# Dropout

Dropout [1] 是一种通过在正向传播中将一些输出随机设置为零，神经网络正则化的方法。在这个练习中，你将实现一个dropout层，并修改你的全连接网络使其可选择的使用dropout

[1] Geoffrey E. Hinton et al, "Improving neural networks by preventing co-adaptation of feature detectors", arXiv 2012

In [35]:
```
# As usual, a bit of setup
from __future__ import print_function
import time
import numpy as np
import matplotlib.pyplot as plt
from daseCV.classifiers.fc_net import *
from daseCV.data_utils import get_CIFAR10_data
from daseCV.gradient_check import eval_numerical_gradient, eval_numerical_gradient_array
from daseCV.solver import Solver

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

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


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

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

In [36]:
```
# 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 正向传播

在文件 `daseCV/layers.py` 中完成dropout的正向传播过程。由于dropout在训练和测试期间的行为是不同的，因此请确保两种模式下都实现完成。

完成此操作后，运行下面的cell以测试你的代码。

In [37]:
```
np.random.seed(114514)
```

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

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

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

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

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

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

# Dropout 反向传播

在文件 `daseCV/layers.py` 中完成dropout的反向传播。完成之后运行以下cell以对你的实现代码进行梯度检查。

In [38]:

```python
np.random.seed(114514)
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],

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

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

## 问题 1:

在dropout层，如果不让inverse dropout技术过的数据除以p，会发生什么？为什么会这样呢？

## 回答:

特征之和的期望会和dropout之前不同, 影响对各维特征均值敏感的层.

同时让反传梯度的scale减小, 使得离输入层远的层权重难更新.

# 全连接网络的Dropout

修改 `daseCV/classifiers/fc_net.py` 文件完成使用dropout的部分。具体来说，如果网络的构造函数收到的 `dropout` 参数值不为1，则应在每个ReLU之后添加一个dropout层。完成之后，运行以下命令以对你的代码进行梯度检查。

In [39]:
```python
np.random.seed(114514)
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.float64,
                            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_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
```

# 正则化实验

作为实验，我们将在500个样本上训练一对双层网络：一个不使用dropout，另一个使用概率为0.25的dropout。之后，我们将可视化这两个网络训练和验证的准确度。

In [40]:
```
# Train two identical nets, one with dropout and one without
np.random.seed(114514)
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: 7.856644
(Epoch 0 / 25) train acc: 0.260000; val_acc: 0.184000
(Epoch 1 / 25) train acc: 0.416000; val_acc: 0.258000
(Epoch 2 / 25) train acc: 0.482000; val_acc: 0.276000
(Epoch 3 / 25) train acc: 0.534000; val_acc: 0.276000
(Epoch 4 / 25) train acc: 0.602000; val_acc: 0.272000
(Epoch 5 / 25) train acc: 0.708000; val_acc: 0.294000
(Epoch 6 / 25) train acc: 0.724000; val_acc: 0.280000
(Epoch 7 / 25) train acc: 0.828000; val_acc: 0.255000
(Epoch 8 / 25) train acc: 0.868000; val_acc: 0.274000
(Epoch 9 / 25) train acc: 0.904000; val_acc: 0.284000
(Epoch 10 / 25) train acc: 0.906000; val_acc: 0.260000
(Epoch 11 / 25) train acc: 0.926000; val_acc: 0.266000
(Epoch 12 / 25) train acc: 0.950000; val_acc: 0.293000
(Epoch 13 / 25) train acc: 0.968000; val_acc: 0.312000
(Epoch 14 / 25) train acc: 0.962000; val_acc: 0.310000
(Epoch 15 / 25) train acc: 0.968000; val_acc: 0.292000
(Epoch 16 / 25) train acc: 0.978000; val_acc: 0.285000
(Epoch 17 / 25) train acc: 0.966000; val_acc: 0.286000
(Epoch 18 / 25) train acc: 0.962000; val_acc: 0.294000
(Epoch 19 / 25) train acc: 0.984000; val_acc: 0.302000
(Epoch 20 / 25) train acc: 0.974000; val_acc: 0.308000
(Iteration 101 / 125) loss: 0.222015
(Epoch 21 / 25) train acc: 0.986000; val_acc: 0.295000
(Epoch 22 / 25) train acc: 0.988000; val_acc: 0.286000
(Epoch 23 / 25) train acc: 0.982000; val_acc: 0.295000
(Epoch 24 / 25) train acc: 0.984000; val_acc: 0.291000
(Epoch 25 / 25) train acc: 0.996000; val_acc: 0.299000

0.25
```

```
(Iteration 1 / 125) loss: 17.318481
(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: 0.297000
(Epoch 5 / 25) train acc: 0.562000; val_acc: 0.296000
(Epoch 6 / 25) train acc: 0.620000; val_acc: 0.291000
(Epoch 7 / 25) train acc: 0.630000; val_acc: 0.298000
(Epoch 8 / 25) train acc: 0.680000; val_acc: 0.313000
(Epoch 9 / 25) train acc: 0.710000; val_acc: 0.295000
(Epoch 10 / 25) train acc: 0.728000; val_acc: 0.303000
(Epoch 11 / 25) train acc: 0.754000; val_acc: 0.313000
(Epoch 12 / 25) train acc: 0.772000; val_acc: 0.270000
(Epoch 13 / 25) train acc: 0.830000; val_acc: 0.314000
(Epoch 14 / 25) train acc: 0.838000; val_acc: 0.351000
(Epoch 15 / 25) train acc: 0.838000; val_acc: 0.341000
(Epoch 16 / 25) train acc: 0.850000; val_acc: 0.314000
(Epoch 17 / 25) train acc: 0.866000; val_acc: 0.306000
(Epoch 18 / 25) train acc: 0.850000; val_acc: 0.310000
(Epoch 19 / 25) train acc: 0.898000; val_acc: 0.328000
(Epoch 20 / 25) train acc: 0.872000; val_acc: 0.313000
(Iteration 101 / 125) loss: 5.019241
(Epoch 21 / 25) train acc: 0.878000; val_acc: 0.317000
(Epoch 22 / 25) train acc: 0.884000; val_acc: 0.290000
(Epoch 23 / 25) train acc: 0.902000; val_acc: 0.305000
(Epoch 24 / 25) train acc: 0.912000; val_acc: 0.320000
(Epoch 25 / 25) train acc: 0.938000; val_acc: 0.310000
```

In [41]:

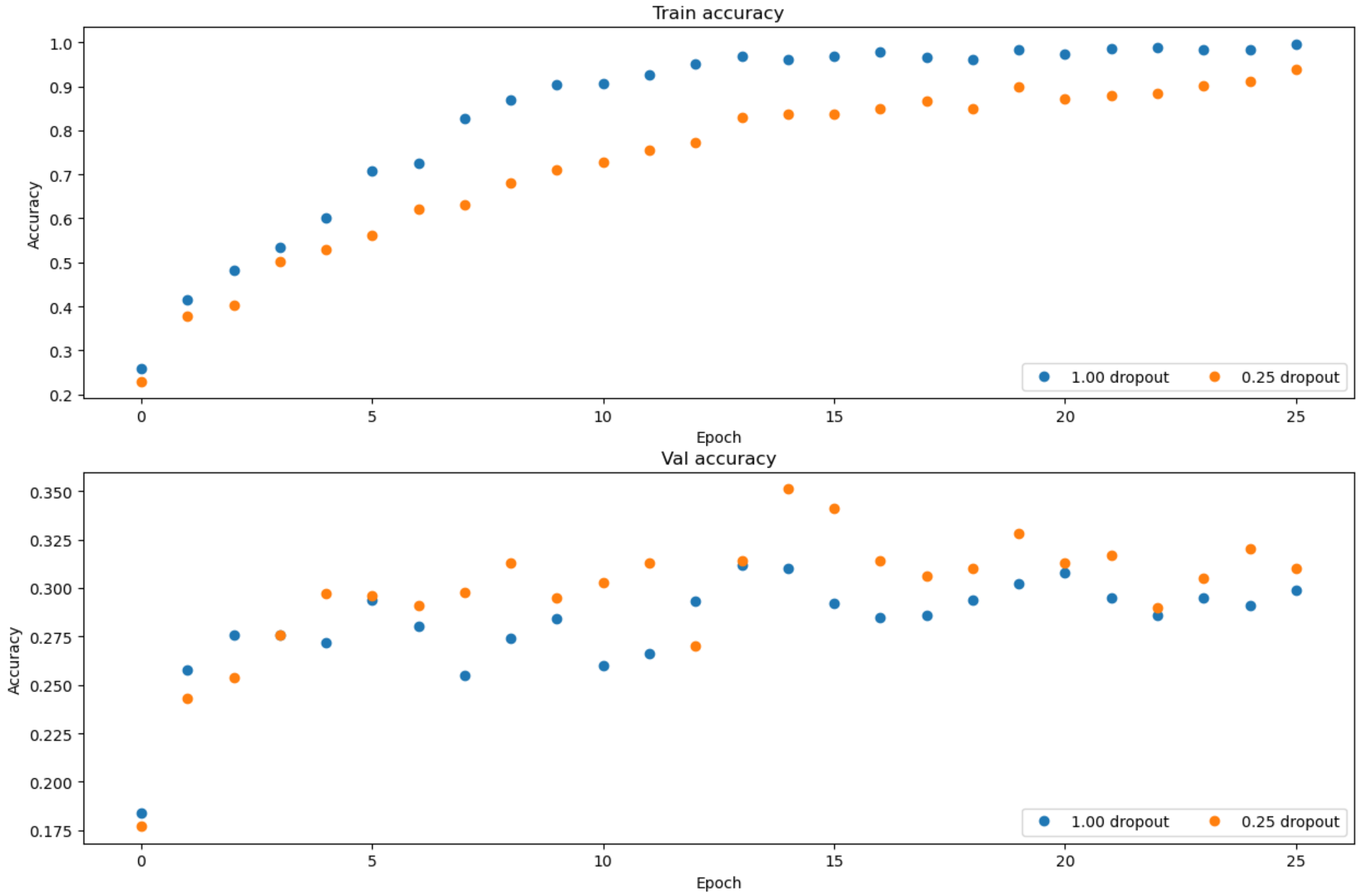
```python
# Plot train and validation accuracies of the two models

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()
```




# 问题 2:

对比有无dropout的验证和训练的精度，你的结果表示什么？

# 回答:

添加dropout时, 训练精度要稍微差一点, 但是测试精度是一样的, 甚至有时会高一些.

这说明dropout确实是一种正则化手段, 它降低了模型的复杂程度, 增加了测试的精度.

# 问题三 3:

假设我们正在训练一个深层的全连接网络用以进行图像分类，并隐层之后dropout（通过使用概率p进行参数化）。如果我们担心过度拟合而决定减小隐层的大小（即每层中的节点数）时，应该如何修改p（如果有的话）？

# 回答:

如果希望隐层大小等比例减少, 那么其实不需要修改p的值. 令n为隐层大小, p * n随n等比例减小.