

## 1 Optimization and Fitting

1. The implementation of the forward and the backward pass is completed.
2. The implementation of the gradient descent is completed. I chose the learning rate as  $1e-4$ . The figure is shown in Figure 1:

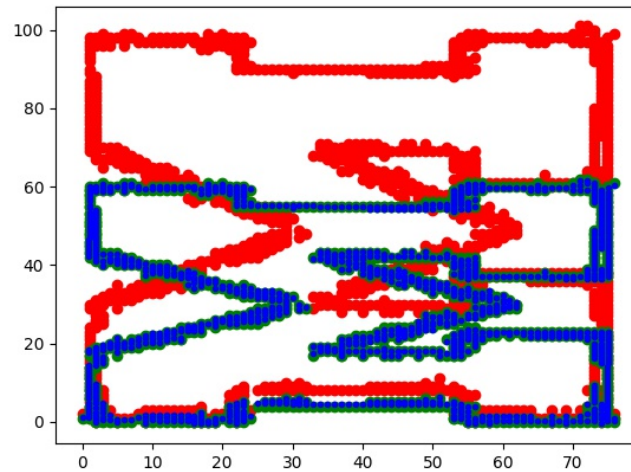


Figure 1: case.jpg

## 2 Softmax Classifier Plus 1-layer NN

1. The implementation of ReLU layer and softmax layer is finished. The implementation of the softmax classifier is finished.
2. Hyperparameters and train accuracy vs. validation accuracy.

I use the default hyperparameters for this single layer, i.e.,  $\text{learning\_rate} = 5e-3$ ,  $\text{lr\_decay} = 0.9$ ,  $\text{num\_epochs} = 60$ ,  $\text{batch\_size} = 256$ ,  $\text{reg} = 0.0$ .

Below Figure 7 is the training vs val curve.

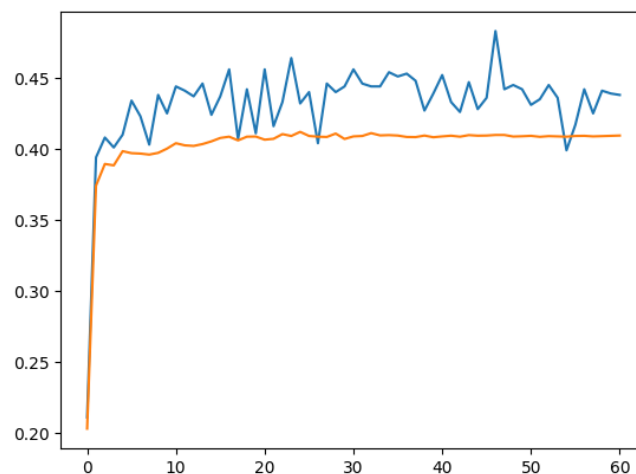


Figure 2: train vs val

x axis is epoch. y axis is accuracy. Orange is validation. Blue is training.

3. Test set accuracy evaluation.

Test accuracy: 41.07%

4. Ablation studies for hyperparameters. We use the default hyperparameters as the baseline and do the ablation study over different hyperparameters. First again, the default hyperparameters are as following:

the default hyperparameters for this single layer, i.e.,  $\text{learning\_rate} = 5e-3$ ,  $\text{lr\_decay} = 0.9$ ,  $\text{num\_epochs} = 30$ ,  $\text{batch\_size} = 256$ ,  $\text{reg} = 0.0$ .

Then, we ablate each hyperparameter one by one to do the ablation study and experiment over different hyperparameters training the CIFAR10.

- (a) Discussion over the regularizer;

**Test Acc with Various Reg Coeff**

<u>Aa</u> Regularization Coeff	<u>#</u> Test Acc	-
<b>0.0</b>	0.4098	
<b>0.001</b>	0.4103	
<b>0.01</b>	0.4101	
<b>0.1</b>	0.4108	

Figure 3: reg

we can see that the training performance is not sensitive to the choice of regularizer.

- (b) Discussion over the batch-size;

**Test Acc with Various Batch Size**

<u>Aa</u> Batch Size	<u>#</u> Test Acc	
<b>128</b>	0.4125	
<b>256</b>	0.4111	
<b>512</b>	0.4059	
<b>1024</b>	0.3997	

Figure 4: batch size

we can see that with a larger batch\_size in this model, the test acc is worse.

- (c) Discussion over the learning-rate;

**Test Acc with diff. LR**

<u>Aa</u> Learning Rate	<u>#</u> Test Acc	
<b>1e-3</b>	0.409	
<b>5e-3</b>	0.4088	
<b>1e-2</b>	0.4078	
<b>5e-2</b>	0.3968	

Figure 5: LR

we can see that when the learning rate is too large, the test acc is low because the large LR may lead to underfitting.

(d) Discussion over the LR decay;

**Test Acc with diff. LR decay**

<u>Aa</u> LR Decay	<u>#</u> Test Acc
<b>1</b>	<b>0.3988</b>
<b>0.99</b>	<b>0.4051</b>
<b>0.9</b>	<b>0.4092</b>
<b>0.8</b>	<b>0.4108</b>

Figure 6: decay

we can see the magic of the learning rate decay, which means after epoch the learning rate should be tuned smaller for better fine-grained optimization. Otherwise without learning rate decay, the test acc is very low.

### 3 Softmax Classifier with Hidden Layers

1. The Implementation of the NN is finished.
2. Hyperparameters and train accuracy vs. validation accuracy.

I chose 0 regularizer coeff, 128 batch size, 0.1 learning rate, 0.9 lr decay, 100 hidden dim. 30 epoches for training

The training val curve is below:

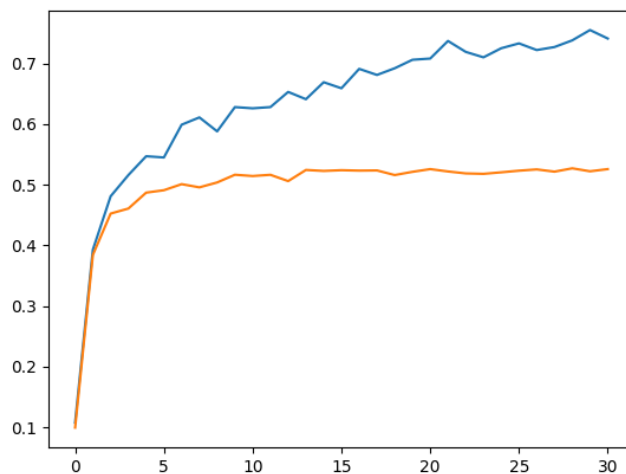


Figure 7: train vs val

The axis meaning and the color is as last problem.

3. Test set accuracy evaluation.

Test accuracy is 51.4%

4. Ablation studies for hyperparamters.

Then, we ablate each hyperparamter one by one to do the ablation study and experiment over different hyperparamters training the CIFAR10.

- (a) Discussion over the hidden dim:

**Test Acc with Various Hidden Dim**

<b>Aa</b> Hidden Dim	<b>#</b> Test Acc
<b>50</b>	<b>0.503</b>
<b>100</b>	<b>0.514</b>
<b>150</b>	<b>0.518</b>
<b>200</b>	<b>0.5272</b>

Figure 8: hidden dim

we can see that the training performance really depends on the dim of the hidden layer. when the hidden layer size is larger, we can possibly get even better test accuracy.

(b) Discussion over the batch-size;

**Test Acc with Various Batch Size**

<b>Aa</b> Batch Size	<b>#</b> Test Acc
<b>128</b>	<b>0.514</b>
<b>256</b>	<b>0.5052</b>
<b>512</b>	<b>0.4946</b>
<b>1024</b>	<b>0.4696</b>

Figure 9: batch size

we can see that with a larger batch\_size in this model, the test acc is worse.

(c) Discussion over the learning-rate;

**Test Acc with diff. LR**

<b>Aa</b> Learning Rate	<b>#</b> Test Acc
<b>0.2</b>	<b>0.4944</b>
<b>0.1</b>	<b>0.514</b>
<b>0.05</b>	<b>0.4996</b>
<b>0.01</b>	<b>0.4621</b>

Figure 10: LR

we can see that when the learning rate is too large or too low, the test acc is low because the large LR may lead to underfitting. This teaches me that we need to finetune the learning rate for SGD carefully.

(d) Discussion over the LR decay;

**Test Acc with diff. LR decay**

<u>Aa</u> LR Decay	<u>#</u> Test Acc
<b>1</b>	<b>0.4844</b>
<b>0.99</b>	<b>0.4941</b>
<b>0.9</b>	<b>0.514</b>
<b>0.8</b>	<b>0.5024</b>

Figure 11: decay

we can see the magic of the learning rate decay again, which means after epoch the learning rate should be tuned smaller for better fine-grained optimization. Otherwise without learning rate decay, the test acc is very low. Also, you should tune the decay carefully, either too large or too small may lead to underfitting.

## 4 Fooling Images: Adversarial Examples for the NN in the last section

1. The gradients w.r.t. the input are implemented in the code.
2. Target PGD attack implementation. Ascent gradient is implemented in the code.
3. Discussions over the robustness of the model. It is obvious that my model is not adversarially robust at all considering such a small imperceptible perturbation can lead to our model's misclassification over a previously correctly classified image. In detail, the correct truck image is original correctly classified. After one-step target attack, the resulted image is fooling the model to classify the image as automobile.

The difference norm is 91 in the scale of  $3 \times 32 \times 32$   $[0, 255]$  pixel-value image, which is really small, and the figure is black due to almost 0 pixel value.

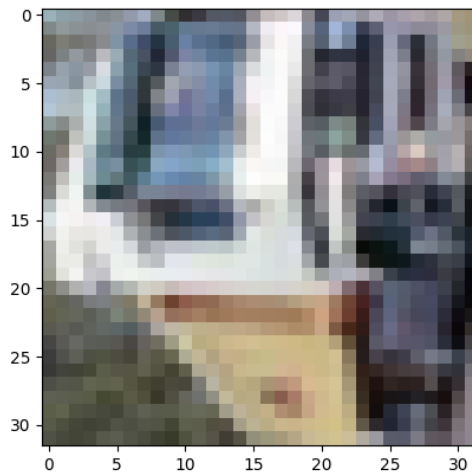


Figure 12: correct



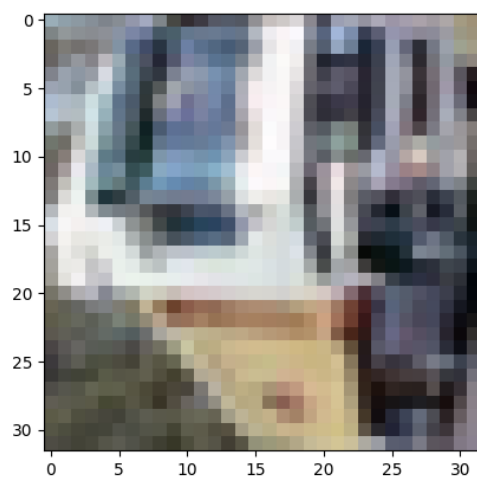


Figure 13: fooled

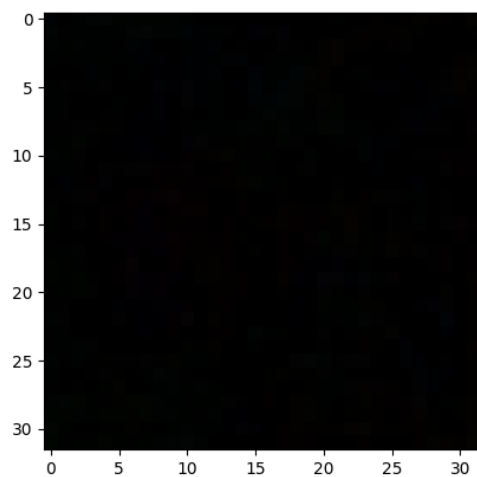


Figure 14: diff