# Assignment 1: Test Your Neural Network on a Toy Dataset

Use this notebook to build your neural network by first implementing the following functions in the python files under assignment2/algorithms,

1. linear.py
2. relu.py
3. softmax.py
4. loss_func.py

First you will be testing your 2 layer neural network implementation on a toy dataset.

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```
import sys
sys.path.append("../")
# Setup
import matplotlib.pyplot as plt
import numpy as np

from layers.sequential import Sequential
from layers.linear import Linear
from layers.relu import ReLU
from layers.softmax import Softmax
from layers.loss_func import CrossEntropyLoss
from utils.optimizer import SGD

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

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

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

We will use the class Sequential as implemented in the file assignment2/layers/sequential.py to build a layer by layer model of our neural network. Below we initialize the toy model and the toy random data that you will use to develop your implementation.

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```
# Create a small net and some toy data to check your implementations.
# Note that we set the random seed for repeatable experiments.

input_size = 4
hidden_size = 10
num_classes = 3 # Output
num_inputs = 10 # N
```

```
def init_toy_model():
    np.random.seed(0)
    l1 = Linear(input_size, hidden_size)
    l2 = Linear(hidden_size, num_classes)

    r1 = ReLU()
    softmax = Softmax()
    return Sequential([l1, r1, l2, softmax])

def init_toy_data():
    np.random.seed(0)
    X = 10 * np.random.randn(num_inputs, input_size)
    y = np.random.randint(num_classes, size=num_inputs)
    #y = np.array([0, 1, 2, 2, 1])
    return X, y

net = init_toy_model()
X, y = init_toy_data()
```

## Forward Pass: Compute Scores (20%)

Implement the forward functions in Linear, Relu and Softmax layers and get the output by passing our toy data X The output must match the given output scores

```
scores = net.forward(X)
print('Your scores:')
print(scores)
print()
print('correct scores:')
correct_scores = np.asarray([[0.33333514, 0.33333826, 0.33332661],
 [0.3333351,  0.33333828, 0.33332661],
 [0.3333351,  0.33333828, 0.33332662],
 [0.3333351,  0.33333828, 0.33332662],
 [0.33333509, 0.33333829, 0.33332662],
 [0.33333508, 0.33333829, 0.33332662],
 [0.33333511, 0.33333828, 0.33332661],
 [0.33333512, 0.33333827, 0.33332661],
 [0.33333508, 0.33333829, 0.33332662],
 [0.33333511, 0.33333828, 0.33332662]])
print(correct_scores)

# The difference should be very small. We get < 1e-7
print('Difference between your scores and correct scores:')
print(np.sum(np.abs(scores - correct_scores)))
```

```
Your scores:
[[0.33333514 0.33333826 0.33332661]
 [0.3333351  0.33333828 0.33332661]
 [0.3333351  0.33333828 0.33332662]
 [0.3333351  0.33333828 0.33332662]
 [0.33333509 0.33333829 0.33332662]
 [0.33333508 0.33333829 0.33332662]
 [0.33333511 0.33333828 0.33332661]
 [0.33333512 0.33333827 0.33332661]
 [0.33333508 0.33333829 0.33332662]
 [0.33333511 0.33333828 0.33332662]]

correct scores:
[[0.33333514 0.33333826 0.33332661]
 [0.3333351  0.33333828 0.33332661]
```

```
 [0.3333351  0.33333828 0.33332662]
 [0.3333351  0.33333828 0.33332662]
 [0.33333509 0.33333829 0.33332662]
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 [0.33333511 0.33333828 0.33332661]
 [0.33333512 0.33333827 0.33332661]
 [0.33333508 0.33333829 0.33332662]
 [0.33333511 0.33333828 0.33332662]]
Difference between your scores and correct scores:
8.799388540037256e-08
```

## Forward Pass: Compute loss given the output scores from the previous step (10%)

Implement the forward function in the loss_func.py file, and output the loss value. The loss value must match the given loss value.

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```
Loss = CrossEntropyLoss()
loss = Loss.forward(scores,y)
correct_loss = 1.098612723362578
print(loss)
# should be very small, we get < 1e-12
print('Difference between your loss and correct loss:')
print(np.sum(np.abs(loss - correct_loss)))
```

```
1.098612723362578
Difference between your loss and correct loss:
0.0
```

## Backward Pass (40%)

Implement the rest of the functions in the given files. Specifically, implement the backward function in all the 4 files as mentioned in the files. Note: No backward function in the softmax file, the gradient for softmax is jointly calculated with the cross entropy loss in the loss_func.backward function.

You will use the chain rule to calculate gradient individually for each layer. You can assume that this calculated gradeint then is passed to the next layers in a reversed manner due to the Sequential implementation. So all you need to worry about is implementing the gradient for the current layer and multiply it will the incoming gradient (passed to the backward function as dout) to calculate the total gradient for the parameters of that layer.

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```
# No need to edit anything in this block ( 20% of the above 40% )
net.backward(Loss.backward())

gradients = []
for module in net._modules:
    for para, grad in zip(module.parameters, module.grads):
        assert grad is not None, "No Gradient"
        #Print gradients of the linear layer
        print(grad.shape)
        gradients.append(grad)

# Check shapes of your gradient. Note that only the linear layer has parameters
```

```
#(4, 10) -> Layer 1 W
#(10,)   -> Layer 1 b
#(10, 3) -> Layer 2 W
#(3,)    -> Layer 2 b

(4, 10)
(10,)
(10, 3)
(3,)
```

```
52 # No need to edit anything in this block ( 20% of the above 40% )
   # Now we check the values for these gradients. Here are the values for these gradients, Below we calculat
   # difference, you must get difference < 1e-10
   grad_w1 = np.array([[-6.24320917e-05,  3.41037180e-06, -1.69125969e-05,
            2.41514079e-05,  3.88697976e-06,  7.63842314e-05,
           -8.88925758e-05,  3.34909890e-05, -1.42758303e-05,
           -4.74748560e-06],
          [-7.16182867e-05,  4.63270039e-06, -2.20344270e-05,
           -2.72027034e-06,  6.52903437e-07,  8.97294847e-05,
           -1.05981609e-04,  4.15825391e-05, -2.12210745e-05,
            3.06061658e-05],
          [-1.69074923e-05, -8.83185056e-06,  3.10730840e-05,
            1.23010428e-05,  5.25830316e-05, -7.82980115e-06,
            3.02117990e-05, -3.37645284e-05,  6.17276346e-05,
           -1.10735656e-05],
          [-4.35902272e-05,  3.71512704e-06, -1.66837877e-05,
            2.54069557e-06, -4.33258099e-06,  5.72310022e-05,
           -6.94881762e-05,  2.92408329e-05, -1.89369767e-05,
            2.01692516e-05]])
   grad_b1 = np.array([-2.27150209e-06,  5.14674340e-07, -2.04284403e-06,  6.08849787e-07, -1.92177796e-06,
                       3.92085824e-06, -5.40772636e-06,  2.93354593e-06, -3.14568138e-06,  5.27501592e-11])

   grad_w2 = np.array([[ 1.28932983e-04,  1.19946731e-04, -2.48879714e-04],
          [ 1.08784150e-04,  1.55140199e-04, -2.63924349e-04],
          [ 6.96017544e-05,  1.42748410e-04, -2.12350164e-04],
          [ 9.92512487e-05,  1.73257611e-04, -2.72508860e-04],
          [ 2.05484895e-05,  4.96161144e-05, -7.01646039e-05],
          [ 8.20539510e-05,  9.37063861e-05, -1.75760337e-04],
          [ 2.45831715e-05,  8.74369112e-05, -1.12020083e-04],
          [ 1.34073379e-04,  1.86253064e-04, -3.20326443e-04],
          [ 8.86473128e-05,  2.35554414e-04, -3.24201726e-04],
          [ 3.57433149e-05,  1.91164061e-04, -2.26907376e-04]])

   grad_b2 = np.array([-0.1666649 ,  0.13333828,  0.03332662])

   difference = np.sum(np.abs(gradients[0]-grad_w1)) + np.sum(np.abs(gradients[1]-grad_b1)) + np.sum(np.abs(
                np.sum(np.abs(gradients[3]-grad_b2))
   print("Difference in Gradient values", difference)


   Difference in Gradient values 7.70191643436727e-09
```

## Train the complete network on the toy data.

To train the network we will use stochastic gradient descent (SGD), we have implemented the optimizer for you. You do not implement any more functions in the python files. Below we implement the training procedure, you should get yourself familiar with the training process. Specifically looking at which functions to call and when.

Once you have implemented the method and tested various parts in the above blocks, run the code below to train a two-layer network on toy data. You should see your the training loss decrease to

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```
# Training Procedure
# Initialize the optimizer. DO NOT change any of the hyper-parameters here or above.
# We have implemented the SGD optimizer class for you here, which visits each layer sequentially to
# get the gradients and optimize the respective parameters.
# You should work with the given parameters and only edit your implementation in the .py files

epochs = 1000
optim = SGD(net, lr=0.1, weight_decay=0.00001)

epoch_loss = []
for epoch in range(epochs):
            # Get output scores from the network
            output_x = net(X)
            # Calculate the loss for these output scores, given the true labels
            loss = Loss.forward(output_x, y)
            # Initialize your gradients to None in each epoch
            optim.zero_grad()
            # Make a backward pass to update the internal gradients in the layers
            net.backward(Loss.backward())
            # call the step function in the optimizer to update the values of the params with the gradien
            optim.step()
            # Append the loss at each iteration
            epoch_loss.append(loss)

            print("Epoch Loss: {:3f}".format(epoch_loss[-1]))
```

```
Epoch Loss: 1.098613
Epoch Loss: 1.094024
Epoch Loss: 1.089737
Epoch Loss: 1.085733
Epoch Loss: 1.081994
Epoch Loss: 1.078505
Epoch Loss: 1.075248
Epoch Loss: 1.072208
Epoch Loss: 1.069372
Epoch Loss: 1.066726
Epoch Loss: 1.064257
Epoch Loss: 1.061952
Epoch Loss: 1.059799
Epoch Loss: 1.057785
Epoch Loss: 1.055899
Epoch Loss: 1.054124
Epoch Loss: 1.052445
Epoch Loss: 1.050839
Epoch Loss: 1.049277
Epoch Loss: 1.047713
Epoch Loss: 1.046081
Epoch Loss: 1.044279
Epoch Loss: 1.042147
Epoch Loss: 1.039435
Epoch Loss: 1.035774
Epoch Loss: 1.030637
Epoch Loss: 1.023365
Epoch Loss: 1.013337
Epoch Loss: 1.000400
Epoch Loss: 0.985502
Epoch Loss: 0.970780
Epoch Loss: 0.958224
```

```
Epoch Loss: 0.948146
Epoch Loss: 0.939687
Epoch Loss: 0.932411
Epoch Loss: 0.926597
Epoch Loss: 0.920919
Epoch Loss: 0.914630
Epoch Loss: 0.908446
Epoch Loss: 0.902708
Epoch Loss: 0.895794
Epoch Loss: 0.889273
Epoch Loss: 0.882132
Epoch Loss: 0.875647
Epoch Loss: 0.870536
Epoch Loss: 0.861775
Epoch Loss: 0.855117
Epoch Loss: 0.848626
Epoch Loss: 0.839904
Epoch Loss: 0.832706
Epoch Loss: 0.827365
Epoch Loss: 0.815973
Epoch Loss: 0.810844
Epoch Loss: 0.802194
Epoch Loss: 0.790601
Epoch Loss: 0.783502
Epoch Loss: 0.770632
Epoch Loss: 0.760160
Epoch Loss: 0.749472
Epoch Loss: 0.739295
Epoch Loss: 0.732478
Epoch Loss: 0.719142
Epoch Loss: 0.713844
Epoch Loss: 0.700037
Epoch Loss: 0.693629
Epoch Loss: 0.689958
Epoch Loss: 0.674298
Epoch Loss: 0.659023
Epoch Loss: 0.647852
Epoch Loss: 0.638275
Epoch Loss: 0.628526
Epoch Loss: 0.622772
Epoch Loss: 0.617140
Epoch Loss: 0.608889
Epoch Loss: 0.601315
Epoch Loss: 0.590965
Epoch Loss: 0.588483
Epoch Loss: 0.580111
Epoch Loss: 0.580237
Epoch Loss: 0.579590
Epoch Loss: 0.575265
Epoch Loss: 0.583167
Epoch Loss: 0.569299
Epoch Loss: 0.567051
Epoch Loss: 0.558750
Epoch Loss: 0.570455
Epoch Loss: 0.550303
Epoch Loss: 0.556647
Epoch Loss: 0.528476
Epoch Loss: 0.523165
Epoch Loss: 0.503276
Epoch Loss: 0.508981
Epoch Loss: 0.493973
Epoch Loss: 0.512211
Epoch Loss: 0.477031
Epoch Loss: 0.483331
Epoch Loss: 0.456475
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Epoch Loss: 0.472357
Epoch Loss: 0.443569
Epoch Loss: 0.454687
Epoch Loss: 0.429413
Epoch Loss: 0.441666
Epoch Loss: 0.413838
Epoch Loss: 0.443494
Epoch Loss: 0.407146
Epoch Loss: 0.444991
Epoch Loss: 0.403453
Epoch Loss: 0.436572
Epoch Loss: 0.397764
Epoch Loss: 0.439797
Epoch Loss: 0.422846
Epoch Loss: 0.526893
Epoch Loss: 0.553876
Epoch Loss: 0.728167
Epoch Loss: 0.582263
Epoch Loss: 0.547702
Epoch Loss: 0.416240
Epoch Loss: 0.453693
Epoch Loss: 0.381732
Epoch Loss: 0.362521
Epoch Loss: 0.324897
Epoch Loss: 0.338047
Epoch Loss: 0.342623
Epoch Loss: 0.326819
Epoch Loss: 0.392589
Epoch Loss: 0.292861
Epoch Loss: 0.314854
Epoch Loss: 0.235608
Epoch Loss: 0.227234
Epoch Loss: 0.207276
Epoch Loss: 0.220121
Epoch Loss: 0.208397
Epoch Loss: 0.249017
Epoch Loss: 0.226502
Epoch Loss: 0.284894
Epoch Loss: 0.233826
Epoch Loss: 0.259128
Epoch Loss: 0.195131
Epoch Loss: 0.177242
Epoch Loss: 0.156995
Epoch Loss: 0.147287
Epoch Loss: 0.142642
Epoch Loss: 0.139515
Epoch Loss: 0.136126
Epoch Loss: 0.135978
Epoch Loss: 0.130053
Epoch Loss: 0.127937
Epoch Loss: 0.122477
Epoch Loss: 0.120641
Epoch Loss: 0.118350
Epoch Loss: 0.117382
Epoch Loss: 0.112601
Epoch Loss: 0.111264
Epoch Loss: 0.106784
Epoch Loss: 0.105601
Epoch Loss: 0.105261
Epoch Loss: 0.103690
Epoch Loss: 0.099740
Epoch Loss: 0.097608
Epoch Loss: 0.094972
Epoch Loss: 0.094597
Epoch Loss: 0.093439
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Epoch Loss: 0.092069
Epoch Loss: 0.090610
Epoch Loss: 0.087682
Epoch Loss: 0.085767
Epoch Loss: 0.084664
Epoch Loss: 0.083181
Epoch Loss: 0.082531
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Epoch Loss: 0.077149
Epoch Loss: 0.075943
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Epoch Loss: 0.072842
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Epoch Loss: 0.065619
Epoch Loss: 0.065236
Epoch Loss: 0.064023
Epoch Loss: 0.063155
Epoch Loss: 0.062142
Epoch Loss: 0.061411
Epoch Loss: 0.060913
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Epoch Loss: 0.044038
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Epoch Loss: 0.024557
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Epoch Loss: 0.023803
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Epoch Loss: 0.022017
Epoch Loss: 0.021940
Epoch Loss: 0.021877
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Epoch Loss: 0.021474
Epoch Loss: 0.021424
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Epoch Loss: 0.021282
Epoch Loss: 0.021211
Epoch Loss: 0.021137
Epoch Loss: 0.021074
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Epoch Loss: 0.020940
Epoch Loss: 0.020878
Epoch Loss: 0.020819
Epoch Loss: 0.020751
Epoch Loss: 0.020688
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Epoch Loss: 0.020504
Epoch Loss: 0.020451
Epoch Loss: 0.020385
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Epoch Loss: 0.020251
Epoch Loss: 0.020197
Epoch Loss: 0.020169
Epoch Loss: 0.020110
Epoch Loss: 0.020046
Epoch Loss: 0.019971
Epoch Loss: 0.019898
Epoch Loss: 0.019833
Epoch Loss: 0.019767
Epoch Loss: 0.019698
Epoch Loss: 0.019641
Epoch Loss: 0.019610
Epoch Loss: 0.019540
Epoch Loss: 0.019472
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Epoch Loss: 0.019407
Epoch Loss: 0.019350
Epoch Loss: 0.019300
Epoch Loss: 0.019235
Epoch Loss: 0.019172
Epoch Loss: 0.019116
Epoch Loss: 0.019053
Epoch Loss: 0.018993
Epoch Loss: 0.018957
Epoch Loss: 0.018905
Epoch Loss: 0.018855
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Epoch Loss: 0.007614
Epoch Loss: 0.007606
Epoch Loss: 0.007601
Epoch Loss: 0.007593
```

55
```
# Test your predictions. The predictions must match the labels
print(net.predict(X))
print(y)
```

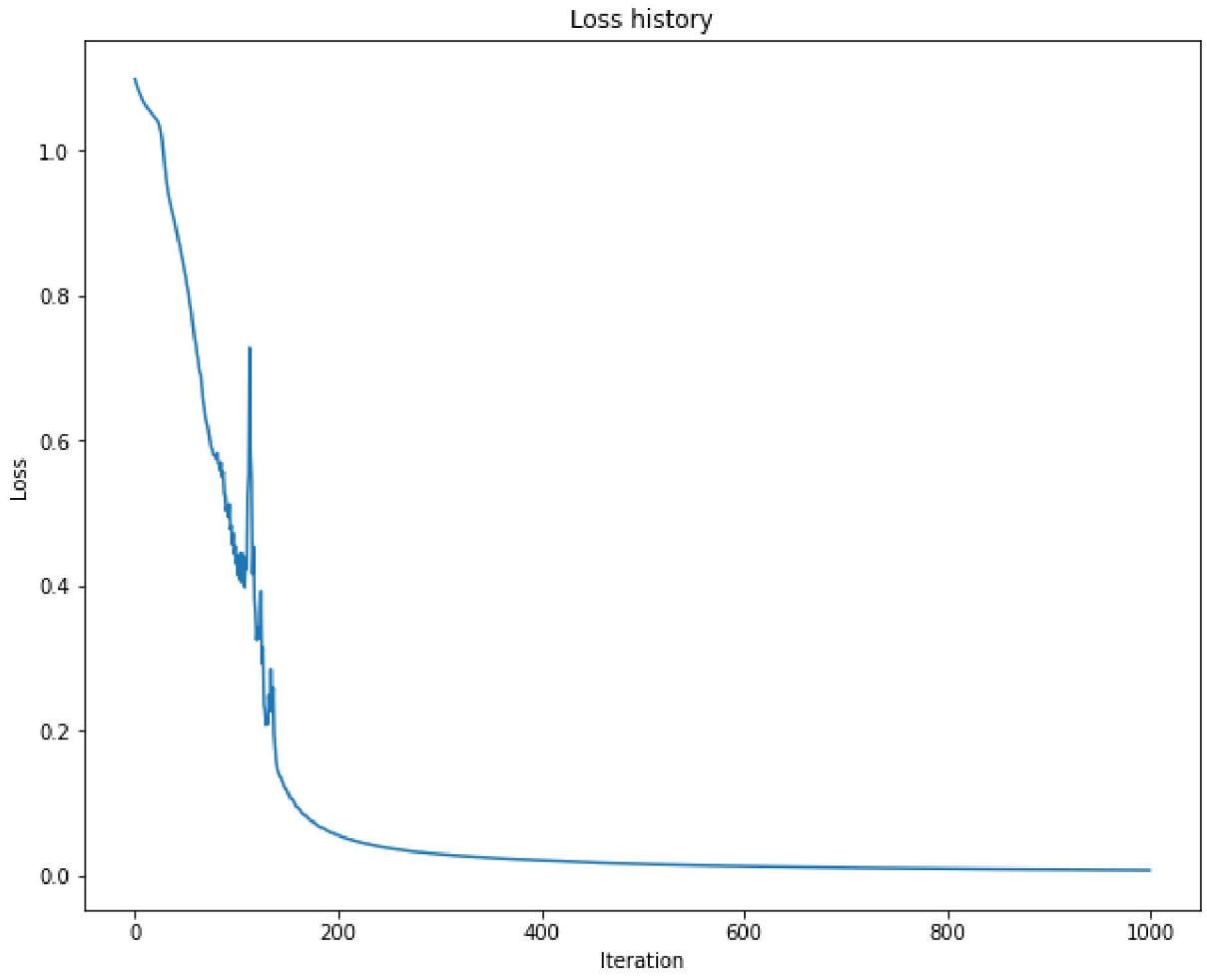
```
[2 1 0 1 2 0 0 2 0 0]
```

```
[2 1 0 1 2 0 0 2 0 0]
```

```
# You should be able to achieve a training loss of less than 0.02 (10%)
print("Final training loss", epoch_loss[-1])
```

```
# Plot the training loss curve. The loss in the curve should be decreasing (20%)
plt.plot(epoch_loss)
plt.title('Loss history')
plt.xlabel('Iteration')
plt.ylabel('Loss')
```

```
Text(0, 0.5, 'Loss')
```



# Assignment 1: Train and test your model on CIFAR20 dataset

Now that you have developed and tested your model on the toy dataset set. It's time to get down and get dirty with a standard dataset such as cifar20. At this point, you will be using the provided training data to tune the hyper-parameters of your network such that it works with cifar20 for the task of multi-class classification.

Important: Recall that now we have non-linear decision boundaries, thus we do not need to do one vs all classification. We learn a single non-linear decision boundary instead. Our non-linear boundaries (thanks to relu non-linearity) will take care of differentiating between all the classes

1
```
# Prepare Packages
import numpy as np
import matplotlib.pyplot as plt

from utils.data_processing import get_cifar20_data
from utils.evaluation import get_classification_accuracy


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

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

# Use a subset of CIFAR20 for the assignment
dataset = get_cifar20_data(
    subset_train = 8000,
    subset_val = 2000,
    subset_test = 2000,
)

print(dataset.keys())
print("Training Set Data  Shape: ", dataset['x_train'].shape)
print("Training Set Label Shape: ", dataset['y_train'].shape)
print("Validation Set Data  Shape: ", dataset['x_val'].shape)
print("Validation Set Label Shape: ", dataset['y_val'].shape)
print("Test Set Data  Shape: ", dataset['x_test'].shape)
print("Test Set Label Shape: ", dataset['y_test'].shape)
```

```
dict_keys(['x_train', 'y_train', 'x_val', 'y_val', 'x_test', 'y_test'])
Training Set Data  Shape:  (8000, 3072)
Training Set Label Shape:  (8000,)
Validation Set Data  Shape:  (2000, 3072)
Validation Set Label Shape:  (2000,)
Test Set Data  Shape:  (2000, 3072)
Test Set Label Shape:  (2000,)
```

2
```
x_train = dataset['x_train']
y_train = dataset['y_train']
```

```
x_val = dataset['x_val']
y_val = dataset['y_val']
x_test = dataset['x_test']
y_test = dataset['y_test']
```

```
# Import more utilies and the layers you have implemented
from layers.sequential import Sequential
from layers.linear import Linear
from layers.relu import ReLU
from layers.softmax import Softmax
from layers.loss_func import CrossEntropyLoss
from utils.optimizer import SGD
from utils.dataset import DataLoader
from utils.trainer import Trainer
```

# Visualize some examples from the dataset.

```
# We show a few examples of training images from each class.
classes = ['apple', 'fish', 'baby', 'bear', 'beaver', 'bed', 'bee', 'beetle', 'bicycle', 'bottle',
           'bowl', 'boy', 'bridge', 'bus' ,'butterfly', 'camel', 'can', 'castle', 'caterpillar', 'cattle'
samples_per_class = 7

def visualize_data(dataset, classes, samples_per_class):
    num_classes = len(classes)
    for y, cls in enumerate(classes):
      idxs = np.flatnonzero(y_train == y)
      idxs = np.random.choice(idxs, samples_per_class, replace=False)
      for i, idx in enumerate(idxs):
        plt_idx = i * num_classes + y + 1
        plt.subplot(samples_per_class, num_classes, plt_idx)
        plt.imshow(dataset[idx])
        plt.axis('off')
        if i == 0:
          plt.title(cls)
    plt.show()

# Visualize the first 10 classes
# visualize_data(x_train.reshape(8000, 3, 32, 32).transpose(0, 2, 3, 1), classes[0:10], samples_per_class
```

# Initialize the model

```
input_size = 3072
hidden_size = 50 # Hidden layer size (Hyper-parameter)
num_classes = 20 # Output

# For a default setting we use the same model we used for the toy dataset.
# This tells you the power of a 2 layered Neural Network. Recall the Universal Approximation Theorem.
# A 2 layer neural network with non-linearities can approximate any function, given large enough hidden l
def init_model():
    np.random.seed(0) # No need to fix the seed here
    l1 = Linear(input_size, hidden_size)
    l2 = Linear(hidden_size, num_classes)
    r1 = ReLU()
    softmax = Softmax()
    return Sequential([l1, r1, l2, softmax])
```

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```
# Initialize the dataset with the dataloader class
dataset = DataLoader(x_train, y_train, x_val, y_val, x_test, y_test)
net = init_model()
optim = SGD(net, lr=0.1, weight_decay=0.1)
loss_func = CrossEntropyLoss()
epoch = 200 # (Hyper-parameter)
batch_size = 200 # (Reduce the batch size if your computer is unable to handle it)
```

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```
#Initialize the trainer class by passing the above modules
trainer = Trainer(dataset, optim, net, loss_func, epoch, batch_size, validate_interval=10)
```

20
```
# Call the trainer function we have already implemented for you. This trains the model for the given
# hyper-parameters. It follows the same procedure as in the last ipython notebook you used for the toy-da
train_error, validation_accuracy = trainer.train()
```

```
Epoch 0
Epoch Average Loss: 2.995561
Validate Acc: 0.038
Epoch 10
Epoch Average Loss: 2.827114
Validate Acc: 0.102
Epoch 20
Epoch Average Loss: 2.685121
Validate Acc: 0.183
Epoch 30
Epoch Average Loss: 2.643985
Validate Acc: 0.175
Epoch 40
Epoch Average Loss: 2.653347
Validate Acc: 0.179
Epoch 50
Epoch Average Loss: 2.641449
Validate Acc: 0.170
Epoch 60
Epoch Average Loss: 2.638679
Validate Acc: 0.210
Epoch 70
Epoch Average Loss: 2.637001
Validate Acc: 0.222
Epoch 80
Epoch Average Loss: 2.634001
Validate Acc: 0.153
Epoch 90
Epoch Average Loss: 2.628490
Validate Acc: 0.207
Epoch 100
Epoch Average Loss: 2.638195
Validate Acc: 0.230
Epoch 110
Epoch Average Loss: 2.630941
Validate Acc: 0.236
Epoch 120
Epoch Average Loss: 2.639778
Validate Acc: 0.212
Epoch 130
Epoch Average Loss: 2.639395
Validate Acc: 0.225
Epoch 140
Epoch Average Loss: 2.645378
```

```
Validate Acc: 0.211
Epoch 150
Epoch Average Loss: 2.633613
Validate Acc: 0.196
Epoch 160
Epoch Average Loss: 2.622255
Validate Acc: 0.163
Epoch 170
Epoch Average Loss: 2.627064
Validate Acc: 0.220
Epoch 180
Epoch Average Loss: 2.620537
Validate Acc: 0.224
Epoch 190
Epoch Average Loss: 2.627495
Validate Acc: 0.157
```

## Print the training and validation accuracies for the default hyper-parameters provided

21
```
from utils.evaluation import get_classification_accuracy
out_train = net.predict(x_train)
acc = get_classification_accuracy(out_train, y_train)
print("Training acc: ",acc)
out_val = net.predict(x_val)
acc = get_classification_accuracy(out_val, y_val)
print("Validation acc: ",acc)
```

```
Training acc:  0.19
Validation acc:  0.198
```

## Debug the training

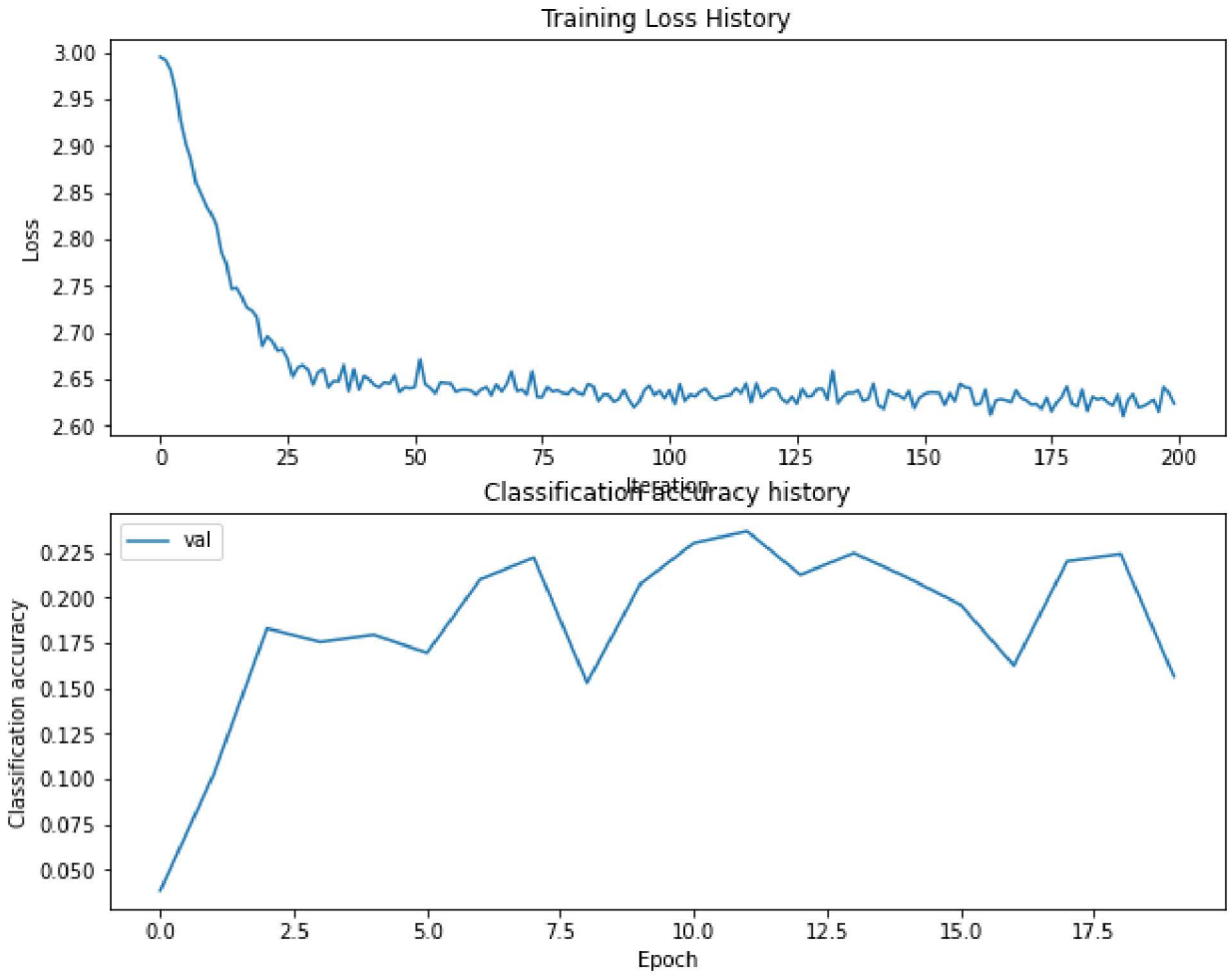
With the default parameters we provided above, you should get a validation accuracy of around ~0.2 on the validation set. This isn't very good.

One strategy for getting insight into what's wrong is to plot the training loss function and the validation accuracies during optimization.

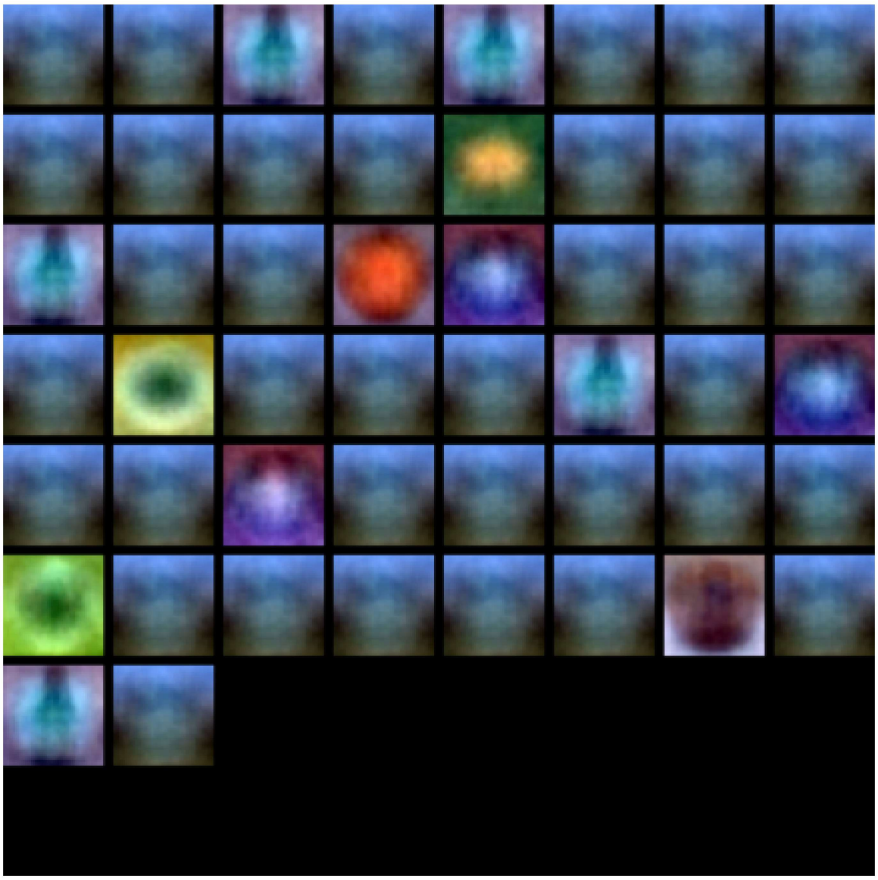
Another strategy is to visualize the weights that were learned in the first layer of the network. In most neural networks trained on visual data, the first layer weights typically show some visible structure when visualized.

22
```
# Plot the training loss function and validation accuracies
plt.subplot(2, 1, 1)
plt.plot(train_error)
plt.title('Training Loss History')
plt.xlabel('Iteration')
plt.ylabel('Loss')

plt.subplot(2, 1, 2)
#plt.plot(stats['train_acc_history'], label='train')
plt.plot(validation_accuracy, label='val')
plt.title('Classification accuracy history')
plt.xlabel('Epoch')
plt.ylabel('Classification accuracy')
```

```
plt.legend()
plt.show()
```




23
```
from utils.vis_utils import visualize_grid
# Credits: http://cs231n.stanford.edu/

# Visualize the weights of the network

def show_net_weights(net):
    W1 = net._modules[0].parameters[0]
    W1 = W1.reshape(3, 32, 32, -1).transpose(3, 1, 2, 0)
    plt.imshow(visualize_grid(W1, padding=3).astype('uint8'))
    plt.gca().axis('off')
    plt.show()

show_net_weights(net)
```



# Tune your hyperparameters (50%)

**What's wrong?**. Looking at the visualizations above, we see that the loss is decreasing more or less linearly, which seems to suggest that the learning rate may be too low. Moreover, there is no gap between the training and validation accuracy, suggesting that the model we used has low capacity, and that we should increase its size. On the other hand, with a very large model we would expect to see more overfitting, which would manifest itself as a very large gap between the training and validation accuracy.

**Tuning**. Tuning the hyperparameters and developing intuition for how they affect the final performance is a large part of using Neural Networks, so we want you to get a lot of practice. Below, you should experiment with different values of the various hyperparameters, including hidden layer size, learning rate, numer of training epochs, and regularization strength.

**Approximate results**. You should be aim to achieve a classification accuracy of greater than 40% on the validation set. Our best network gets over 40% on the validation set.

**Experiment**: You goal in this exercise is to get as good of a result on CIFAR-20 as you can (40% could serve as a reference), with a fully-connected Neural Network.

```
14 import os
```

```
batch_size = 128 # (Reduce the batch size if your computer is unable to handle it)
best_param, best_acc = (50, 0.1, 0.1, 200), 0.190
(hidden_size, lr, weight_decay, epoch) = (200, 0.1, 0.01, 401)
dataset = DataLoader(x_train, y_train, x_val, y_val, x_test, y_test)
net = init_model()
optim = SGD(net, lr=lr, weight_decay=weight_decay)
loss_func = CrossEntropyLoss()
trainer = Trainer(dataset, optim, net, loss_func, epoch, batch_size, validate_interval=40,verbose=True)
# for plot
train_error, validation_accuracy = trainer.train()
# For inspection
out_train = net.predict(x_train)
train_acc = get_classification_accuracy(out_train, y_train)
print("parameters", (hidden_size, lr, weight_decay, epoch))
print("Training acc: ",train_acc)
out_val = net.predict(x_val)
val_acc = get_classification_accuracy(out_val, y_val)
print("Validation acc: ",val_acc)

with open('result','a+') as f:
    f.write(f"parameters: ({(hidden_size, lr, weight_decay, epoch)})\n")
    f.write(f"Training acc {train_acc}\n")
    f.write(f"Validation acc {val_acc}\n")
    if val_acc > best_acc:
        best_acc = val_acc
        best_param = (hidden_size, lr, weight_decay, epoch)
        f.write('------best above ----')
# del net
del dataset
```

```
Epoch 0
Epoch Average Loss: 2.993661
Validate Acc: 0.046
Epoch 40
Epoch Average Loss: 2.078066
Validate Acc: 0.314
Epoch 80
Epoch Average Loss: 1.846425
Validate Acc: 0.362
Epoch 120
Epoch Average Loss: 1.718510
Validate Acc: 0.361
Epoch 160
Epoch Average Loss: 1.635295
Validate Acc: 0.408
Epoch 200
Epoch Average Loss: 1.580332
Validate Acc: 0.419
Epoch 240
Epoch Average Loss: 1.550301
Validate Acc: 0.425
Epoch 280
Epoch Average Loss: 1.533148
Validate Acc: 0.427
Epoch 320
Epoch Average Loss: 1.520434
Validate Acc: 0.428
Epoch 360
Epoch Average Loss: 1.513621
Validate Acc: 0.428
Epoch 400
Epoch Average Loss: 1.508251
Validate Acc: 0.425
parameters (200, 0.1, 0.01, 401)
```

```
Training acc:  0.58375
Validation acc:  0.425
```

**Explain your hyperparameter tuning process below.**

*Your Answer :*

1) Intuitively, a weight decay of 0.1 is too high (especially when we do one update for a batch). So, I change it to 0.05 and then 0.01.

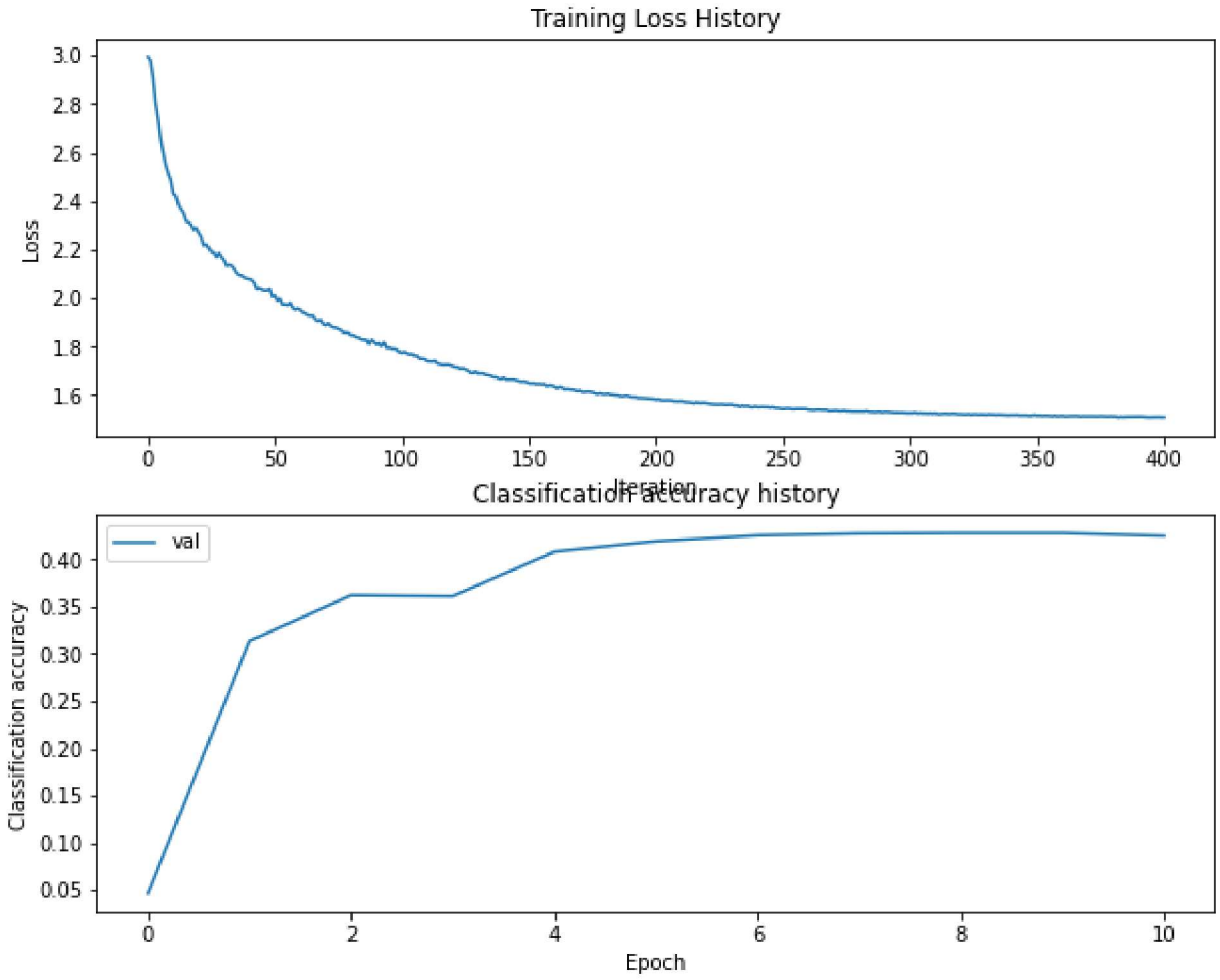
2) Although the hint says the LR is low, experiment with higher LR will corrupt the model. But lr=005 leads to slow convergence and underfit. So, I add exponential lr decay.

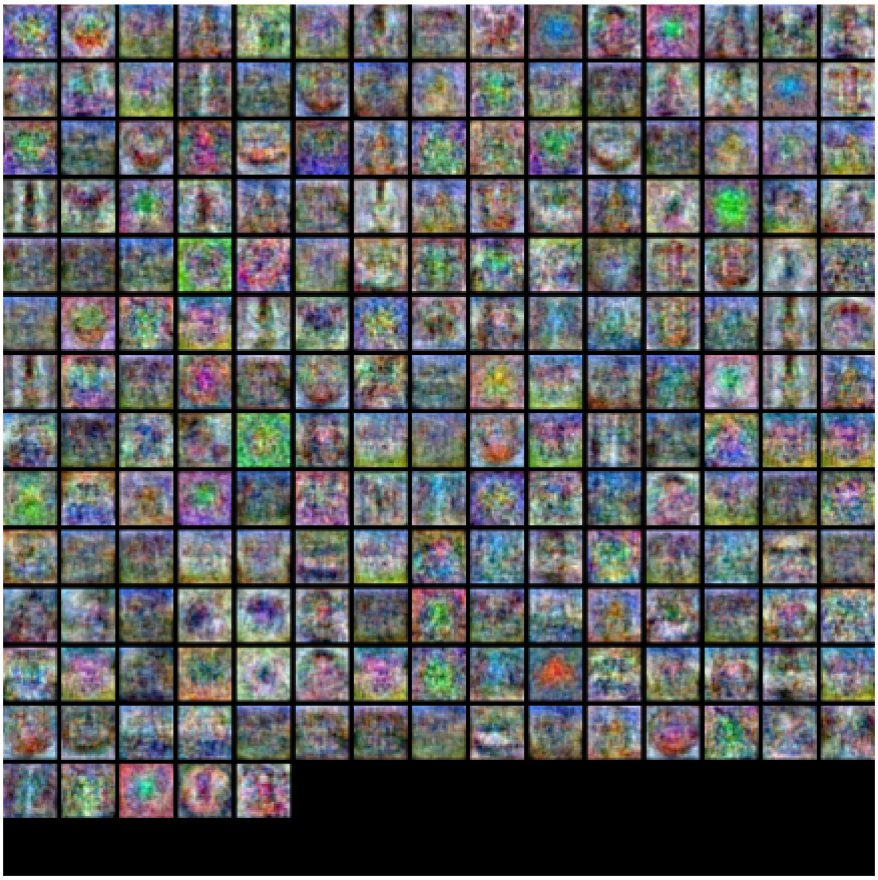
3) With a two layer network, we definitely need to expand the width. So I expand it to 100 then 200.

4) In parameter searching, all epoches are set to 200 for fast training. I did not see overfitting, so in final training I set epoch to 400.

```
# store the best model into this
################################################################################
# TODO: Tune hyperparameters using the validation set. Store your best trained  #
# model hyperparams in best_net.                                                #
#                                                                               #
# To help debug your network, it may help to use visualizations similar to the  #
# ones we used above; these visualizations will have significant qualitative    #
# differences from the ones we saw above for the poorly tuned network.          #
#                                                                               #
# You are now free to test different combinations of hyperparameters to build   #
# various models and test them according to the above plots and visualization   #


# TODO: Show the above plots and visualizations for the default params (already #
# done) and the best hyper-params you obtain. You only need to show this for 2  #
# sets of hyper-params.                                                         #
# You just need to store values for the hyperparameters in best_net_hyperparams #
# as a list in the order
# best_net_hyperparams = [lr, weight_decay, epoch, hidden_size]
################################################################################
best_net = [0.1, 0.01, 401, 200]




# TODO: Plot the training_error and validation_accuracy of the best network (5%)


# Plot the training loss function and validation accuracies
plt.subplot(2, 1, 1)
plt.plot(train_error)
plt.title('Training Loss History')
plt.xlabel('Iteration')
plt.ylabel('Loss')

plt.subplot(2, 1, 2)
#plt.plot(stats['train_acc_history'], label='train')
```

```
plt.plot(validation_accuracy, label='val')
plt.title('Classification accuracy history')
plt.xlabel('Epoch')
plt.ylabel('Classification accuracy')
plt.legend()
plt.show()
# TODO: visualize the weights of the best network (5%)
show_net_weights(net)
```





# Run on the test set (30%)

When you are done experimenting, you should evaluate your final trained network on the test set; you should get above 48%.

```
best_net = net
test_acc = (best_net.predict(x_test) == y_test).mean()
print('Test accuracy: ', test_acc)
```

```
Test accuracy:  0.4125
```

**Inline Question** (10%)

Now that you have trained a Neural Network classifier, you may find that your testing accuracy is much lower than the training accuracy. In what ways can we decrease this gap? Select all that apply.

1. Train on a larger dataset.
2. Add more hidden units.
3. Increase the regularization strength.
4. None of the above.

*Your Answer* :

1 and 3

Train on a larger dataset. Increase the regularization strength.

*Your Explanation* :

The model is over fitting. To reduce overfitting, one approach is adding more data, and another is add penalty to prevent model from over fitting the train data and increase generalization.