```
# 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/assignment1/'
FOLDERNAME = 'Coursework/ENPM703/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/Coursework/ENPM703/assignment2/cs231n/datasets
/content/drive/My Drive/Coursework/ENPM703/assignment2
```

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

```
# 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))))

# 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,)
```

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

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: 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.

```
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:  5.445608148733387e-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:

What happens when we don't divide by p

If values are not divided by p, the network will produce outputs on the incorrect scale during testing than it did during training, resulting in incorrect predictions.

Without scaling the expected output of any neuron producing y^ becomes:

E|y^|=py^+(1−p)0=py^

where:

- py^ - probability of getting the output
- (1−p)0 probability of not getting the output

What happens when we divide by p

To guarantee that the size of outputs at test time matches the scale of the predicted outputs at training time, we must scale output activations by 1/p. For example, dividing by p results in the following expectation:

E|y^|=p/p y^+(1−p)p 0=y^

Which means during test time we don't need to do anything.

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.

```python
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
    )

    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:  2.300479089768492
W1 relative error: 2.42e-07
W2 relative error: 1.01e-05
W3 relative error: 5.13e-07
b1 relative error: 4.81e-09
b2 relative error: 1.20e-09
b3 relative error: 1.60e-10

Running check with dropout =  0.75
Initial loss:  2.3023714897044125
W1 relative error: 1.85e-07
W2 relative error: 1.30e-06
W3 relative error: 2.91e-08
b1 relative error: 4.73e-09
b2 relative error: 1.57e-09
b3 relative error: 1.14e-10

Running check with dropout =  0.5
Initial loss:  2.3042759220785896
W1 relative error: 3.11e-07
W2 relative error: 5.55e-08
W3 relative error: 6.66e-08
b1 relative error: 3.65e-08
b2 relative error: 2.99e-09
b3 relative error: 1.29e-10
```

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: 7.856644
(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: 0.532000; 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: 0.306000
(Epoch 18 / 25) train acc: 0.992000; val_acc: 0.312000
(Epoch 19 / 25) train acc: 0.990000; val_acc: 0.311000
(Epoch 20 / 25) train acc: 0.990000; val_acc: 0.287000
(Iteration 101 / 125) loss: 0.001695
(Epoch 21 / 25) train acc: 0.994000; val_acc: 0.289000
(Epoch 22 / 25) train acc: 0.998000; val_acc: 0.307000
(Epoch 23 / 25) train acc: 0.994000; val_acc: 0.308000
(Epoch 24 / 25) train acc: 0.998000; val_acc: 0.311000
(Epoch 25 / 25) train acc: 0.992000; val_acc: 0.310000

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: 0.848000; val_acc: 0.338000
(Epoch 16 / 25) train acc: 0.842000; val_acc: 0.306000
(Epoch 17 / 25) train acc: 0.856000; val_acc: 0.301000
(Epoch 18 / 25) train acc: 0.860000; val_acc: 0.317000
(Epoch 19 / 25) train acc: 0.882000; val_acc: 0.313000
(Epoch 20 / 25) train acc: 0.866000; val_acc: 0.312000
(Iteration 101 / 125) loss: 4.185203
(Epoch 21 / 25) train acc: 0.894000; val_acc: 0.332000
(Epoch 22 / 25) train acc: 0.898000; val_acc: 0.313000
(Epoch 23 / 25) train acc: 0.928000; val_acc: 0.314000
(Epoch 24 / 25) train acc: 0.922000; val_acc: 0.315000
```

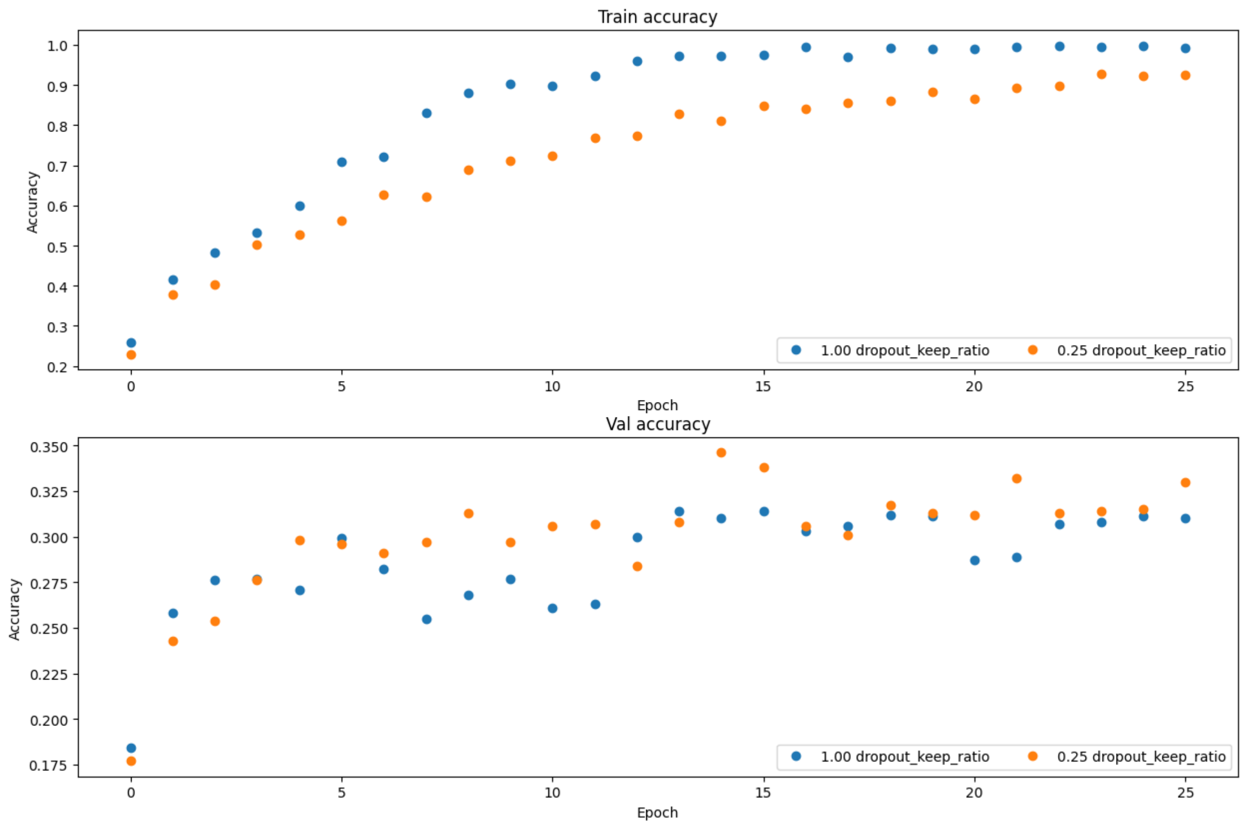
```
(Epoch 25 / 25) train acc: 0.926000; val_acc: 0.330000
```

```
# 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()
```



Inline Question 2:

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

Answer:

Training: By avoiding dropout, the model was able to get greater accuracy throughout training. The model was allowed to use all of its neurons to learn all of the little characteristics. In contrast to the dropout model, it might be seen as a minor overfit.

Validation: Dropout is an excellent regularizer to control overfitting; it promotes network robustness because the model can't rely too heavily on certain neurons. During validation, the model produced slightly better results overall thanks to the usage of dropout.

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:

Modification during: When we reduce the size of the hidden layers, there is no need to change p. Simpler design already addresses overfitting since a simpler model cannot learn all the minute patterns and potential artifacts.

Modification following: once the layers' complexity has been determined, we may use dropout to fine-tune the model. If we cut the layers too much, we could raise the keep probability; if we simplify the model still more, we could lower it.