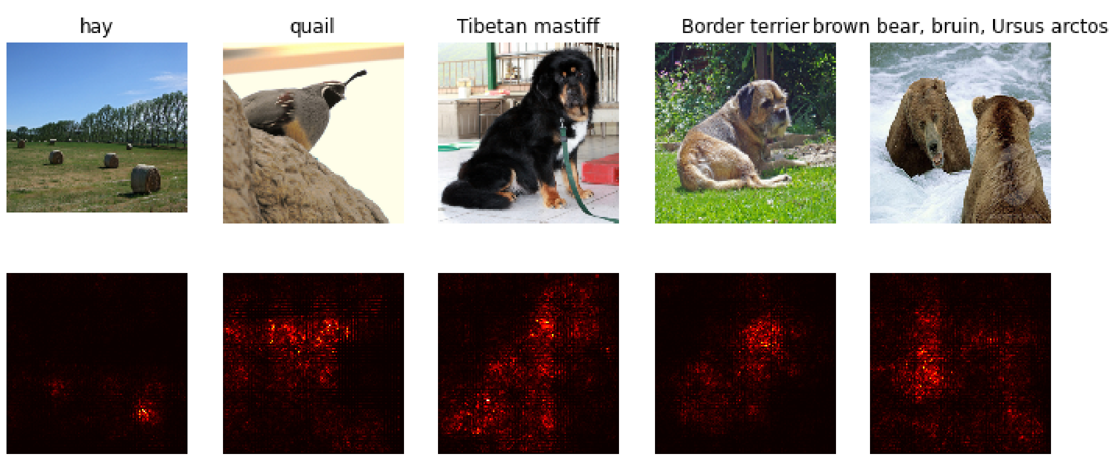
```
tensor([[-0.8755, -0.8590, -0.3338, -0.3407,  0.2006],
        [-0.0460, -0.4130,  0.3412, -0.0709, -2.2107],
        [ 1.5303,  1.5185,  0.5816,  1.9473, -0.8277],
        [-0.6778,  1.0268, -0.4515,  0.8679, -0.1543]])
tensor([1, 2, 1, 3])
tensor([-0.8590,  0.3412,  1.5185,  0.8679])
```

Implement `compute_saliency_maps` function inside `cs231n/net_visualization_pytorch.py`

Once you have completed the implementation above, run the following to visualize some class saliency maps on our example images from the ImageNet validation set:

[7]:
```python
def show_saliency_maps(X, y):
    # Convert X and y from numpy arrays to Torch Tensors
    X_tensor = torch.cat([preprocess(Image.fromarray(x)) for x in X], dim=0)
    y_tensor = torch.LongTensor(y)

    # Compute saliency maps for images in X
    saliency = compute_saliency_maps(X_tensor, y_tensor, model)

    # Convert the saliency map from Torch Tensor to numpy array and show images
    # and saliency maps together.
    saliency = saliency.numpy()
    N = X.shape[0]
    for i in range(N):
        plt.subplot(2, N, i + 1)
        plt.imshow(X[i])
        plt.axis('off')
        plt.title(class_names[y[i]])
        plt.subplot(2, N, N + i + 1)
        plt.imshow(saliency[i], cmap=plt.cm.hot)
        plt.axis('off')
        plt.gcf().set_size_inches(12, 5)
    plt.show()

show_saliency_maps(X, y)
```

```
/usr/local/lib/python3.7/dist-packages/torch/nn/functional.py:780: UserWarning:
Note that order of the arguments: ceil_mode and return_indices will changeto
match the args list in nn.MaxPool2d in a future release.
  warnings.warn("Note that order of the arguments: ceil_mode and return_indices
will change"
```



4 Inline Question 1

A friend of yours suggests that in order to find an image that maximizes the correct score, we can perform gradient ascent on the input image, but instead of the gradient we can actually use the saliency map in each step to update the image. Is this assertion true? Why or why not?

Your Answer: \ Assertion is **false** for RGB images, since they have 3 channels. In the saliency map we are finding the max of the absolute values across the 3 channels, but we don't know the other channels and their distribution, since they could maybe point out to a different wrong class. The saliency map covers abs, and max in the gradient map, so they can't maximize the correct score with gradient ascent. The gradient should be in the form of (3, H, W) so it could be used to update each dimension in the right directions (i.e. both positive and negative sign) not only positive.

On the other hand, this assertion is **true** if the images are in grayscale B/W and the saliency map is computed at each step using the gradients of the correct score with the updated input image since the gradient ascent requires the gradient information which can be obtained from the saliency map. If the saliency map is not updated, then the above method will not work.

5 Fooling Images

We can also use image gradients to generate "fooling images" as discussed in [3]. Given an image and a target class, we can perform gradient **ascent** over the image to maximize the target class, stopping when the network classifies the image as the target class. Implement the following function to generate fooling images.

[3] Szegedy et al, "Intriguing properties of neural networks", ICLR 2014

Implement `make_fooling_image` function inside `cs231n/net_visualization_pytorch.py`

Run the following cell to generate a fooling image. You should ideally see at first glance no major difference between the original and fooling images, and the network should now make an incorrect prediction on the fooling one. However you should see a bit of random noise if you look at the 10x magnified difference between the original and fooling images. Feel free to change the `idx` variable to explore other images.

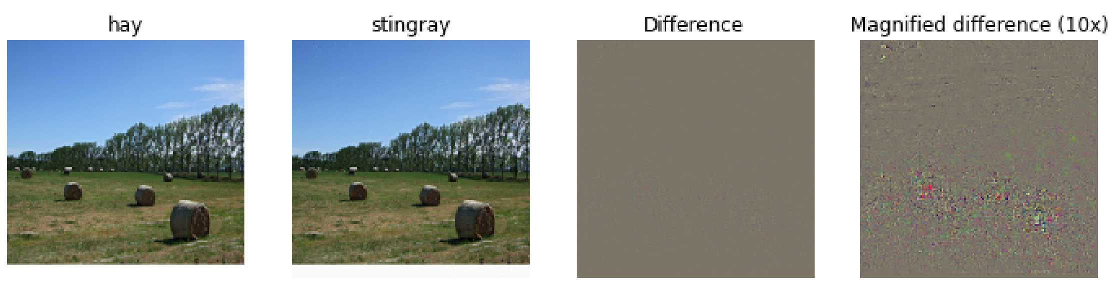
[8]:
```python
idx = 0
target_y = 6

X_tensor = torch.cat([preprocess(Image.fromarray(x)) for x in X], dim=0)
X_fooling = make_fooling_image(X_tensor[idx:idx+1], target_y, model)

scores = model(X_fooling)
assert target_y == scores.data.max(1)[1][0].item(), 'The model is not fooled!'
```

```
/usr/local/lib/python3.7/dist-packages/torch/nn/functional.py:780: UserWarning:
Note that order of the arguments: ceil_mode and return_indices will changeto
match the args list in nn.MaxPool2d in a future release.
```

```
  warnings.warn("Note that order of the arguments: ceil_mode and return_indices
will change"
```

After generating a fooling image, run the following cell to visualize the original image, the fooling image, as well as the difference between them.

[9]:
```
X_fooling_np = deprocess(X_fooling.clone())
X_fooling_np = np.asarray(X_fooling_np).astype(np.uint8)

plt.subplot(1, 4, 1)
plt.imshow(X[idx])
plt.title(class_names[y[idx]])
plt.axis('off')

plt.subplot(1, 4, 2)
plt.imshow(X_fooling_np)
plt.title(class_names[target_y])
plt.axis('off')

plt.subplot(1, 4, 3)
X_pre = preprocess(Image.fromarray(X[idx]))
diff = np.asarray(deprocess(X_fooling - X_pre, should_rescale=False))
plt.imshow(diff)
plt.title('Difference')
plt.axis('off')

plt.subplot(1, 4, 4)
diff = np.asarray(deprocess(10 * (X_fooling - X_pre), should_rescale=False))
plt.imshow(diff)
plt.title('Magnified difference (10x)')
plt.axis('off')

plt.gcf().set_size_inches(12, 5)
plt.show()
```



6 Class Visualization

By starting with a random noise image and performing gradient ascent on a target class, we can generate an image that the network will recognize as the target class. This idea was first presented in [2]; [3] extended this idea by suggesting several regularization techniques that can improve the quality of the generated image.

Concretely, let I be an image and let y be a target class. Let $s_y(I)$ be the score that a convolutional network assigns to the image I for class y; note that these are raw unnormalized scores, not class probabilities. We wish to generate an image I^* that achieves a high score for the class y by solving the problem

$$I^* = \arg\max_I (s_y(I) - R(I))$$

where R is a (possibly implicit) regularizer (note the sign of $R(I)$ in the argmax: we want to minimize this regularization term). We can solve this optimization problem using gradient ascent, computing gradients with respect to the generated image. We will use (explicit) L2 regularization of the form

$$R(I) = \lambda \|I\|_2^2$$

and implicit regularization as suggested by [3] by periodically blurring the generated image. We can solve this problem using gradient ascent on the generated image.

[2] Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman. "Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps", ICLR Workshop 2014.

[3] Yosinski et al, "Understanding Neural Networks Through Deep Visualization", ICML 2015 Deep Learning Workshop

In `cs231n/net_visualization_pytorch.py` complete the implementation of the `class_visualization_update_step` used in the `create_class_visualization` function below. Once you have completed that implementation, run the following cells to generate an image of a Tarantula:

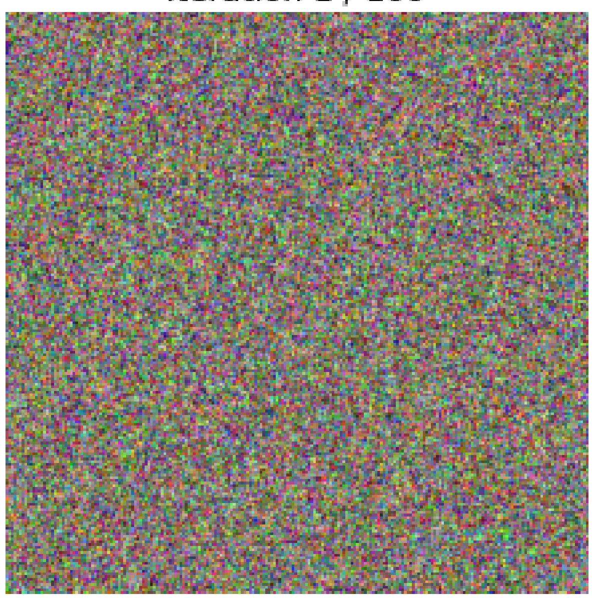
[10]:
```
def create_class_visualization(target_y, model, dtype, **kwargs):
    """
    Generate an image to maximize the score of target_y under a pretrained␣
↪model.

    Inputs:
    - target_y: Integer in the range [0, 1000) giving the index of the class
    - model: A pretrained CNN that will be used to generate the image
    - dtype: Torch datatype to use for computations

    Keyword arguments:
    - l2_reg: Strength of L2 regularization on the image
    - learning_rate: How big of a step to take
```

```
    - num_iterations: How many iterations to use
    - blur_every: How often to blur the image as an implicit regularizer
    - max_jitter: How much to gjitter the image as an implicit regularizer
    - show_every: How often to show the intermediate result
    """
    model.type(dtype)
    l2_reg = kwargs.pop('l2_reg', 1e-3)
    learning_rate = kwargs.pop('learning_rate', 25)
    num_iterations = kwargs.pop('num_iterations', 100)
    blur_every = kwargs.pop('blur_every', 10)
    max_jitter = kwargs.pop('max_jitter', 16)
    show_every = kwargs.pop('show_every', 25)

    # Randomly initialize the image as a PyTorch Tensor, and make it requires␣
↪gradient.
    img = torch.randn(1, 3, 224, 224).mul_(1.0).type(dtype).requires_grad_()

    for t in range(num_iterations):
        # Randomly jitter the image a bit; this gives slightly nicer results
        ox, oy = random.randint(0, max_jitter), random.randint(0, max_jitter)
        img.data.copy_(jitter(img.data, ox, oy))
        class_visualization_update_step(img, model, target_y, l2_reg,␣
↪learning_rate)
        # Undo the random jitter
        img.data.copy_(jitter(img.data, -ox, -oy))

        # As regularizer, clamp and periodically blur the image
        for c in range(3):
            lo = float(-SQUEEZENET_MEAN[c] / SQUEEZENET_STD[c])
            hi = float((1.0 - SQUEEZENET_MEAN[c]) / SQUEEZENET_STD[c])
            img.data[:, c].clamp_(min=lo, max=hi)
        if t % blur_every == 0:
            blur_image(img.data, sigma=0.5)

        # Periodically show the image
        if t == 0 or (t + 1) % show_every == 0 or t == num_iterations - 1:
            plt.imshow(deprocess(img.data.clone().cpu()))
            class_name = class_names[target_y]
            plt.title('%s\nIteration %d / %d' % (class_name, t + 1,␣
↪num_iterations))
            plt.gcf().set_size_inches(4, 4)
            plt.axis('off')
            plt.show()

    return deprocess(img.data.cpu())
```

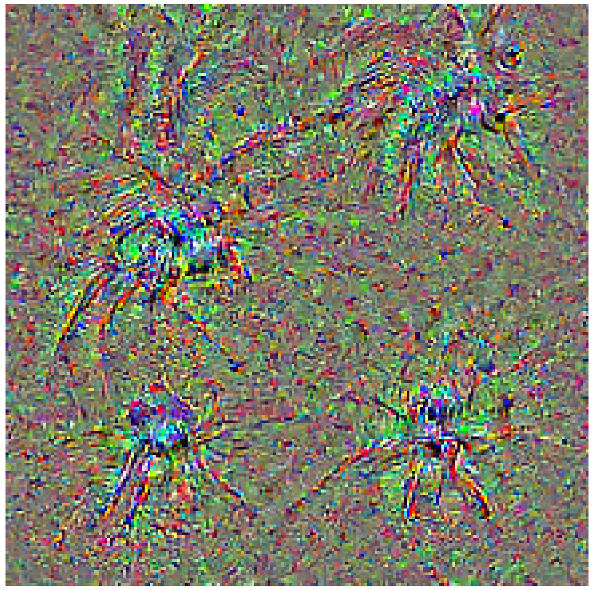
[11]:
```
dtype = torch.FloatTensor
model.type(dtype)

target_y = 76 # Tarantula
# target_y = 78 # Tick
# target_y = 187 # Yorkshire Terrier
# target_y = 683 # Oboe
# target_y = 366 # Gorilla
# target_y = 604 # Hourglass
out = create_class_visualization(target_y, model, dtype)
```

```
/usr/local/lib/python3.7/dist-packages/torch/nn/functional.py:780: UserWarning:
Note that order of the arguments: ceil_mode and return_indices will changeto
match the args list in nn.MaxPool2d in a future release.
  warnings.warn("Note that order of the arguments: ceil_mode and return_indices
will change"
```

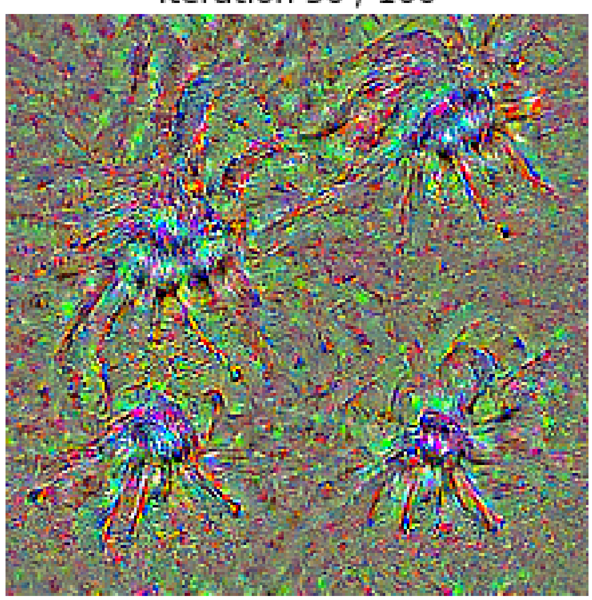
tarantula
Iteration 1 / 100

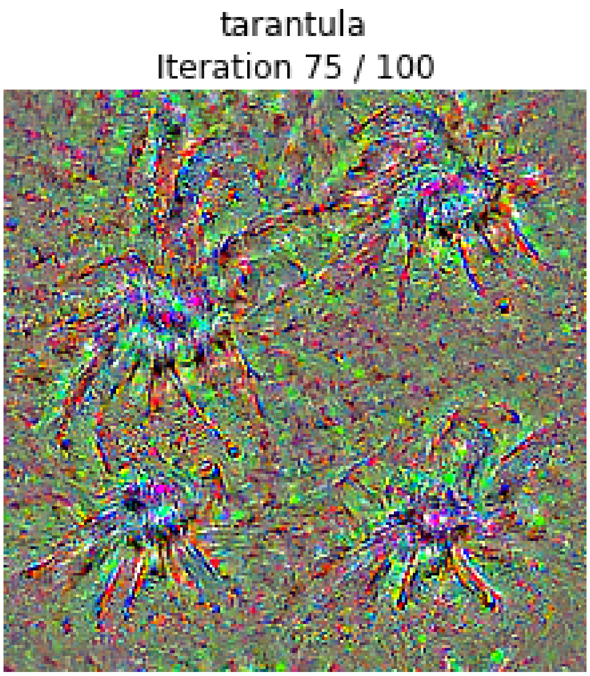


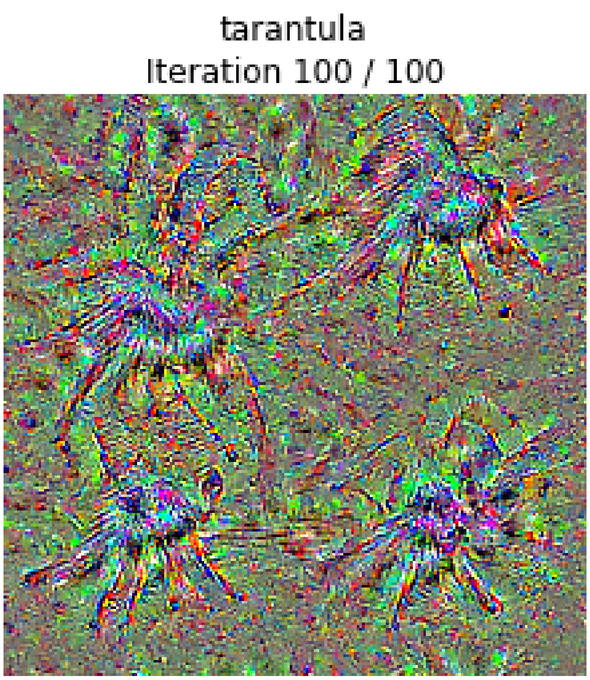
tarantula
Iteration 25 / 100



tarantula
Iteration 50 / 100



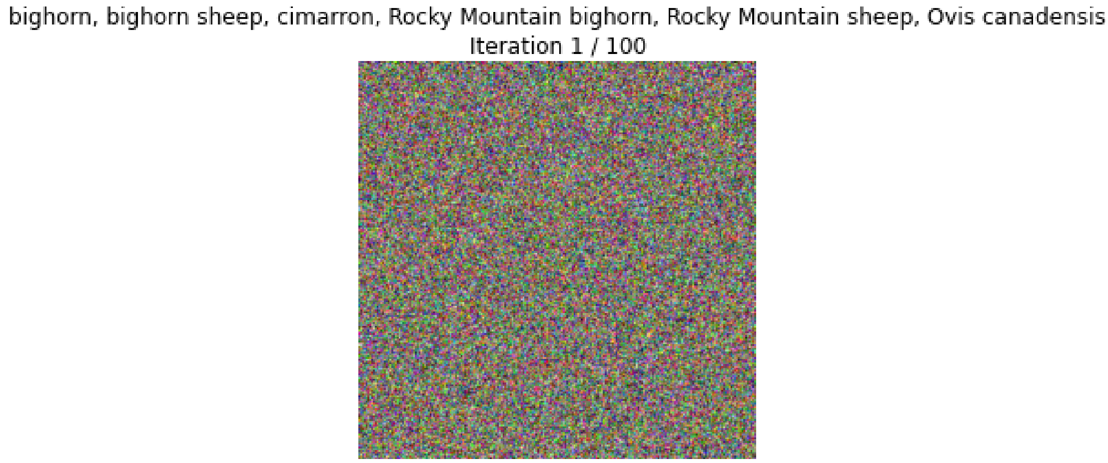


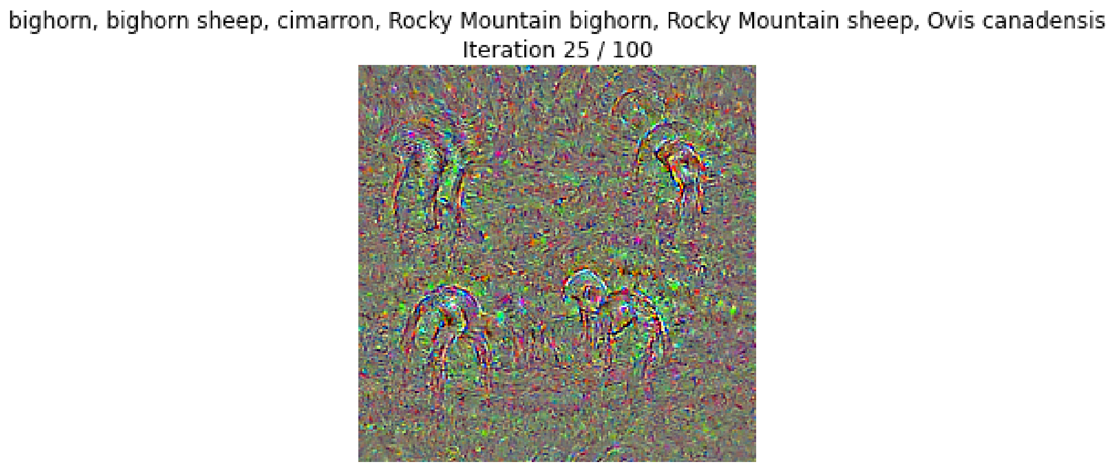


Try out your class visualization on other classes! You should also feel free to play with various hyperparameters to try and improve the quality of the generated image, but this is not required.

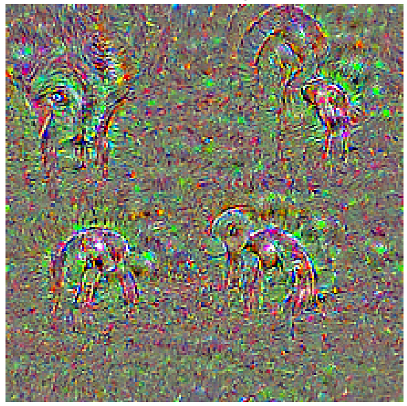
```
[12]: # target_y = 78 # Tick
      # target_y = 187 # Yorkshire Terrier
      # target_y = 683 # Oboe
      # target_y = 366 # Gorilla
      # target_y = 604 # Hourglass
      target_y = np.random.randint(1000)
      print(class_names[target_y])
      X = create_class_visualization(target_y, model, dtype)
```

```
bighorn, bighorn sheep, cimarron, Rocky Mountain bighorn, Rocky Mountain sheep,
Ovis canadensis

/usr/local/lib/python3.7/dist-packages/torch/nn/functional.py:780: UserWarning:
Note that order of the arguments: ceil_mode and return_indices will changeto
match the args list in nn.MaxPool2d in a future release.
  warnings.warn("Note that order of the arguments: ceil_mode and return_indices
will change"
```

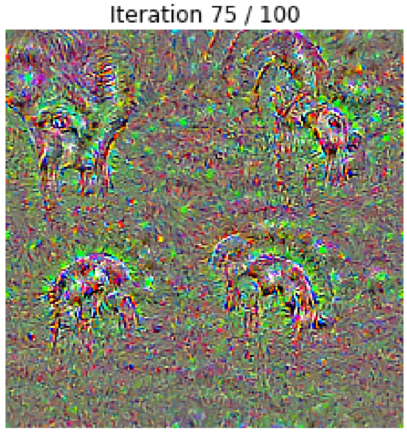




bighorn, bighorn sheep, cimarron, Rocky Mountain bighorn, Rocky Mountain sheep, Ovis canadensis
Iteration 50 / 100



bighorn, bighorn sheep, cimarron, Rocky Mountain bighorn, Rocky Mountain sheep, Ovis canadensis
Iteration 75 / 100



bighorn, bighorn sheep, cimarron, Rocky Mountain bighorn, Rocky Mountain sheep, Ovis canadensis
Iteration 100 / 100