Dropout

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c. Q3(: Dropout (10 points)) 의 결과를 작성한 코드와 함께 출력하세요. (10점)

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)

```
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, eval_numerical_gradient_arra
        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))))
```

```
In [2]: # Load the (preprocessed) CIFAR10 data.

        data = get_CIFAR10_data()
```

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

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

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.

```
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_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.

```
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

        # 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:

dropout은 하나의 layer에서 node를 random으로 일부 node가 활성화지 못하는 상황이므로 활성화가 된 node의 weight는 상대적으로 dropout을 하기 전보다 증폭되어 여러 모델을 앙상블 한 효과를 보게 된다. 그러므로 'p' 로 나누어주는 것은 이러한 증폭현상(exploding gradient)을 낮추어 주는 효과 발생한다.

4 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
```

```python
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
```

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.

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: 0.184000
(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: 0.878000; val_acc: 0.269000
(Epoch 9 / 25) train acc: 0.902000; val_acc: 0.275000
(Epoch 10 / 25) train acc: 0.888000; val_acc: 0.261000
(Epoch 11 / 25) train acc: 0.926000; val_acc: 0.278000
(Epoch 12 / 25) train acc: 0.960000; val_acc: 0.302000
```

```
(Epoch 13 / 25) train acc: 0.964000; val_acc: 0.305000
(Epoch 14 / 25) train acc: 0.966000; val_acc: 0.309000
(Epoch 15 / 25) train acc: 0.976000; val_acc: 0.288000
(Epoch 16 / 25) train acc: 0.988000; val_acc: 0.301000
(Epoch 17 / 25) train acc: 0.988000; val_acc: 0.305000
(Epoch 18 / 25) train acc: 0.990000; val_acc: 0.308000
(Epoch 19 / 25) train acc: 0.988000; val_acc: 0.311000
(Epoch 20 / 25) train acc: 0.990000; val_acc: 0.311000
(Iteration 101 / 125) loss: 0.006070
(Epoch 21 / 25) train acc: 0.998000; val_acc: 0.313000
(Epoch 22 / 25) train acc: 0.976000; val_acc: 0.322000
(Epoch 23 / 25) train acc: 0.986000; val_acc: 0.314000
(Epoch 24 / 25) train acc: 0.990000; val_acc: 0.310000
(Epoch 25 / 25) train acc: 0.994000; 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: 0.297000
(Epoch 6 / 25) train acc: 0.626000; val_acc: 0.290000
(Epoch 7 / 25) train acc: 0.628000; val_acc: 0.298000
(Epoch 8 / 25) train acc: 0.686000; val_acc: 0.310000
(Epoch 9 / 25) train acc: 0.722000; val_acc: 0.289000
(Epoch 10 / 25) train acc: 0.724000; val_acc: 0.300000
(Epoch 11 / 25) train acc: 0.760000; val_acc: 0.305000
(Epoch 12 / 25) train acc: 0.772000; val_acc: 0.280000
(Epoch 13 / 25) train acc: 0.814000; val_acc: 0.303000
(Epoch 14 / 25) train acc: 0.814000; val_acc: 0.341000
(Epoch 15 / 25) train acc: 0.856000; val_acc: 0.352000
(Epoch 16 / 25) train acc: 0.838000; val_acc: 0.303000
(Epoch 17 / 25) train acc: 0.840000; val_acc: 0.291000
(Epoch 18 / 25) train acc: 0.844000; val_acc: 0.315000
(Epoch 19 / 25) train acc: 0.864000; val_acc: 0.325000
(Epoch 20 / 25) train acc: 0.862000; val_acc: 0.308000
(Iteration 101 / 125) loss: 5.259476
(Epoch 21 / 25) train acc: 0.896000; val_acc: 0.320000
(Epoch 22 / 25) train acc: 0.872000; val_acc: 0.298000
(Epoch 23 / 25) train acc: 0.906000; val_acc: 0.317000
(Epoch 24 / 25) train acc: 0.906000; val_acc: 0.320000
(Epoch 25 / 25) train acc: 0.910000; val_acc: 0.325000
```

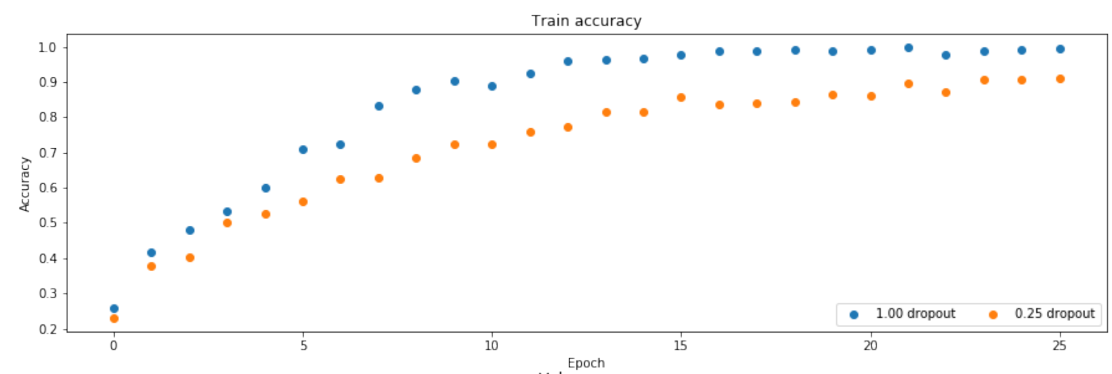
```
In [7]: # Plot train and validation accuracies of the two models
```

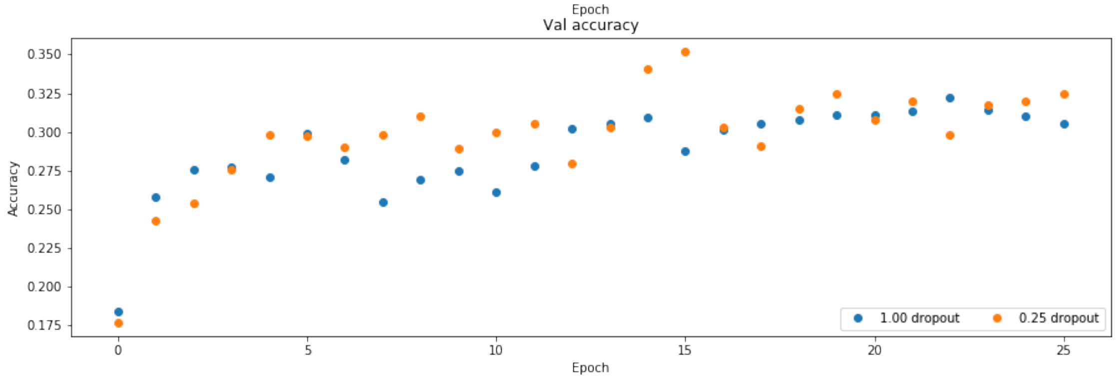
```
train_accs = []
val_accs = []
for dropout in dropout_choices:
  solver = solvers[dropout]
  train_accs.append(solver.train_acc_history[-1])
  val_accs.append(solver.val_acc_history[-1])

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()
```





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:

dropout을 안하는 모델은 현재 overfitting 현상을 보여주고 있다. dropout을 하는 모델은 이러한 overfitiing 문제를 해결을 해주는 현상을 보여주고 dropout을 하지 않는 모델을 보다 우수한 성능을 보여주고 있다.

5.3 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)?

5.4 Answer:

layer의 노드 수를 줄이는 효과는 dropout과 비슷한 노드의 수가 줄어 드는 효과를 보여준다. 하나의 layer의 노드의 수를 줄인다면 'p' 그에 상응하게 줄여한다.