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)

In [1]:

```
# As usual, a bit of setup
from __future__ import print_function
import time
import numpy as np
import matplotlib.pyplot as plt
from cs231n.classifiers.fc_net import *
from cs231n.data_utils import get_CIFAR10_data
from cs231n.gradient_check import eval_numerical_gradient, eva
l_numerical_gradient_array
from cs231n.solver import Solver

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

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

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

In [2]:

```
# Load the (preprocessed) CIFAR10 data.

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

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

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.

In [3]:

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

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

  print('Running tests with p = ', p)
  print('Mean of input: ', x.mean())
  print('Mean of train-time output: ', out.mean())
  print('Mean of test-time output: ', out_test.mean())
  print('Fraction of train-time output set to zero: ', (out ==
0).mean())
  print('Fraction of test-time output set to zero: ', (out_tes
t == 0).mean())
  print()
```

```
Running tests with p =  0.25
Mean of input:  10.000207878477502
Mean of train-time output:  9.99559079897757
Mean of test-time output:  10.000207878477502
Fraction of train-time output set to zero:  0.2502
16
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:  10.01506802495506
Mean of test-time output:  10.000207878477502
Fraction of train-time output set to zero:  0.3992
04
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:  10.029131799886338
Mean of test-time output:  10.000207878477502
Fraction of train-time output set to zero:  0.6992
6
Fraction of test-time output set to zero:  0.0
```

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.

In [4]:

```
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:  5.445612718272284e-11
```

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?

Answer:

If we do not divide the values by p then at test time we will not be considering the average of the training output. Thus, we will be considering only the summation of all possible sub-networks which may lead to large values (exploding gradients). This happens because at test time we require an approximation of the expected output produced by the training phase, due to we only perform a forward call without dropping neurons out.

Fully-connected nets with Dropout

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

In [5]:

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

for dropout in [1, 0.75, 0.5]:
  print('Running check with dropout = ', dropout)
  model = FullyConnectedNet([H1, H2], input_dim=D, num_classes
=C,
                            weight_scale=5e-2, dtype=np.float6
4,
                            dropout=dropout, seed=123)

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

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

```
Running check with dropout =  1
Initial loss:  2.300479089768492
W1 relative error: 1.03e-07
W2 relative error: 2.21e-05
W3 relative error: 4.56e-07
b1 relative error: 4.66e-09
b2 relative error: 2.09e-09
b3 relative error: 1.69e-10

Running check with dropout =  0.75
Initial loss:  2.3001748924793235
W1 relative error: 3.05e-08
W2 relative error: 2.05e-09
W3 relative error: 1.93e-09
b1 relative error: 8.86e-10
b2 relative error: 3.33e-01
b3 relative error: 6.54e-11

Running check with dropout =  0.5
Initial loss:  2.310136908722148
W1 relative error: 2.57e-08
W2 relative error: 1.49e-08
W3 relative error: 4.49e-08
b1 relative error: 3.93e-10
b2 relative error: 1.91e-09
b3 relative error: 9.51e-11
```

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.

In [6]:

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

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

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

```
1
(Iteration 1 / 125) loss: 7.856643
(Epoch 0 / 25) train acc: 0.260000; val_acc: 0.184
000
(Epoch 1 / 25) train acc: 0.416000; val_acc: 0.258
000
(Epoch 2 / 25) train acc: 0.482000; val_acc: 0.276
000
(Epoch 3 / 25) train acc: 0.532000; val_acc: 0.277
000
(Epoch 4 / 25) train acc: 0.600000; val_acc: 0.271
000
(Epoch 5 / 25) train acc: 0.708000; val_acc: 0.299
000
(Epoch 6 / 25) train acc: 0.722000; val_acc: 0.282
000
(Epoch 7 / 25) train acc: 0.832000; val_acc: 0.255
000
(Epoch 8 / 25) train acc: 0.878000; val_acc: 0.269
```

```
000
(Epoch 9 / 25) train acc: 0.902000; val_acc: 0.275
000
(Epoch 10 / 25) train acc: 0.888000; val_acc: 0.26
1000
(Epoch 11 / 25) train acc: 0.926000; val_acc: 0.27
7000
(Epoch 12 / 25) train acc: 0.962000; val_acc: 0.30
2000
(Epoch 13 / 25) train acc: 0.964000; val_acc: 0.30
7000
(Epoch 14 / 25) train acc: 0.966000; val_acc: 0.30
9000
(Epoch 15 / 25) train acc: 0.978000; val_acc: 0.29
1000
(Epoch 16 / 25) train acc: 0.986000; val_acc: 0.30
2000
(Epoch 17 / 25) train acc: 0.986000; val_acc: 0.31
5000
(Epoch 18 / 25) train acc: 0.996000; val_acc: 0.31
9000
(Epoch 19 / 25) train acc: 0.992000; val_acc: 0.31
2000
(Epoch 20 / 25) train acc: 0.984000; val_acc: 0.31
5000
(Iteration 101 / 125) loss: 0.129474
(Epoch 21 / 25) train acc: 0.994000; val_acc: 0.31
5000
(Epoch 22 / 25) train acc: 0.970000; val_acc: 0.31
7000
(Epoch 23 / 25) train acc: 0.984000; val_acc: 0.30
8000
(Epoch 24 / 25) train acc: 0.982000; val_acc: 0.30
1000
(Epoch 25 / 25) train acc: 0.992000; val_acc: 0.30
3000

0.25
(Iteration 1 / 125) loss: 11.814033
(Epoch 0 / 25) train acc: 0.264000; val_acc: 0.193
000
(Epoch 1 / 25) train acc: 0.368000; val_acc: 0.244
000
(Epoch 2 / 25) train acc: 0.528000; val_acc: 0.264
000
(Epoch 3 / 25) train acc: 0.586000; val_acc: 0.257
000
(Epoch 4 / 25) train acc: 0.642000; val_acc: 0.290
```

```
000
(Epoch 5 / 25) train acc: 0.756000; val_acc: 0.292
000
(Epoch 6 / 25) train acc: 0.784000; val_acc: 0.277
000
(Epoch 7 / 25) train acc: 0.818000; val_acc: 0.275
000
(Epoch 8 / 25) train acc: 0.814000; val_acc: 0.258
000
(Epoch 9 / 25) train acc: 0.880000; val_acc: 0.322
000
(Epoch 10 / 25) train acc: 0.908000; val_acc: 0.29
3000
(Epoch 11 / 25) train acc: 0.918000; val_acc: 0.29
0000
(Epoch 12 / 25) train acc: 0.922000; val_acc: 0.26
9000
(Epoch 13 / 25) train acc: 0.950000; val_acc: 0.30
3000
(Epoch 14 / 25) train acc: 0.924000; val_acc: 0.30
6000
(Epoch 15 / 25) train acc: 0.924000; val_acc: 0.29
9000
(Epoch 16 / 25) train acc: 0.942000; val_acc: 0.28
1000
(Epoch 17 / 25) train acc: 0.970000; val_acc: 0.30
2000
(Epoch 18 / 25) train acc: 0.932000; val_acc: 0.30
0000
(Epoch 19 / 25) train acc: 0.958000; val_acc: 0.29
6000
(Epoch 20 / 25) train acc: 0.960000; val_acc: 0.30
0000
(Iteration 101 / 125) loss: 0.390323
(Epoch 21 / 25) train acc: 0.976000; val_acc: 0.30
1000
(Epoch 22 / 25) train acc: 0.956000; val_acc: 0.29
6000
(Epoch 23 / 25) train acc: 0.966000; val_acc: 0.30
2000
(Epoch 24 / 25) train acc: 0.970000; val_acc: 0.30
7000
(Epoch 25 / 25) train acc: 0.974000; val_acc: 0.28
5000
```

In [7]:

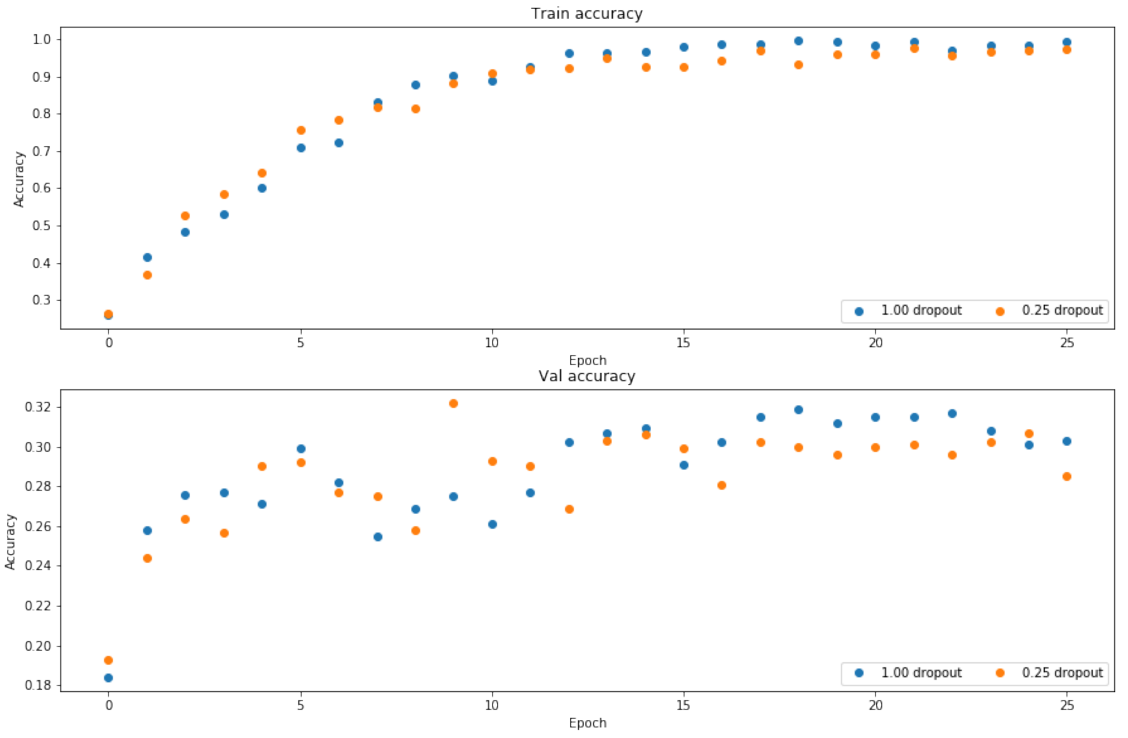
```
# Plot train and validation accuracies of the two models

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

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

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

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



Inline Question 2:

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

Answer:

The results show that we are overfitting the model. In the training phase, when we do not use dropout the accuracies are very high (at epoch 25: ~0.99); however, with dropout the accuracies are smaller (at epoch 25: ~0.93). This suggests that with dropout we are learning a simpler model and therefore we are trying to avoid overfitting. In the validation phase, we can see that with dropout we obtained slighly better results. This suggest that effectively with dropout we are regularizing our model and we are reducing overfitting.

Inline Question 3:

Suppose we are training a deep fully-connected network for image classification, with dropout after hidden layers (parameterized by keep probability p). If we are concerned about overfitting, how should we modify p (if at all) when we decide to decrease the size of the hidden layers (that is, the number of nodes in each layer)?

Answer:

If we decide to decrease the size of the hidden layers, we are not required to modify p because the number of neurons, which will be dropped out, will be proportional according to the size of the hidden layers. As an example, let's suppose we have n=1024 neurons in a hidden layer and we are using p=0.5. Thus, the expected number of dropped neurons is p*n=0.5*1024=512. If we reduce the number of neurons in the hidden layer to n=512 and by using the same p=0.5, the expected number of dropped neurons will be p*n=0.5*512=256. Therefore, we do not require to modify the keep probability p when we vary the size of the hidden layers.

In [ ]:

```

```