

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.

```
47 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.

```
48 # 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

```

49 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]
[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]]
```

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.

```
50 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.

```
51 # 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 calculate
# 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)

```

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

```
53 # 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 gradient
    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

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

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
Epoch Loss: 0.081955
Epoch Loss: 0.079550
Epoch Loss: 0.078298
Epoch Loss: 0.077149
Epoch Loss: 0.075943
Epoch Loss: 0.074927
Epoch Loss: 0.074027
Epoch Loss: 0.074400
Epoch Loss: 0.072842
Epoch Loss: 0.071362
Epoch Loss: 0.070140
Epoch Loss: 0.069109
Epoch Loss: 0.068189
Epoch Loss: 0.067438
Epoch Loss: 0.066542
Epoch Loss: 0.065878
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
Epoch Loss: 0.060049
Epoch Loss: 0.059368
Epoch Loss: 0.059265
Epoch Loss: 0.058653
Epoch Loss: 0.057884
Epoch Loss: 0.057724
Epoch Loss: 0.056640
Epoch Loss: 0.055911
Epoch Loss: 0.055581
Epoch Loss: 0.054974
Epoch Loss: 0.054336
Epoch Loss: 0.053731
Epoch Loss: 0.053237
Epoch Loss: 0.052698
Epoch Loss: 0.052610
Epoch Loss: 0.052149
Epoch Loss: 0.051605
Epoch Loss: 0.051018
Epoch Loss: 0.050427
Epoch Loss: 0.050176
Epoch Loss: 0.050089
Epoch Loss: 0.049610
Epoch Loss: 0.048936
Epoch Loss: 0.048407
Epoch Loss: 0.048042
Epoch Loss: 0.047693
Epoch Loss: 0.047232
Epoch Loss: 0.047006
Epoch Loss: 0.046590
Epoch Loss: 0.046342
Epoch Loss: 0.045836
Epoch Loss: 0.045452
Epoch Loss: 0.045112
Epoch Loss: 0.044795
Epoch Loss: 0.044464

Epoch Loss: 0.044038
Epoch Loss: 0.043724
Epoch Loss: 0.043653
Epoch Loss: 0.043454
Epoch Loss: 0.042933
Epoch Loss: 0.042565
Epoch Loss: 0.042280
Epoch Loss: 0.041901
Epoch Loss: 0.041709
Epoch Loss: 0.041528
Epoch Loss: 0.041169
Epoch Loss: 0.040963
Epoch Loss: 0.040683
Epoch Loss: 0.040507
Epoch Loss: 0.040178
Epoch Loss: 0.039961
Epoch Loss: 0.039609
Epoch Loss: 0.039391
Epoch Loss: 0.039159
Epoch Loss: 0.038825
Epoch Loss: 0.038546
Epoch Loss: 0.038335
Epoch Loss: 0.038039
Epoch Loss: 0.037768
Epoch Loss: 0.037602
Epoch Loss: 0.037523
Epoch Loss: 0.037224
Epoch Loss: 0.036954
Epoch Loss: 0.036836
Epoch Loss: 0.036784
Epoch Loss: 0.036457
Epoch Loss: 0.036186
Epoch Loss: 0.035966
Epoch Loss: 0.035764
Epoch Loss: 0.035549
Epoch Loss: 0.035444
Epoch Loss: 0.035394
Epoch Loss: 0.035143
Epoch Loss: 0.034874
Epoch Loss: 0.034649
Epoch Loss: 0.034474
Epoch Loss: 0.034245
Epoch Loss: 0.034032
Epoch Loss: 0.033865
Epoch Loss: 0.033680
Epoch Loss: 0.033470
Epoch Loss: 0.033298
Epoch Loss: 0.033177
Epoch Loss: 0.032968
Epoch Loss: 0.032779
Epoch Loss: 0.032638
Epoch Loss: 0.032442
Epoch Loss: 0.032259
Epoch Loss: 0.032117
Epoch Loss: 0.032015
Epoch Loss: 0.032165
Epoch Loss: 0.031888
Epoch Loss: 0.031721
Epoch Loss: 0.031566
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Epoch Loss: 0.031292
Epoch Loss: 0.031094
Epoch Loss: 0.030956
Epoch Loss: 0.030888
Epoch Loss: 0.030697

Epoch Loss: 0.030521
Epoch Loss: 0.030383
Epoch Loss: 0.030241
Epoch Loss: 0.030111
Epoch Loss: 0.029963
Epoch Loss: 0.029830
Epoch Loss: 0.029668
Epoch Loss: 0.029528
Epoch Loss: 0.029408
Epoch Loss: 0.029255
Epoch Loss: 0.029114
Epoch Loss: 0.029005
Epoch Loss: 0.028858
Epoch Loss: 0.028718
Epoch Loss: 0.028612
Epoch Loss: 0.028480
Epoch Loss: 0.028342
Epoch Loss: 0.028228
Epoch Loss: 0.028112
Epoch Loss: 0.028042
Epoch Loss: 0.028009
Epoch Loss: 0.027869
Epoch Loss: 0.027722
Epoch Loss: 0.027666
Epoch Loss: 0.027744
Epoch Loss: 0.027542
Epoch Loss: 0.027385
Epoch Loss: 0.027244
Epoch Loss: 0.027115
Epoch Loss: 0.027015
Epoch Loss: 0.026908
Epoch Loss: 0.026801
Epoch Loss: 0.026707
Epoch Loss: 0.026660
Epoch Loss: 0.026527
Epoch Loss: 0.026404
Epoch Loss: 0.026311
Epoch Loss: 0.026192
Epoch Loss: 0.026078
Epoch Loss: 0.025984
Epoch Loss: 0.025883
Epoch Loss: 0.025771
Epoch Loss: 0.025673
Epoch Loss: 0.025583
Epoch Loss: 0.025474
Epoch Loss: 0.025383
Epoch Loss: 0.025316
Epoch Loss: 0.025206
Epoch Loss: 0.025106
Epoch Loss: 0.025025
Epoch Loss: 0.024921
Epoch Loss: 0.024822
Epoch Loss: 0.024753
Epoch Loss: 0.024686
Epoch Loss: 0.024655
Epoch Loss: 0.024557
Epoch Loss: 0.024513
Epoch Loss: 0.024400
Epoch Loss: 0.024295
Epoch Loss: 0.024202
Epoch Loss: 0.024120
Epoch Loss: 0.024023
Epoch Loss: 0.023949
Epoch Loss: 0.023882
Epoch Loss: 0.023873

Epoch Loss: 0.023803
Epoch Loss: 0.023696
Epoch Loss: 0.023608
Epoch Loss: 0.023513
Epoch Loss: 0.023421
Epoch Loss: 0.023337
Epoch Loss: 0.023263
Epoch Loss: 0.023175
Epoch Loss: 0.023089
Epoch Loss: 0.023058
Epoch Loss: 0.022986
Epoch Loss: 0.022898
Epoch Loss: 0.022820
Epoch Loss: 0.022764
Epoch Loss: 0.022686
Epoch Loss: 0.022602
Epoch Loss: 0.022536
Epoch Loss: 0.022452
Epoch Loss: 0.022371
Epoch Loss: 0.022310
Epoch Loss: 0.022230
Epoch Loss: 0.022152
Epoch Loss: 0.022091
Epoch Loss: 0.022017
Epoch Loss: 0.021940
Epoch Loss: 0.021877
Epoch Loss: 0.021808
Epoch Loss: 0.021733
Epoch Loss: 0.021676
Epoch Loss: 0.021642
Epoch Loss: 0.021625
Epoch Loss: 0.021543
Epoch Loss: 0.021474
Epoch Loss: 0.021424
Epoch Loss: 0.021348
Epoch Loss: 0.021282
Epoch Loss: 0.021211
Epoch Loss: 0.021137
Epoch Loss: 0.021074
Epoch Loss: 0.021011
Epoch Loss: 0.020940
Epoch Loss: 0.020878
Epoch Loss: 0.020819
Epoch Loss: 0.020751
Epoch Loss: 0.020688
Epoch Loss: 0.020633
Epoch Loss: 0.020566
Epoch Loss: 0.020504
Epoch Loss: 0.020451
Epoch Loss: 0.020385
Epoch Loss: 0.020313
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

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
Epoch Loss: 0.018792
Epoch Loss: 0.018782
Epoch Loss: 0.018733
Epoch Loss: 0.018664
Epoch Loss: 0.018605
Epoch Loss: 0.018545
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```

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

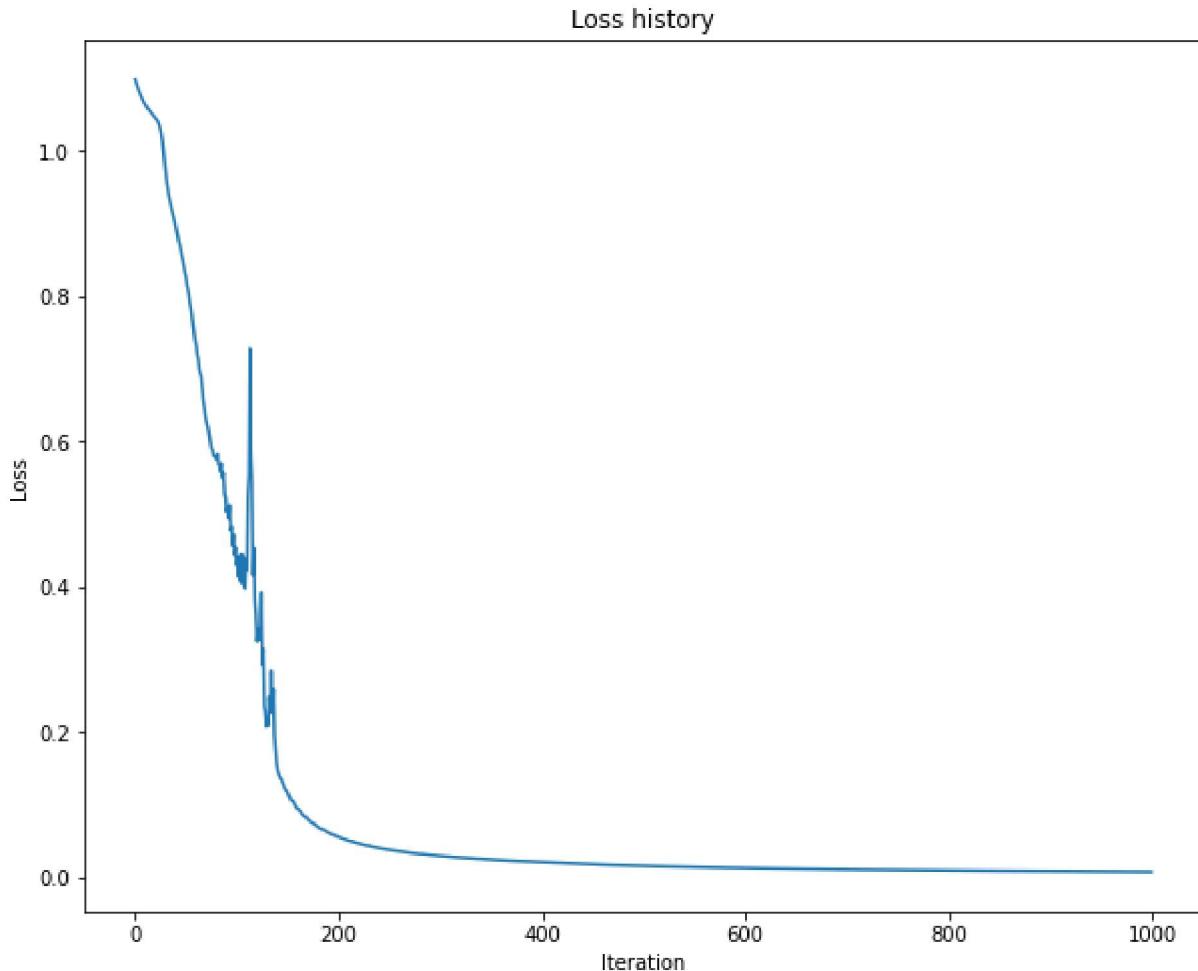
[2 1 0 1 2 0 0 2 0 0]
```

```
[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])

56 # 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')

56 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']

3 # Import more utilities 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.

```

4 # 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

```

7 input_size = 3072
hidden_size = 100 # 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])

```

```

6 # 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)

7 #Initialize the trainer class by passing the above modules
trainer = Trainer(dataset, optim, net, loss_func, epoch, batch_size, validate_interval=20)

8 # 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 Average Loss: 2.995389
Validate Acc: 0.038
Epoch Average Loss: 2.684753
Validate Acc: 0.155
Epoch Average Loss: 2.651311
Validate Acc: 0.183
Epoch Average Loss: 2.658516
Validate Acc: 0.216
Epoch Average Loss: 2.631377
Validate Acc: 0.213
Epoch Average Loss: 2.630894
Validate Acc: 0.233
Epoch Average Loss: 2.625427
Validate Acc: 0.195
Epoch Average Loss: 2.632189
Validate Acc: 0.206
Epoch Average Loss: 2.632698
Validate Acc: 0.198
Epoch Average Loss: 2.627943
Validate Acc: 0.148

```

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

```

20 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: 0.198875
Validation acc: 0.1975

```

Debug the training

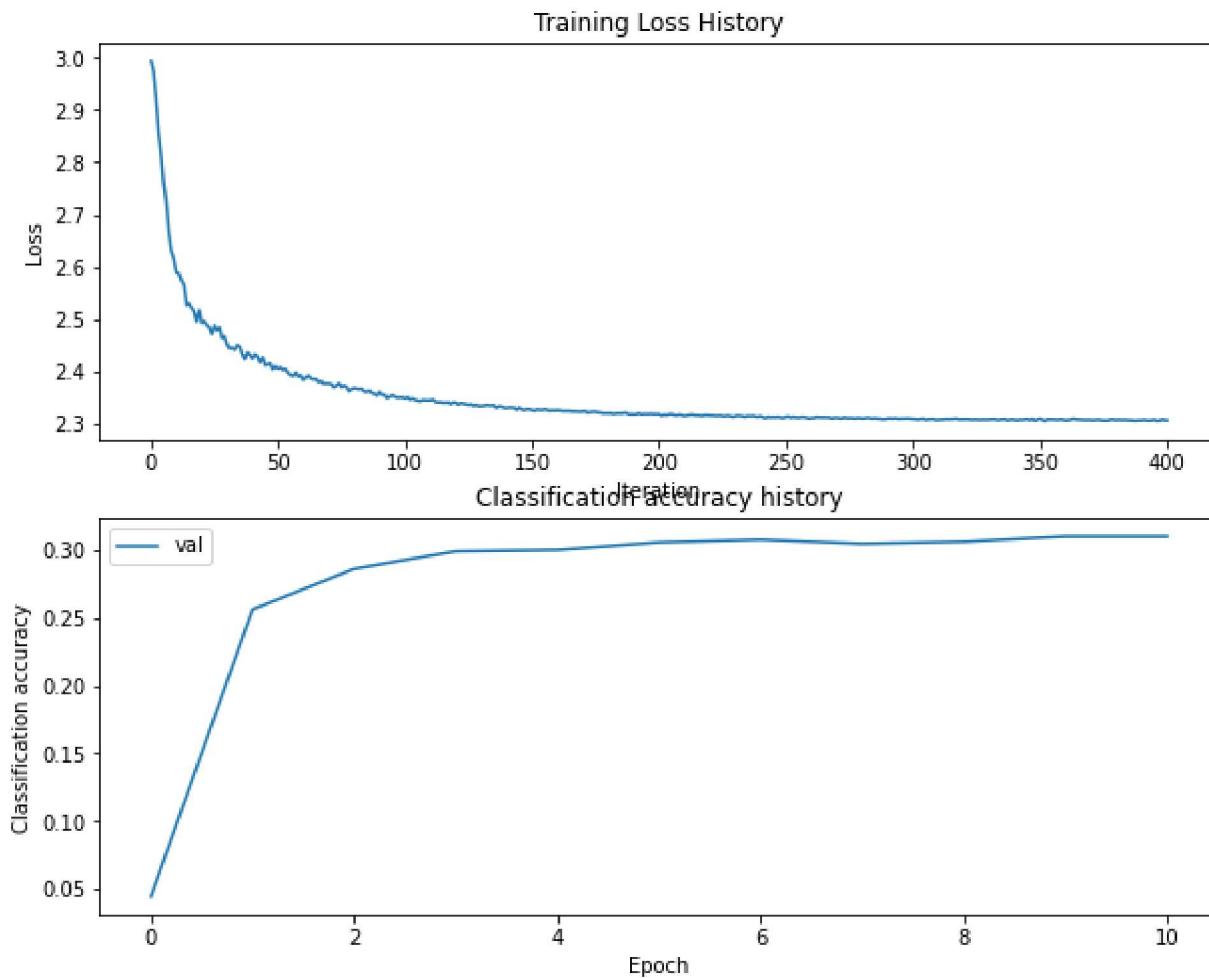
With the default parameters we provided above, you should get a validation accuracy of around ~0.2 on the validation set. This isn't very good.

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.

```
11 # 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()
```

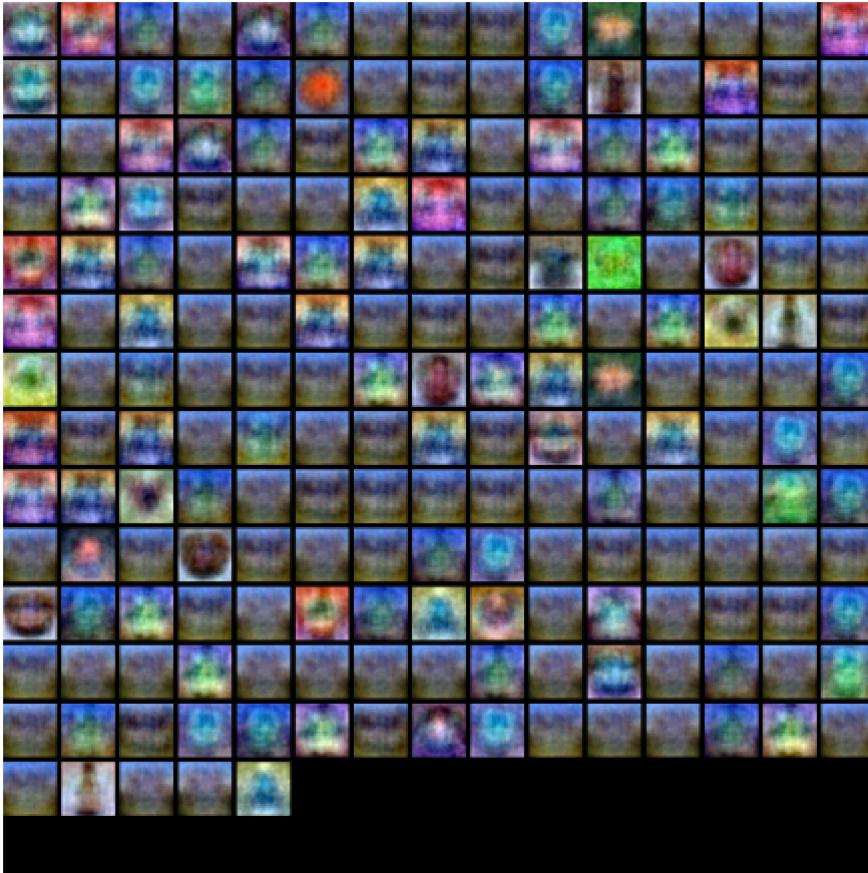


```
12 from utils.vis_utils import visualize_grid
# Credits: http://cs231n.stanford.edu/
```

```
# 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, number 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: Your goal in this exercise is to get as good of a result on CIFAR-10 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=0.05 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%)

```

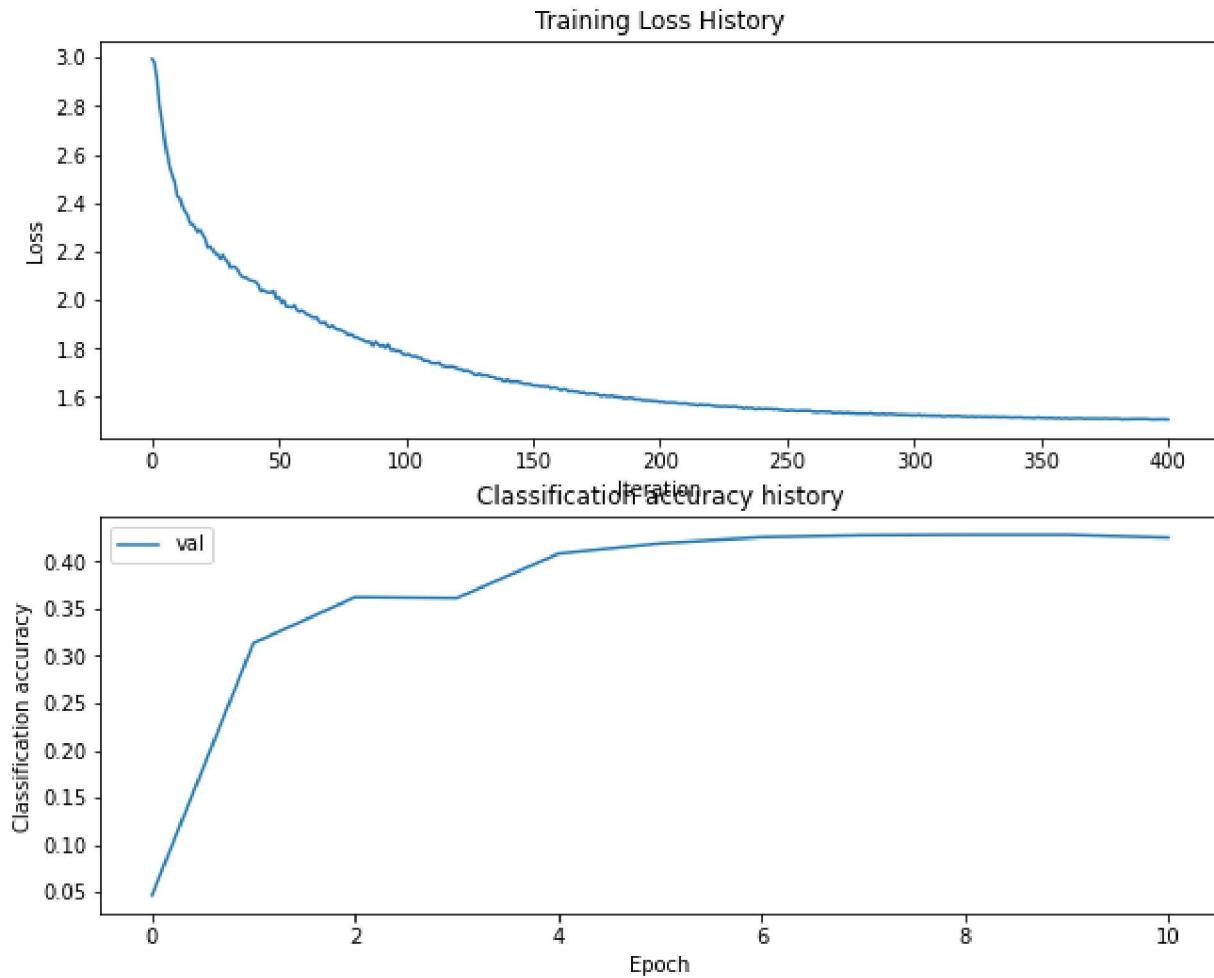
```

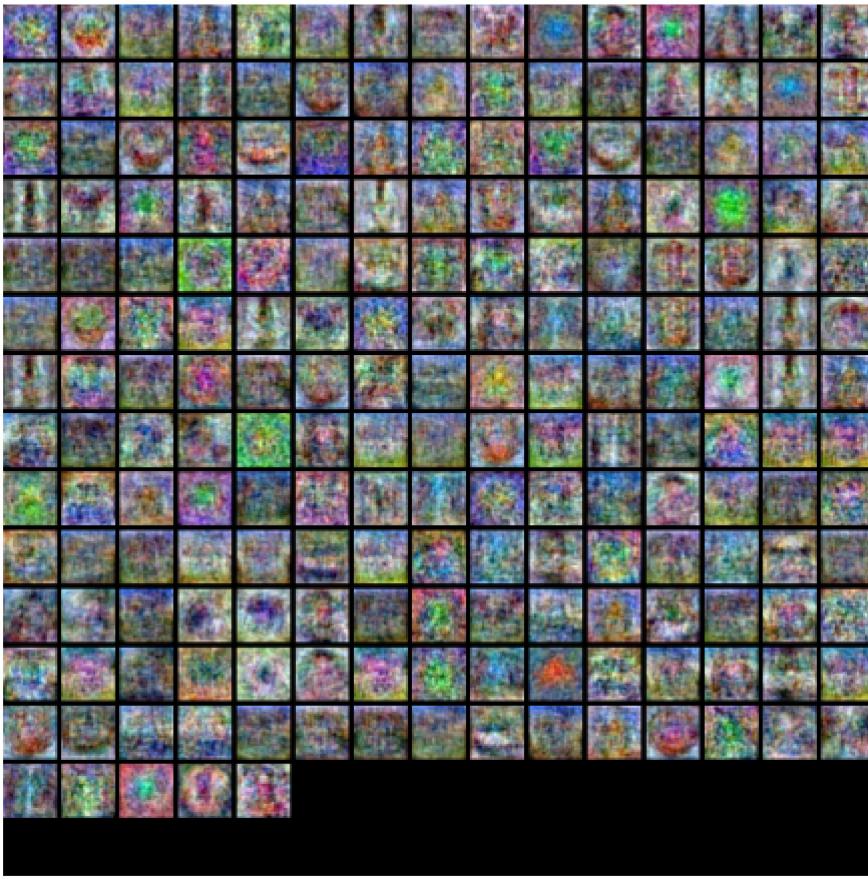
15 # Plot the training loss function and validation accuracies
plt.subplot(2, 1, 1)
plt.plot(train_error)
plt.title('Training Loss History')
plt.xlabel('Iteration')
plt.ylabel('Loss')

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%.

```
16 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.

