1 True/False Questions (30 pts)

Problem 1.1 – False

Explanation: The outputs of BN module do not have to have exactly the zero mean. Batch normalization would generate the outputs such that they have the same mean value.

Problem 1.2 – False

Explanation: With the help of PyTorch, as long as we have defined our optimizer and loss function, we only need to write the code "loss.backward()" to let PyTorch help us compute gradients with back-propagation. Therefore, we do not need to write our own code for back-propagation.

Problem 1.3 – False

Explanation: Data augmentation is suitable for deep neural network, because deep neural network learns better with more data. However, data augmentation may hurt small models as they may underfit. Therefore, data augmentation is not always beneficial for all kinds of CNN models.

Problem 1.4 – False

Explanation: Dropout is enabled during the training phase with the purpose of combatting overfitting. Dropout will introduce extra computation cost during model training, and dropout does not decide whether a CNN model would converge (quickly) or not.

Problem 1.5 – False

Explanation: Dropout sometimes does not cooperate well with L-norm regularization.

Problem 1.6 – False

Explanation: A high sparsity means that there are many 0s in weight parameters. L2 regularization has a circular loss contour, while L1 regularization has a diamond loss contour. L1 loss usually meets the feasible solution loss on the corner of the diamond shape. Therefore, L1 regularization is more likely to obtain sparse weights.

Solutions continue in the next page.

Problem 1.7 – True

Explanation: Compared with ReLU, leaky ReLU could solve the problem of dead neurons because its negative side is not zero. However, the inconsistent slope makes the training process of some neural networks unstable.

Problem 1.8 – True

Explanation: Compare 3 * 3 regular convolution vs. 3 * 3 depthwise-separable convolution, the theoretical speedup could be calculated below.

$$speedup = \frac{3 \times 3 \times M \times N \times D_F \times D_F}{3 \times 3 \times M \times D_F \times D_F + D_F \times D_F \times M \times N}$$

If N and M are large enough, the theoretical speedup is approximately to be 9.

Problem 1.9 – True

Explanation: One strategy of SqueezeNet is to down-sample late in the network to spend more computation budgets (MACs) on larger activation maps. Therefore, it is correct to say that SqueezeNet puts most of the computations in later stage of the CNN design.

Problem 1.10 – False

Explanation: Shortcut connections in ResNet make the loss surface smoother and easier to optimize.

Solutions for Lab (1) are in the next page.

2 Lab (1): Training SimpleNN for CIFAR-10 classification (15 pts)

(a) (2 pts) As a sanity check, we should verify the implementation of the SimpleNN model at **Step 0**. How can you check whether the model is implemented correctly?

Hint: 1) Consider creating dummy inputs that are of the same size as CIFAR-10 images, passing them through the model, and see if the model's outputs are of the correct shape. 2) Count the total number of parameters of all conv/FC layers and see if it meets your expectation.

Question (a) Solution:

To address the 2 hints given in this problem, I made use of some of my codes written in Homework 1. First, I randomly generated 5 data points with the image format (RGB channels * width * height = 3 * 32 * 32). Then I passed them through my SimpleNN model. The model's output has a shape of (5, 10), where 5 is the number of data points and 10 is the number of output channels of the third fully connected layer as well as the total number of classes of all CIFAR-10 images. Second, I created a table to show the shape and the total number of weight parameters of each layer in my SimpleNN. The table is shown below.

Layer Name	**Layer Shape**	**Number of Weight Parameters**
CONV1	(8, 3, 5, 5)	600
CONV2	(16, 8, 3, 3)	1152
FC1	(120, 576)	69120
FC2	(84, 120)	10080
FC3	(10, 84)	840

For CONV1, 8 * 3 * 5 * 5 = 600.

For CONV2, 16 * 8 * 3 * 3 = 1152.

For FC1, 120 * 576 = 69120.

For FC2, 84 * 120 = 10080.

For FC3, 10 * 84 = 840.

The total number of parameters of all layers is 600 + 1152 + 69120 + 10080 + 840 = 81792.

Given the table and calculations above, it is very easy to demonstrate the second hint.

(b) (2 pts) Data preprocessing is crucial to enable successful training and inference of DNN models. Specify the preprocessing functions at **Step 1** and briefly discuss what operations you use and why.

Question (b) Solution:

I used two operations for data preprocessing. First, I used the "ToTensor" function because I want to convert my input NumPy array (image dimension information stored in multidimensional arrays) to a torch tensor, as well as to normalize my array (image pixel values) to a specific range from 0 to 1 (including both 0 and 1). Second, given the hint for this problem, I used the "Normalize" function because I want to normalize my input with the recommended mean and standard deviation for all the red, green and blue (RGB) channels.

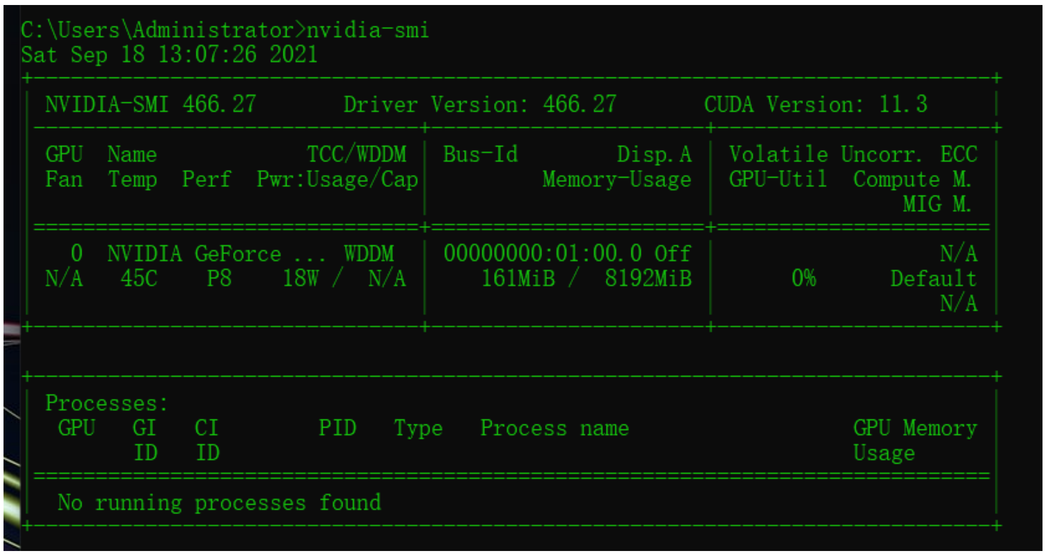
(c) (2 pts) During the training, we need to keep feeding data to the model, which requires an efficient data loading process. This is typically achieved by setting up a `dataset` and a `dataloader`. Please go to **Step 2** and build the actual training/validation datasets and dataloaders. Note, instead of using the `CIFAR10` dataset class from `torchvision.datasets`, here you are asked to use our own CIFAR-10 dataset class, which is imported from `tools.dataset`. As for the dataloader, we encourage you to use `torch.utils.data.DataLoader`.

Question (c) has been completed in code block Step 2.

(d) (2 pts) Go to **Step 3** to instantiate and deploy the SimpleNN model on GPUs for efficient training. How can you verify that your model is indeed deployed on GPU? (Hint: check `nvidia-smi`)

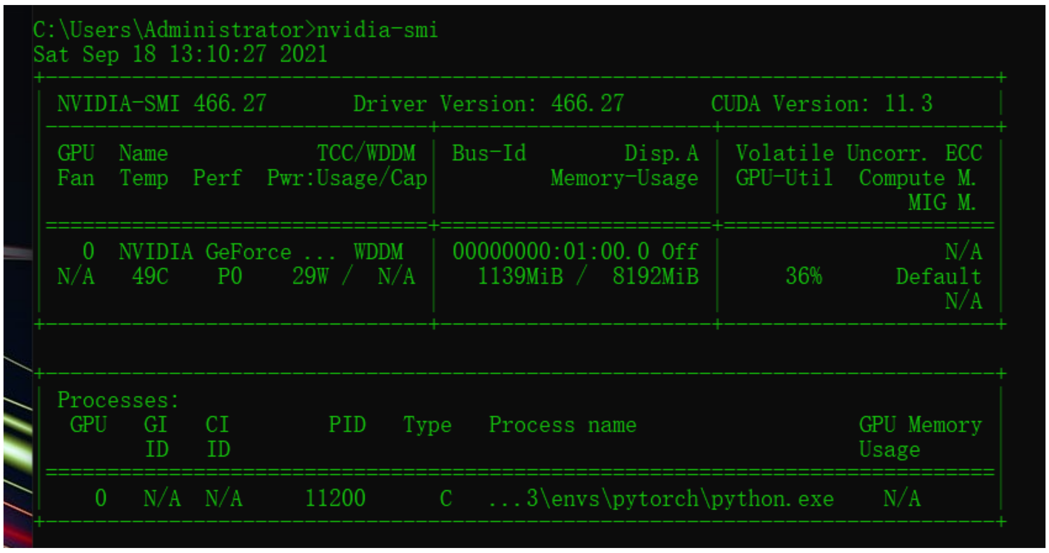
Question (d) Solution:

Before model deployment, I checked whether "cuda" was available. My computer has a RTX 2070, on which I can instantiate and deploy my SimpleNN model. To verify that my model is indeed deployed on my GPU, I typed "nvidia-smi" in the Command Line to check my GPU status before and during model training.



```
C:\Users\Administrator>nvidia-smi
Sat Sep 18 13:07:26 2021
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 466.27       Driver Version: 466.27       CUDA Version: 11.3     |
|-------------------------------+----------------------+----------------------+
| GPU  Name            TCC/WDDM | Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|                               |                      |               MIG M. |
|===============================+======================+======================|
|   0  NVIDIA GeForce ... WDDM  | 00000000:01:00.0 Off |                  N/A |
| N/A   45C    P8    18W /  N/A |    161MiB /  8192MiB |      0%      Default |
|                               |                      |                  N/A |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                                  |
|  GPU   GI   CI        PID   Type   Process name                  GPU Memory |
|        ID   ID                                                   Usage      |
|=============================================================================|
|  No running processes found                                                 |
+-----------------------------------------------------------------------------+
```



```
C:\Users\Administrator>nvidia-smi
Sat Sep 18 13:10:27 2021
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 466.27       Driver Version: 466.27       CUDA Version: 11.3     |
|-------------------------------+----------------------+----------------------+
| GPU  Name            TCC/WDDM | Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|                               |                      |               MIG M. |
|===============================+======================+======================|
|   0  NVIDIA GeForce ... WDDM  | 00000000:01:00.0 Off |                  N/A |
| N/A   49C    P0    29W /  N/A |   1139MiB /  8192MiB |     36%      Default |
|                               |                      |                  N/A |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                                  |
|  GPU   GI   CI        PID   Type   Process name                  GPU Memory |
|        ID   ID                                                   Usage      |
|=============================================================================|
|    0   N/A  N/A     11200      C   ...3\envs\pytorch\python.exe    N/A      |
+-----------------------------------------------------------------------------+
```

Two figures are shown above. The first figure shows my GPU status when my SimpleNN model is not training, and the second figure shows my GPU status when I am training the model. The differences among the above two figures could be concluded in the table below.

Model Status	Not Training	Training
GPU Power Usage	18W	29W
GPU Memory Usage	161MiB / 8192MiB	1139MiB / 8192MiB
GPU Utility	0%	36%
GPU Processes	No running processes found	Process name – python.exe

Therefore, my GPU is indeed working during my SimpleNN model training.

(e) (2 pts) Loss functions are used to encode the learning objective. Now, we need to define this problem's loss function as well as the optimizer which will update our model's parameters to minimize the loss. In **Step 4**, please fill out the loss function and optimizer part.

(f) (2 pts) Please go to **Step 5** to set up the training process of SimpleNN on the CIFAR-10 dataset. Follow the detailed instructions in **Step 5** for guidance.

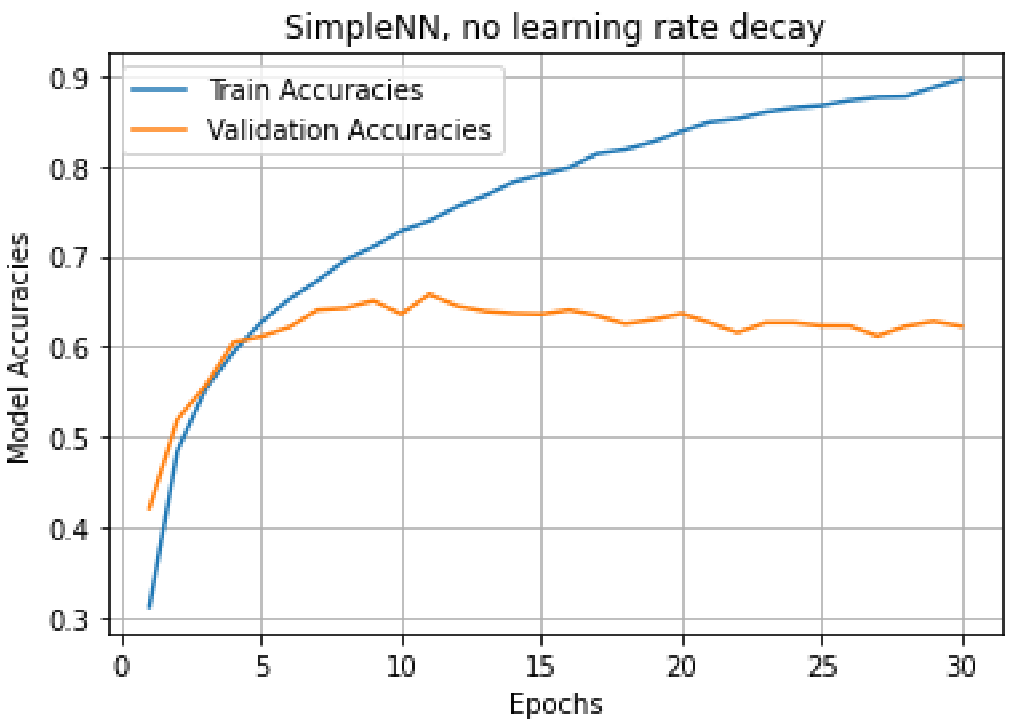
Question (e) and (f) have been completed in code blocks Step 4 and Step 5.

(g) (3 pts) You can start training now **with the provided hyperparameter setting**. What is the initial loss value before you conduct any training step? How is it related to the number of classes in CIFAR-10? What can you observe from **training accuracy** and **validation accuracy**? Do you notice any problems with the current training pipeline?

Question (g) Solution:

The initial loss value before any training step is 2.3086, which is close to 2.31. For SimpleNN model, I use the cross-entropy loss $l_{CE} = -\sum_j y_j \log(s_j)$ as the loss function, and CIFAR-10 image dataset has a total number of 10 classes. Before any training, the model weights are initialized with evenly random numbers, and the model itself is just randomly guessing the output. Therefore, s will be approximately equal to $\frac{1}{N}, N = 10$, and the initial loss would be around the value of $\log(N) \approx 2.31, N = 10$.

Question (g) Solution continues in the next page.



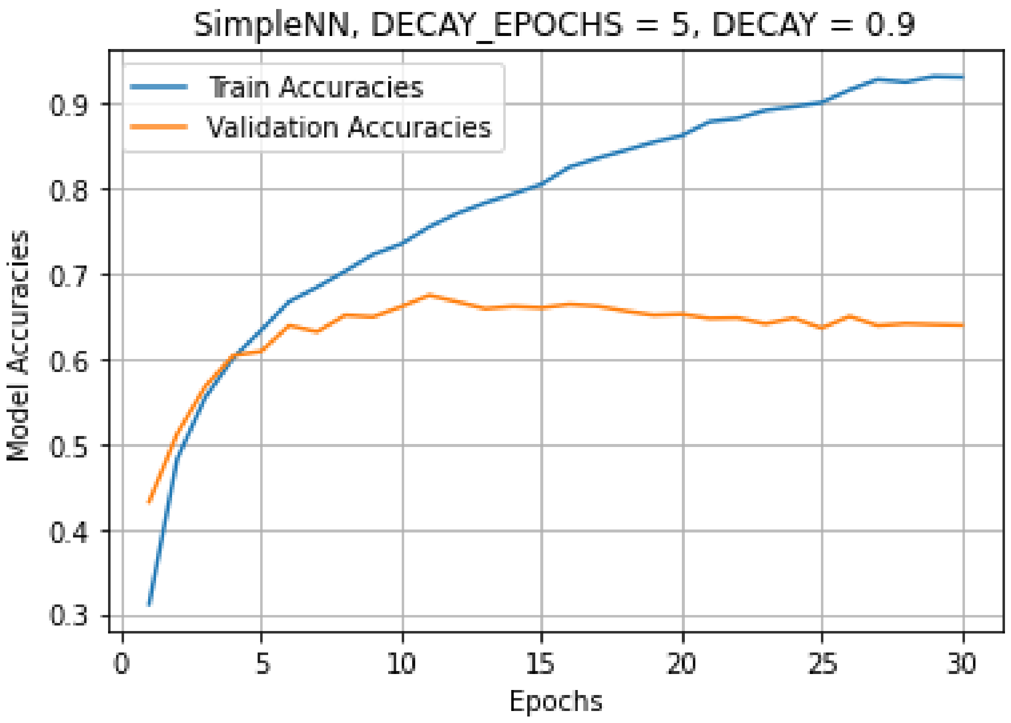
Given the printing result after running code blocks, the best validation accuracy is 65.84%, which is better than 63%. Given the figure shown above, we can observe that the training accuracy continuously increases with more epochs, from around 31% to approximately 90%. However, the validation accuracy slowly increases within the first 10 epochs, from around 42% to about 65%, then fluctuates or even decreases a bit for the rest of 20 epochs. Based on such observation, the current training pipeline would certainly result in model overfitting problem, as well as the problem that the trained model does not have a good validation accuracy.

(h) (**Bonus**, 4 pts) Currently, we do not decay the learning rate during the training. Try to decay the learning rate (you may play with the `DECAY_EPOCHS` and `DECAY` hyperparameters in Step 5). What can you observe compared with no learning rate decay?

Question (h) Solution:

I modified the DECAY_EPOCHS to 5 and DECAY to 0.9, which means every 5 epochs, the learning rate will decay to 90% of its current value. Given the printing result after running code blocks, the best validation accuracy is 67.42%, which is slightly better than 65.84% with no learning rate decay.

Question (h) Solution continues in the next page.



Given the figure above, compared with no learning rate decay model, the best training accuracy and validation accuracy of learning rate decay model are both slightly higher (93% vs. 90% and 67.42% vs. 65.84%), and it takes around 2 more epochs to reach model overfitting. However, the learning rate decay model still has the same two problems as the no learning rate decay model: bad validation accuracy and serious model overfitting.

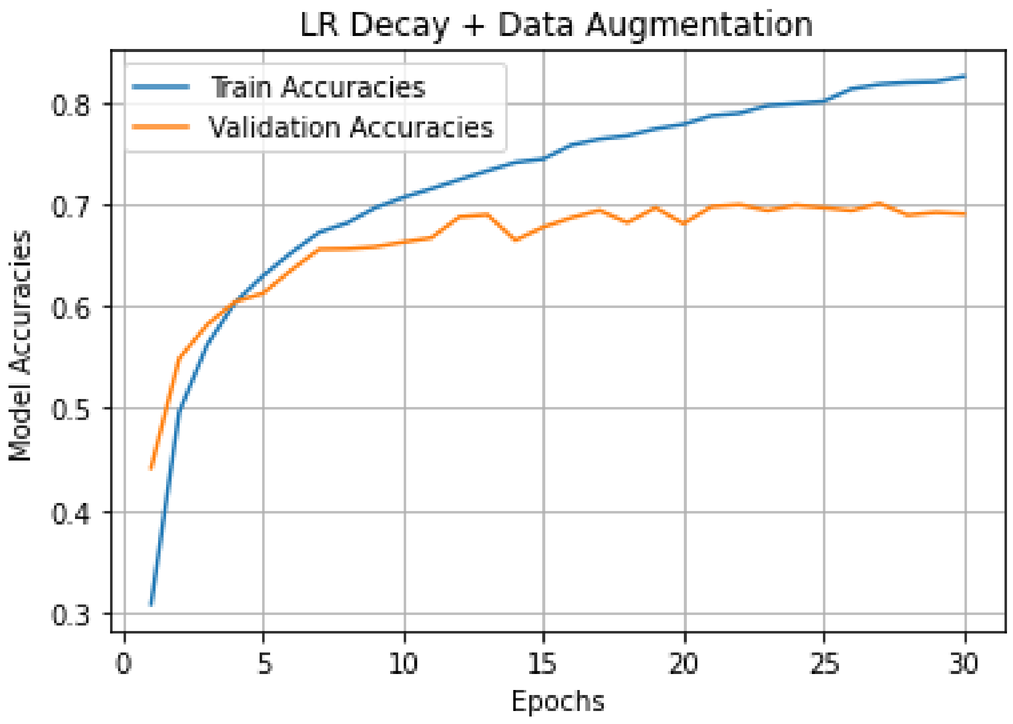
3 Lab (2): Improving the training pipeline (35 pts)

(a) (6 pts) Data augmentation techniques help combat overfitting. Please add two data augmentations — *random crop* and *random flip* — into the training pipeline. You may explore some options (hyperparameters) for these data augmentations. What kind of options (hyperparameters) for these data augmentations can give the best result?

Question (a) Solution:

Incorporating data augmentation into the training pipeline, after several attempts with different hyperparameters, I found that a probability of 0.5 (p = 0.5) for random horizontal flip and setting pad_if_needed as "True" would explicitly improve my model's performance. According to the printing result after running the code block for training and validation, the best validation accuracy is 70.06%, which is better than both models in Lab (1).

Question (a) Solution continues in the next page.

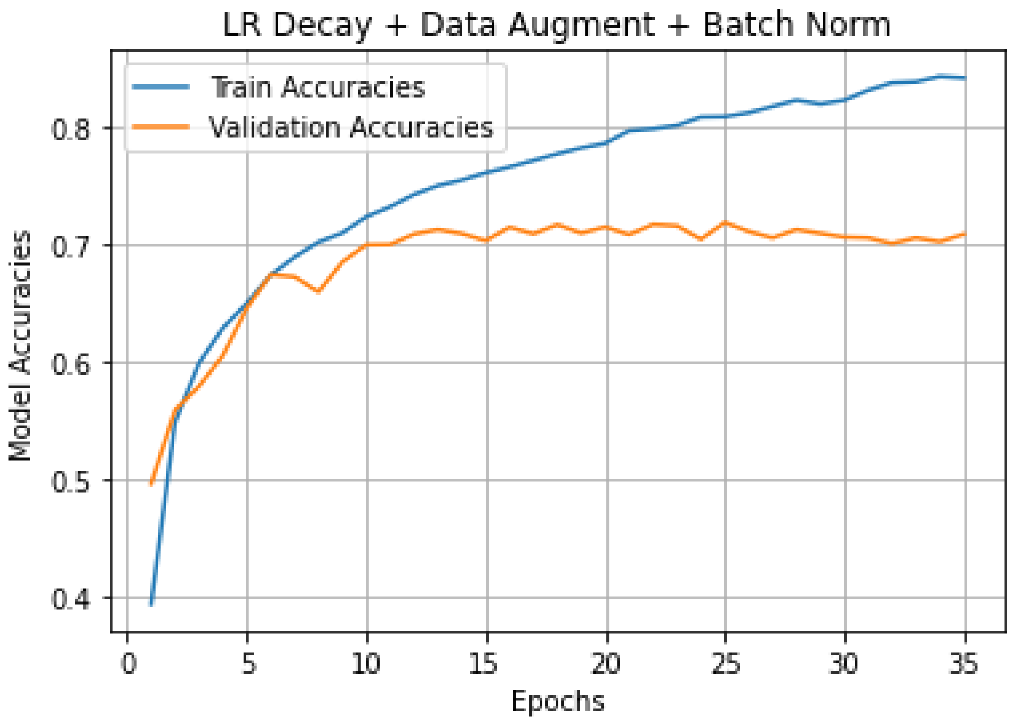


Given the figure above, it is also clear that although the training accuracy can not reach 90% after 30 epochs, the model encounters overfitting problem after about 20 epochs, which demonstrates that data augmentation techniques can indeed help combat overfitting.

(b) (15 pts) Model design is another important factor in determining performance on a given task. Now, modify the design of SimpleNN as instructed below:

Problem (b) Part 1 – Add a batch normalization layer after each convolution layer. What can you observe from the training process?

Solution: Based on the printing result after running the training code block, the best validation accuracy is 71.82%. The figure illustrating the training process is shown below.

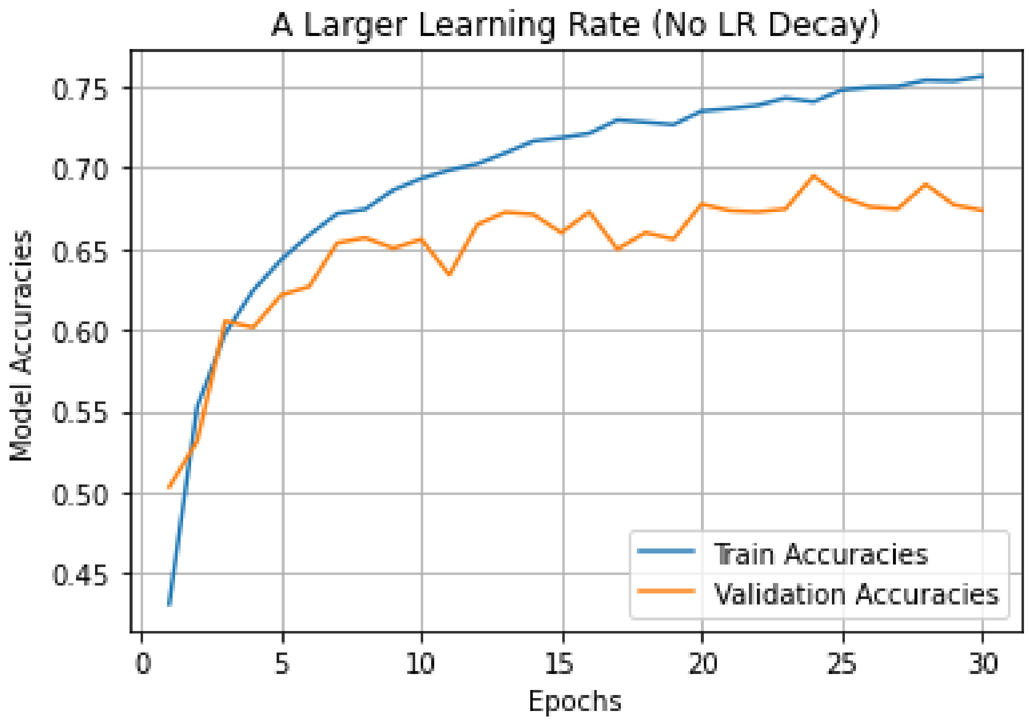


Given the figure shown above, my observation is that batch normalization slightly improves both training accuracies and validation accuracies, and makes model converge in a relatively faster way. Under the same training protocol, batch normalization model achieves 71.82% validation accuracy, approximately 2% better than 70.06%, the validation accuracy of model trained in Lab 2 (a).

Note: Although (a) uses 30 epochs and (b) uses 35 epochs, both models have achieved their best validation accuracies within 30 epochs, therefore their training protocols could be considered "the same".

Problem (b) Part 2 – Use empirical results to show that batch normalization allows a larger learning rate.

Solution: To collect empirical results, I changed the initial learning rate to 0.1, which was 10 times larger than the previously defined initial learning rate. I also cancelled the learning rate decay during training. The figure illustrating the training process is shown below.

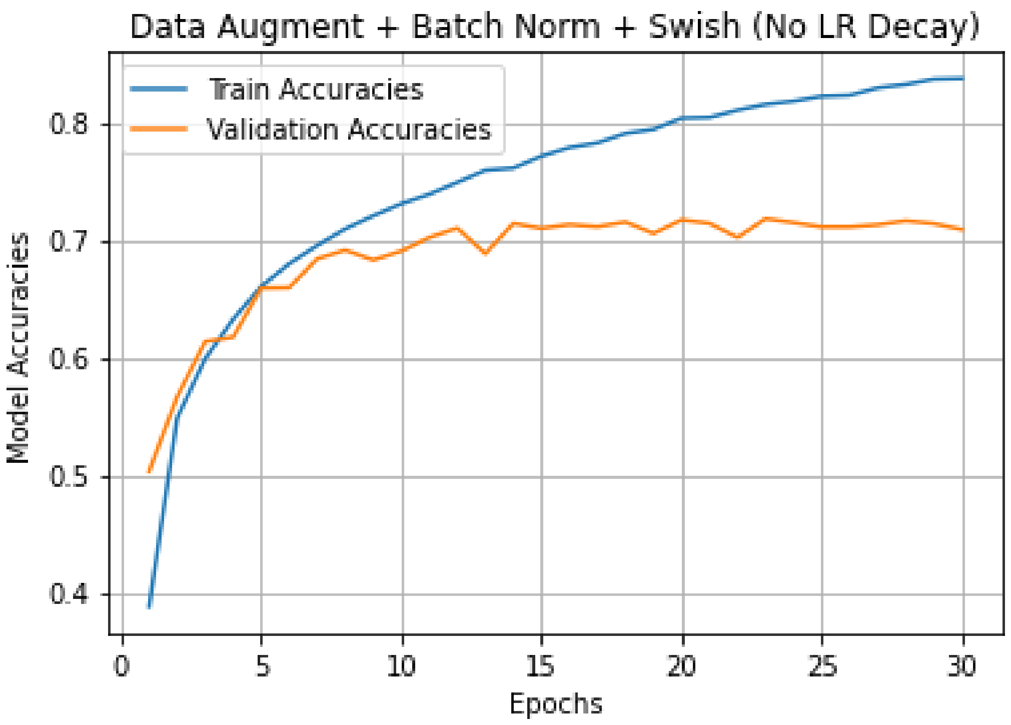


As the above figure shows, the model could still achieve 69.50% validation accuracy after 30 epochs, which shows that batch normalization indeed allows a larger learning rate, given other training protocols are similar.

Conceptual Analysis – To conceptually analyze why batch normalization could allow a larger learning rate, I start with the fact that although a large learning rate could speed up model training, it makes the model more susceptible to encountering either gradient vanishing or gradient exploding during back propagation. Batch normalization, however, makes layers' parameters normalized, therefore preventing some layers' parameters from being too small or too large, and finally resulting in less probability for gradient vanishing or exploding.

Problem (b) Part 3 – Implement Swish [2] activation on your own and replace all of the ReLU activations in SimpleNN to Swish. Does it improve the performance of SimpleNN?

Solution: Since the formula of Swish activation is very similar to the Sigmoid activation function, I implemented the Swish activation function directly by multiplying the input tensor with its Sigmoid in the element-wise format.



Given the above figure and printing result after running model training and validation block, the best validation accuracy is 71.80%, which is similar to the previously found best validation accuracy, 71.82%. Therefore, I think replacing all ReLU activation functions with Swish does not significantly improve the performance of my SimpleNN model.

(c) (14 pts) Hyperparameter settings are very important and can have a large impact on the final model performance. Based on the improvements that you have made to the model design thus far, tune some of the hyperparameters as instructed below:

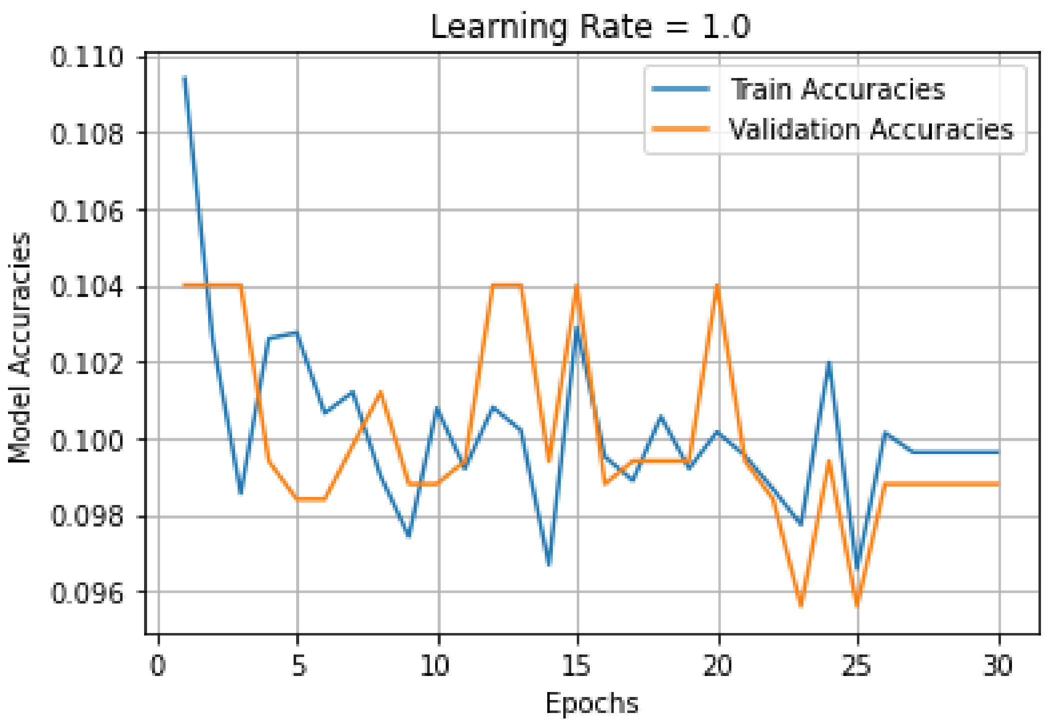
- (7 pts) Apply different learning rate values: 1.0, 0.1, 0.05, 0.02, 0.01, 0.005, 0.002, 0.001, to see how the learning rate affects the model performance, and report results for each. Is a large learning rate usually beneficial for model training? If not, what can you conclude from the choice of learning rate?

Problem (c) Part 1 Solution: To solve this problem, I trained and validated my SimpleNN model eight times given the eight learning rate values respectively. For other hyperparameters and model development techniques, I removed the learning rate decay which may influence model validation results considering learning rates themselves. However, I still kept the data augmentation, batch normalization, and Swish activation functions in my SimpleNN. As for the total number of epochs, I decided to adjust it flexibly based on my learning rates. If the learning rate is too large, I may make the total number of epochs small because the model would easily fail. If the learning rate is too small, I may increase the total number of epochs as long as it is within a maximation training budget of 100 epochs.

Report results for each model given different learning rate values.

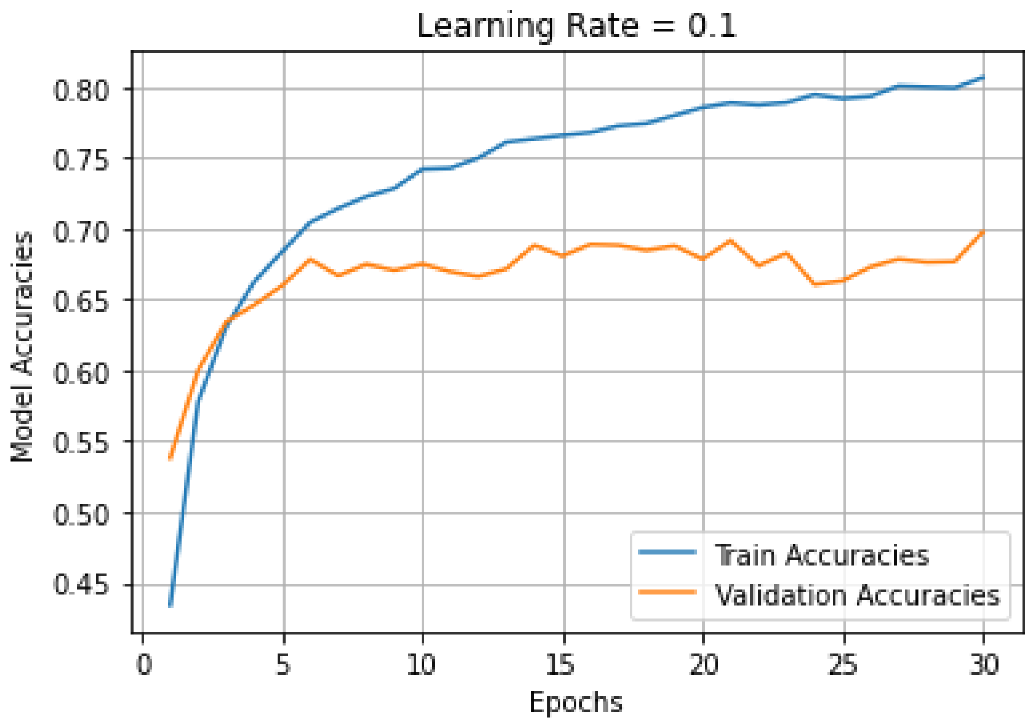
(1) Learning Rate = 1.0, Epochs = 30.

The best validation accuracy is 10.40%.



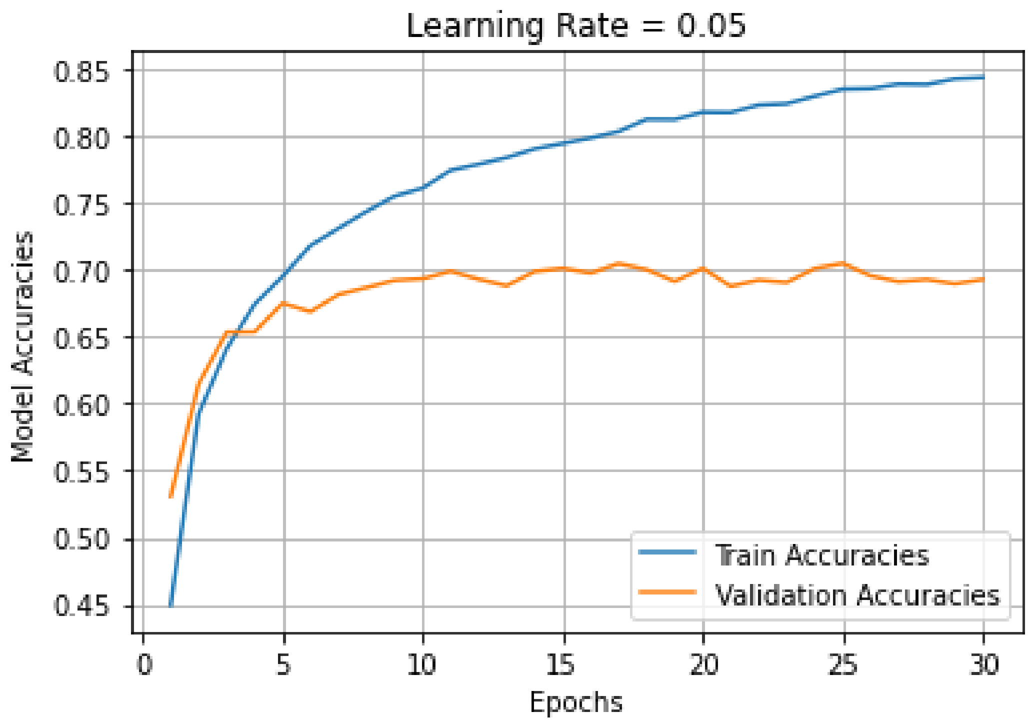
(2) Learning Rate = 0.1, Epochs = 30.

The best validation accuracy is 69.74%.



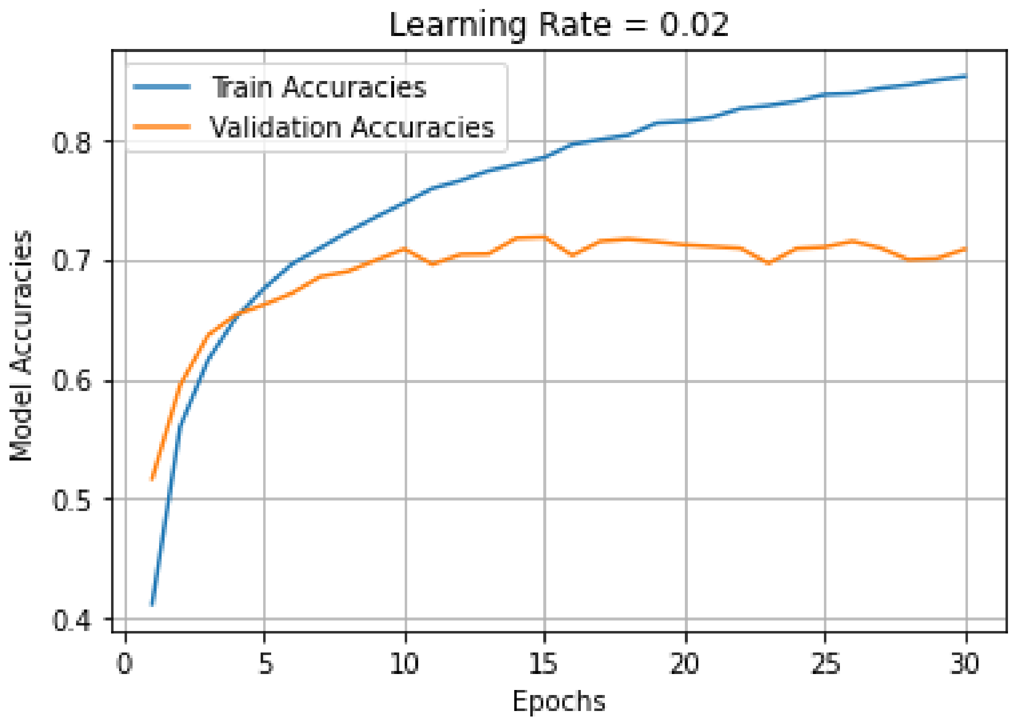
(3) Learning Rate = 0.05, Epochs = 30.

The best validation accuracy is 70.48%.



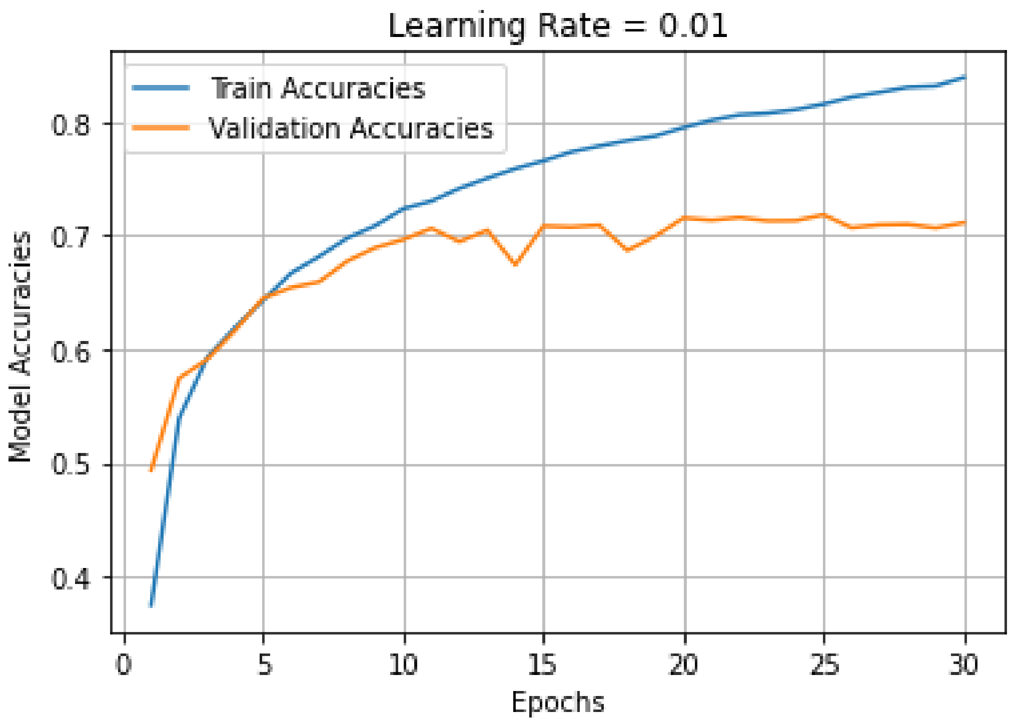
(4) Learning Rate = 0.02, Epochs = 30.

The best validation accuracy is 71.82%.



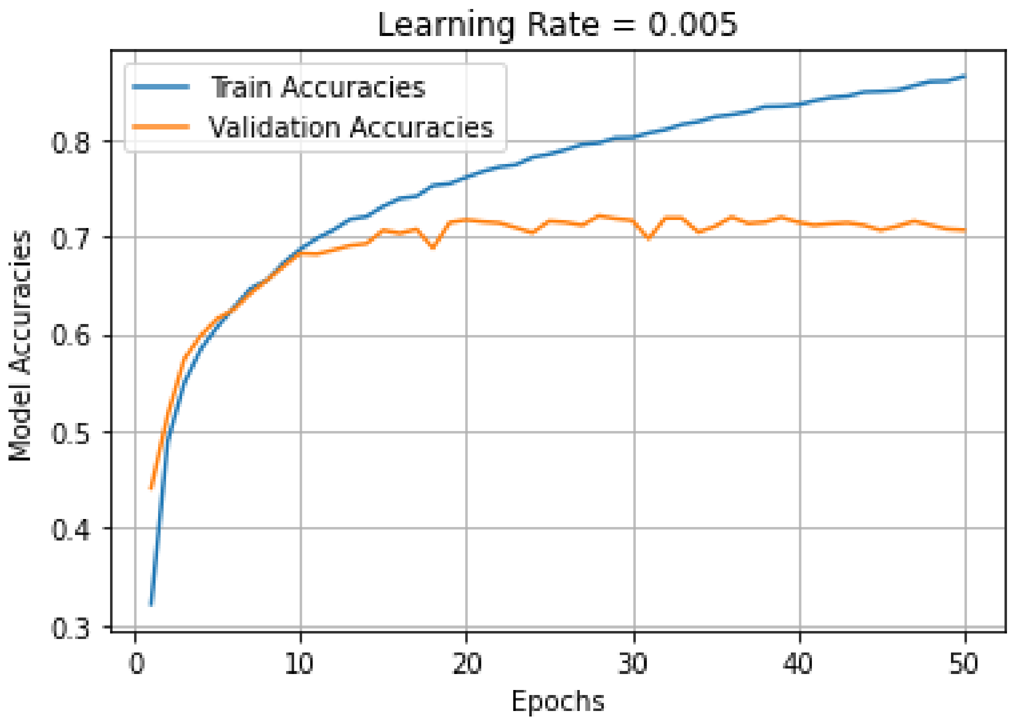
(5) Learning Rate = 0.01, Epochs = 30.

The best validation accuracy is 71.84%.



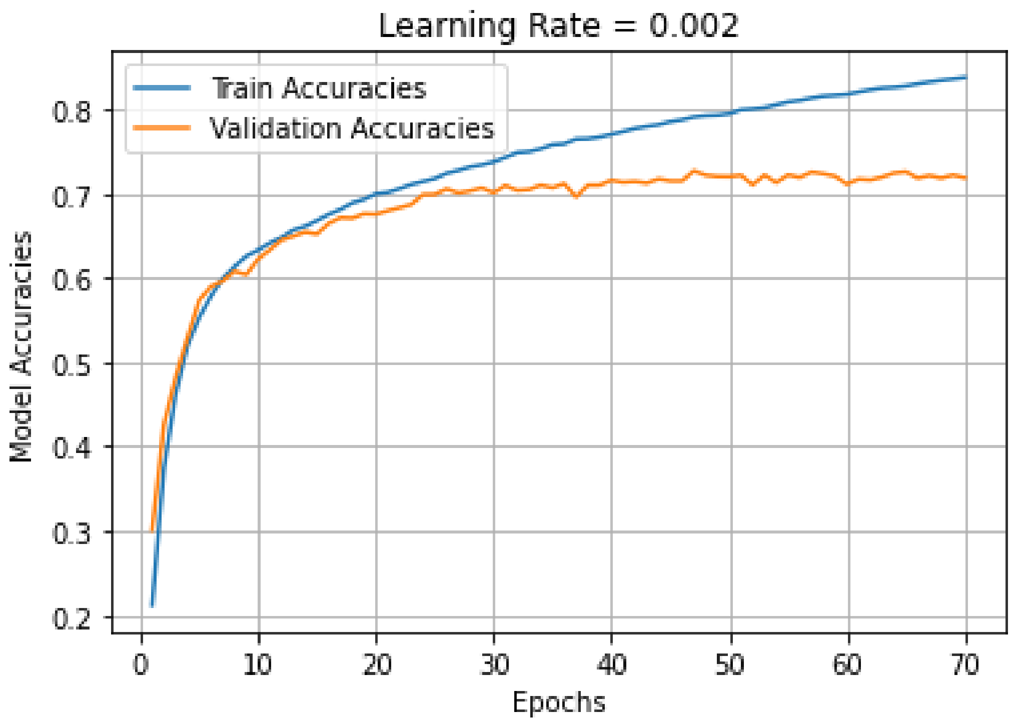
(6) Learning Rate = 0.005, Epochs = 50.

The best validation accuracy is 72.12%.



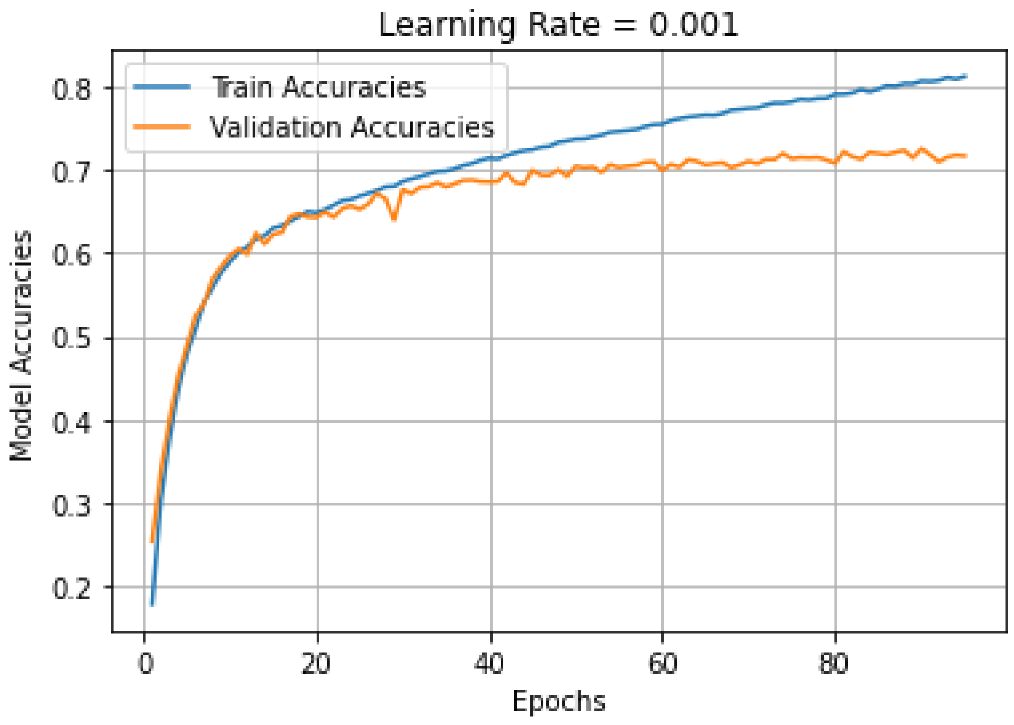
(7) Learning Rate = 0.002, Epochs = 70.

The best validation accuracy is 72.70%.



(8) Learning Rate = 0.001, Epochs = 95.

The best validation accuracy is 72.58%.



Analysis and conclusion of this problem continues in the next page.

A table that records the performance and hyperparameters of all above eight models is shown below.

Model Number	Learning Rate	Total Number of Epochs	Best Validation Accuracy
Model 1	1.0	30	10.40%
Model 2	0.1	30	69.74%
Model 3	0.05	30	70.48%
Model 4	0.02	30	71.82%
Model 5	0.01	30	71.84%
Model 6	0.005	50	72.12%
Model 7	**0.002**	**70**	**72.70%**
Model 8	0.001	95	72.58%

According to the above table, a large learning rate is not usually beneficial for model training. Although a large learning rate could speed up model training, it may cause model to encounter either gradient vanishing or gradient exploding, and finally result in model training failure (very bad training and validation accuracy). Although a relatively small learning rate may usually lead model training to convergence with relatively good training and validation accuracies, it needs more training epochs and therefore requires more computational power/resource/time, which also jeopardizes the trade-off between model accuracy and training cost. To conclude, the learning rate should neither be too large nor too small, it should be defined after several adjusting experiments to balance the aforementioned trade-off.

- (7 pts) Use different L2 regularization strengths: 0.01, 0.001, 0.0001, 0.00001, 0.0, to see how the L2 regularization strength affects the model performance. Report the results for each regularization strength value along with commentary on the importance of this hyperparameter.

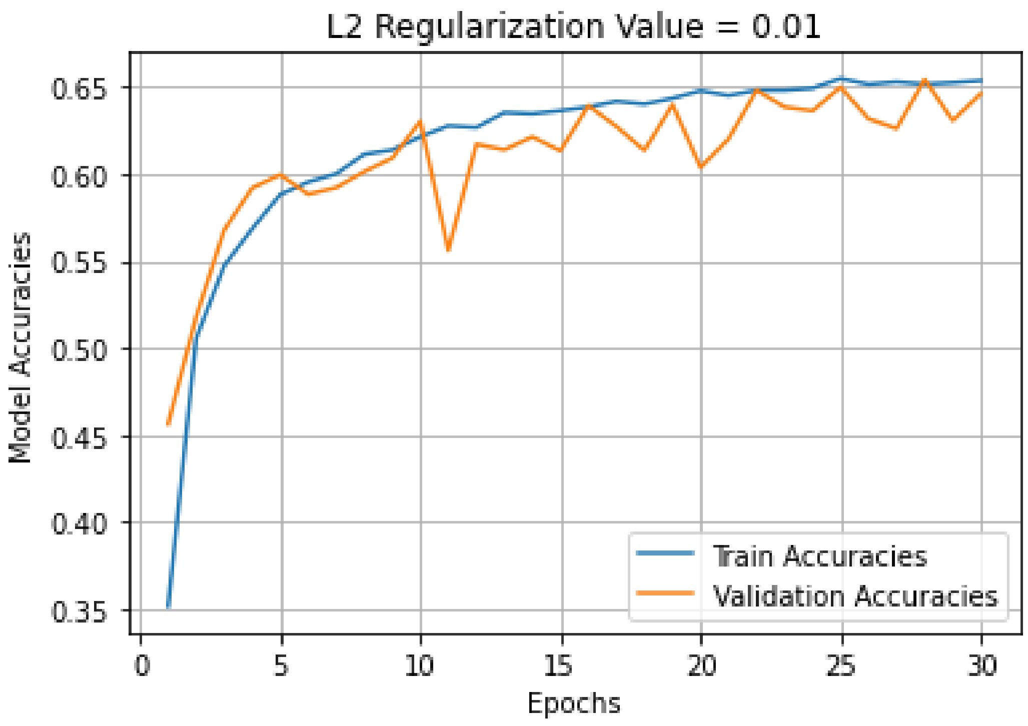
Problem (c) Part 2 Solution: To solve this problem, I trained and validated my SimpleNN model 5 times given different L2 regularization strengths. I decided to apply other hyperparameters of Model 5 trained in Problem (c) Part 1, this model has a learning rate of 0.01 and 30 epochs, with the best validation accuracy of 71.84% (this model also contains data augmentation, batch normalization and Swish activation as usual). Although this is not the model with the best validation accuracy that I ever trained, 30 epochs of training could save a lot of computational power or time while maintaining relatively good validation accuracy.

Problem (c) Part 2 Solution continues in the next page.

Report the results for each regularization strength value.

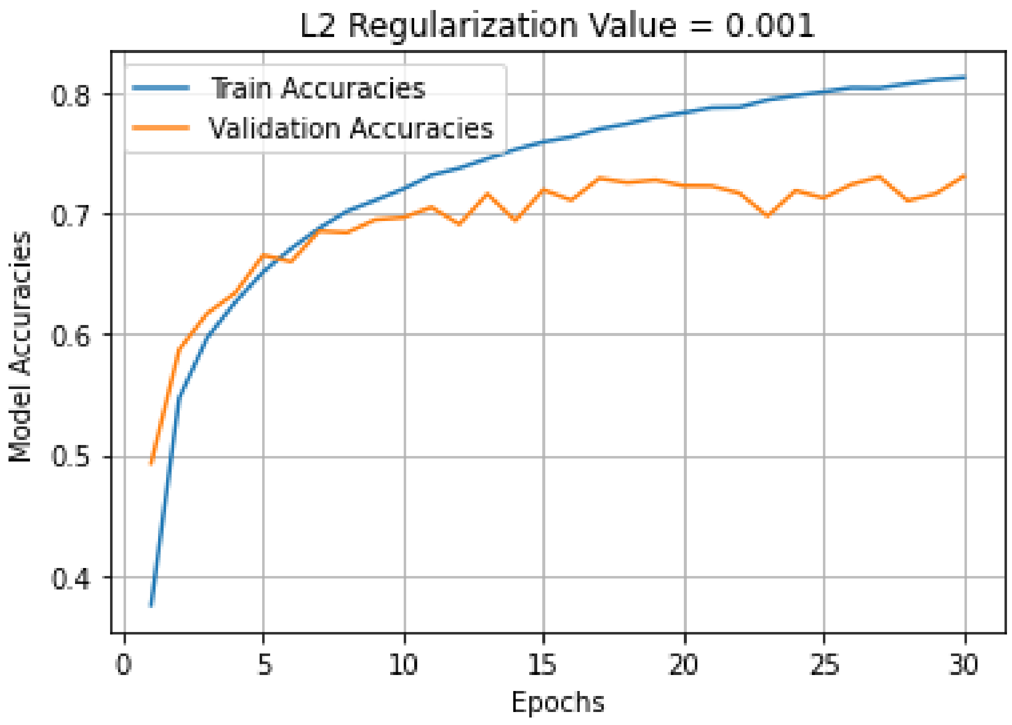
(1) L2 Regularization Value = 0.01.

The best validation accuracy is 65.44%.



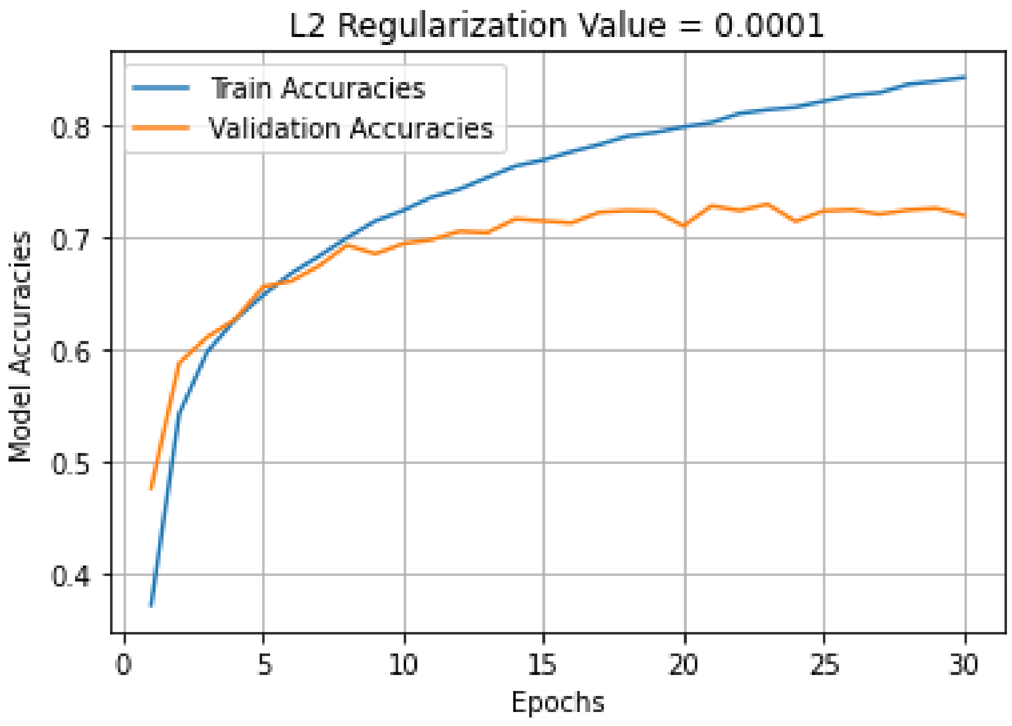
(2) L2 Regularization Value = 0.001.

The best validation accuracy is 73.08%.



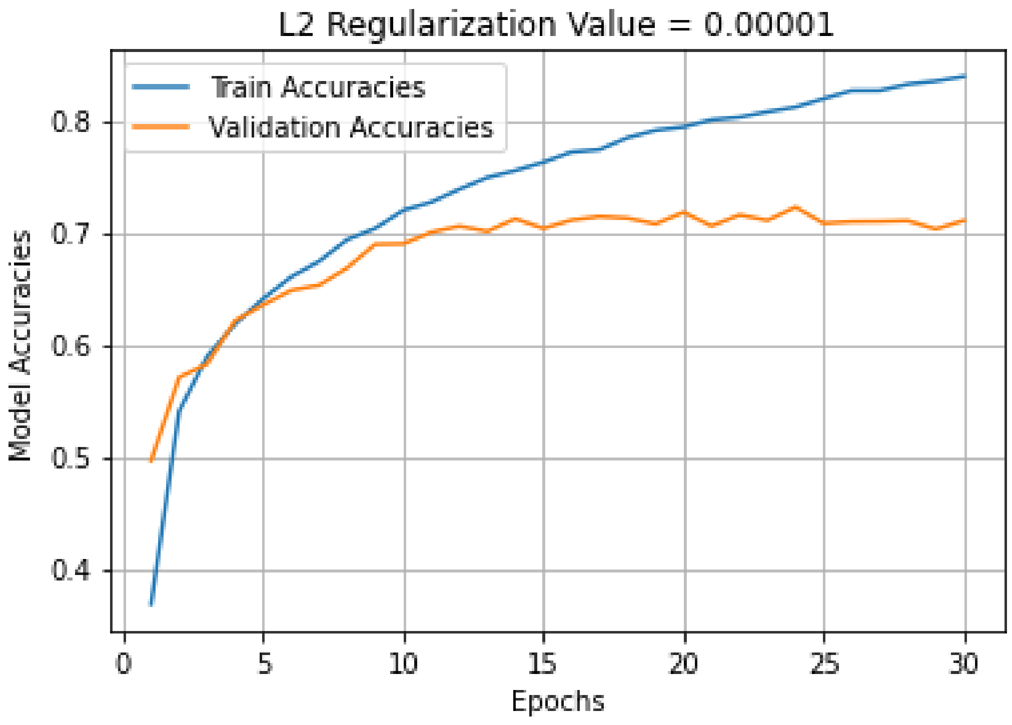
(3) L2 Regularization Value = 0.0001.

The best validation accuracy is 72.88%.



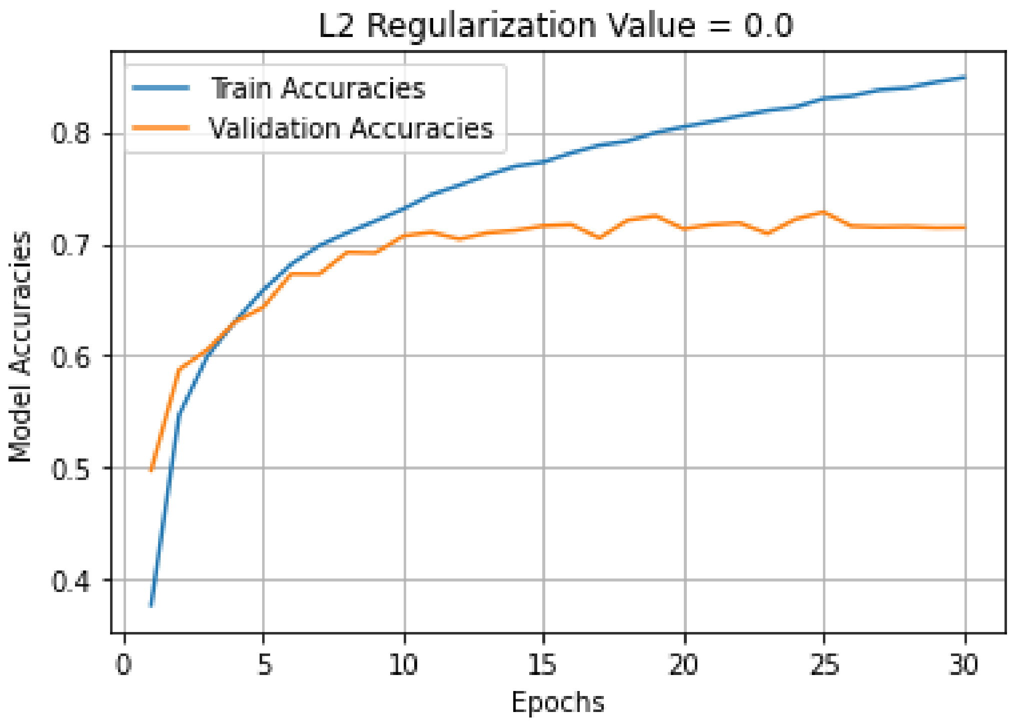
(4) L2 Regularization Value = 0.00001.

The best validation accuracy is 72.24%.



(5) L2 Regularization Value = 0.0.

The best validation accuracy is 72.84%.



A table that records the performance and hyperparameters of all above 5 models is shown below.

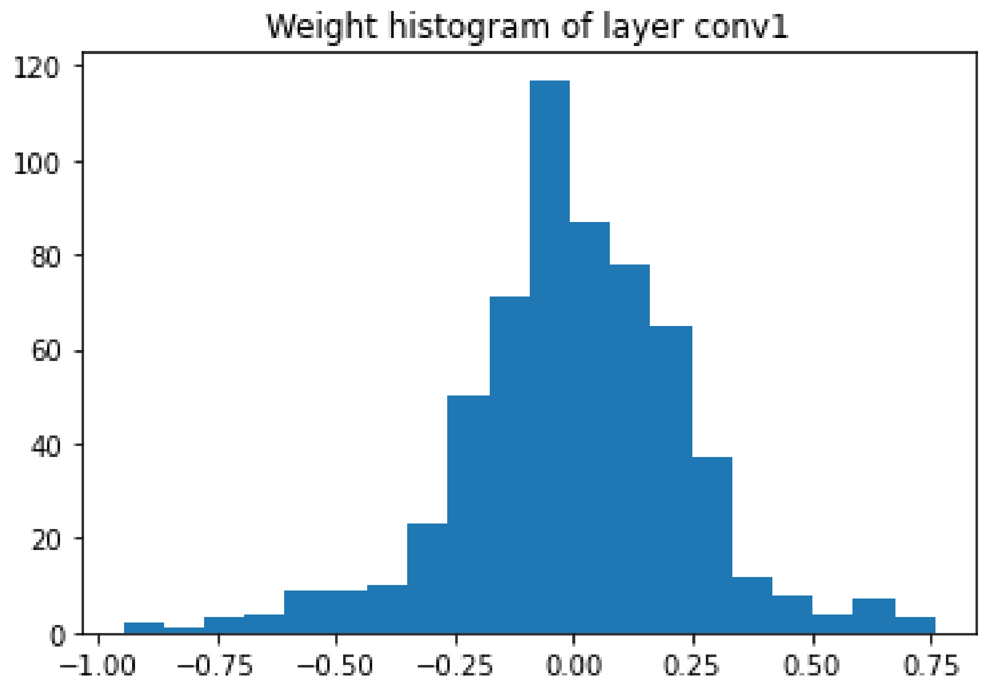
Model Number	L2 Regularization Value	Best Validation Accuracy
Model 1	0.01	65.44%
Model 2	**0.001**	**73.08%**
Model 3	0.0001	72.88%
Model 4	0.00001	72.24%
Model 5	0.0	72.84%

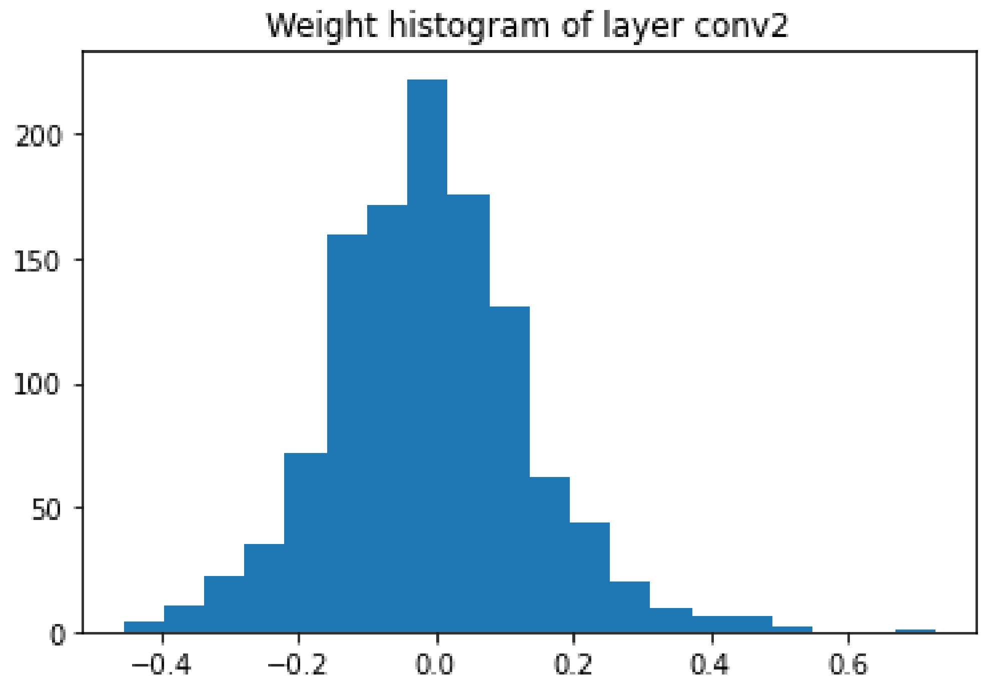
Commentary on the importance of this hyperparameter – If the L2 regularization value is too large, which means the "punishment" upon large layer weight parameters will be severe, and therefore the model would have relatively small weight values after training. Given the above figures and summary table, this would make my model perform very unstably (validation accuracy curve fluctuates drastically for the largest L2 regularization value) during validation, as well as decrease the model's validation accuracy. However, a properly chosen L2 regularization value could help my model combat overfitting, and therefore improve my model's performance during validation, in terms of a higher validation accuracy shown in the above table. All in all, L2 regularization generates more stable results without too much tuning effort, which is also the reason why applying L2 regularization could not significantly improve model performance during validation, compared with the model which does not have any L2 regularization.

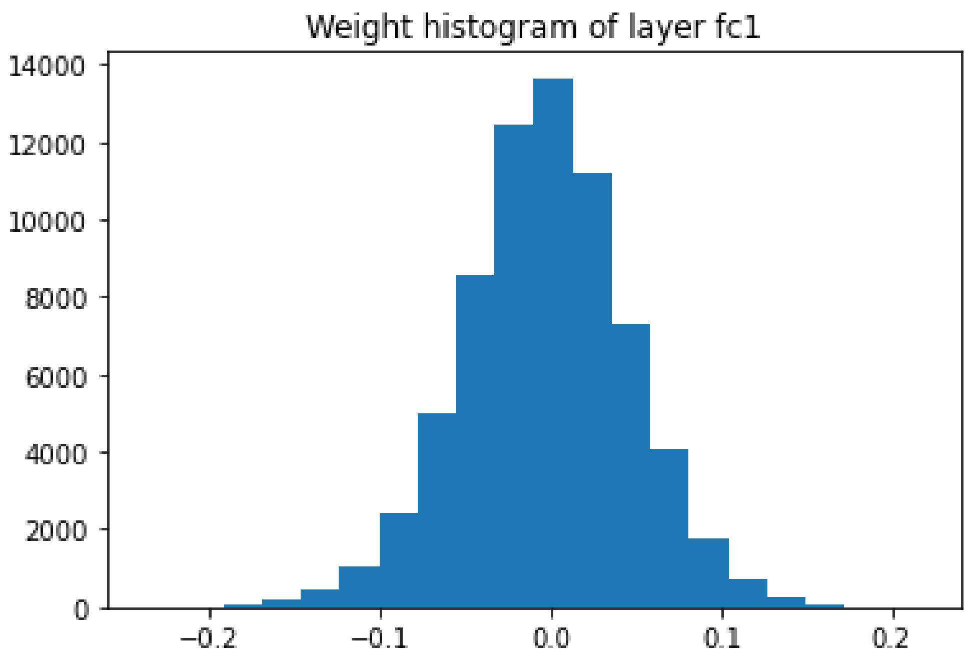
- (Bonus, 6 pts) Switch the regularization penalty from L2 penalty to L1 penalty. This means you may not use the `weight_decay` parameter in PyTorch builtin optimizers, as it does not support L1 regularization. Instead, you can try to add L1 penalty as a part of the loss function. Compare the distribution of weight parameters after L1/L2 regularization. Describe your observations.

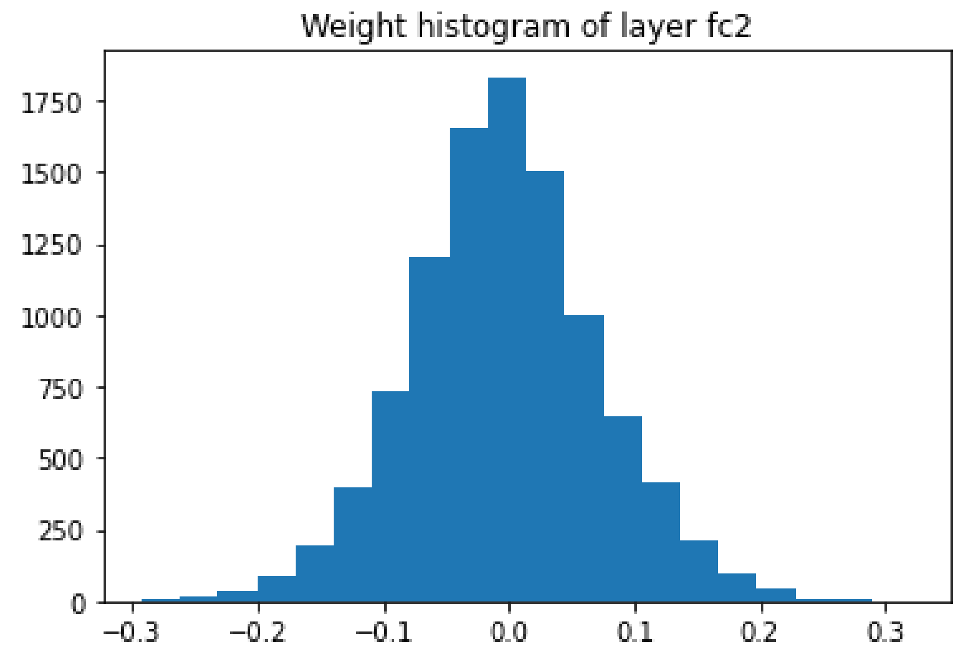
Problem (c) Part 3 (Bonus) Solution: To compare the distribution of weight parameters after L1/L2 regularization, I decided to draw weight histogram for each layer in my SimpleNN after model training is complete.

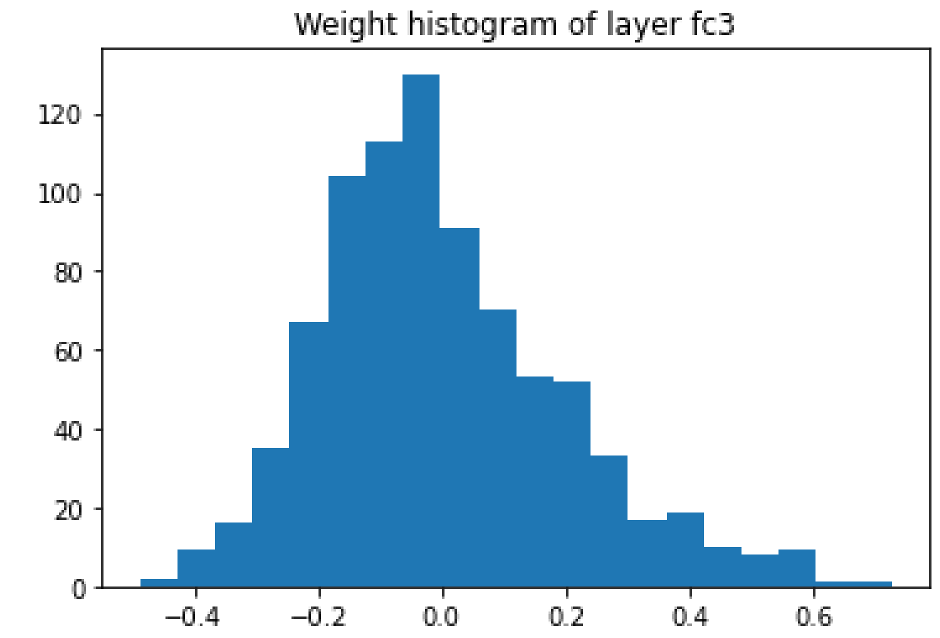
Below are five weight histogram figures for my SimpleNN given L2 regularization value is 0.001.



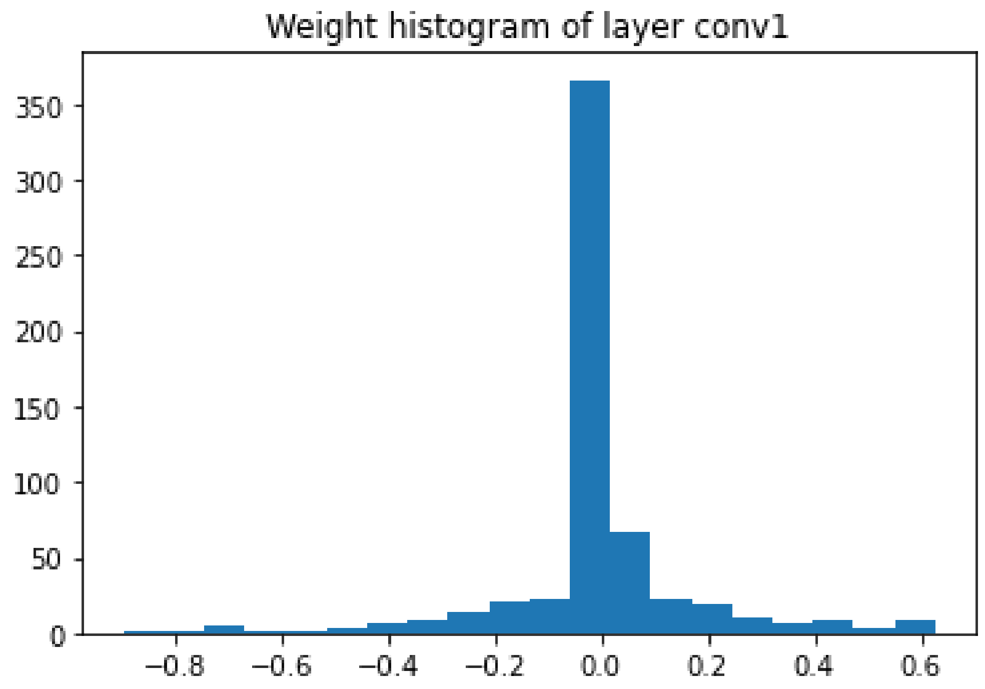


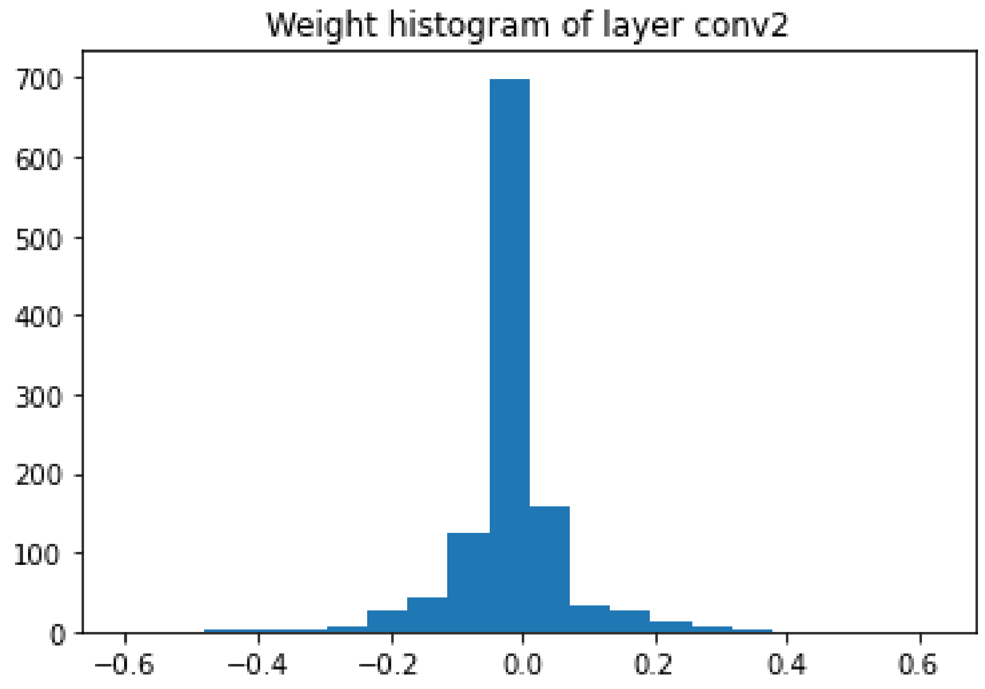

Weight histogram of layer fc1
14000
12000
10000
8000
6000
4000
2000
0
−0.2
−0.1
0.0
0.1
0.2

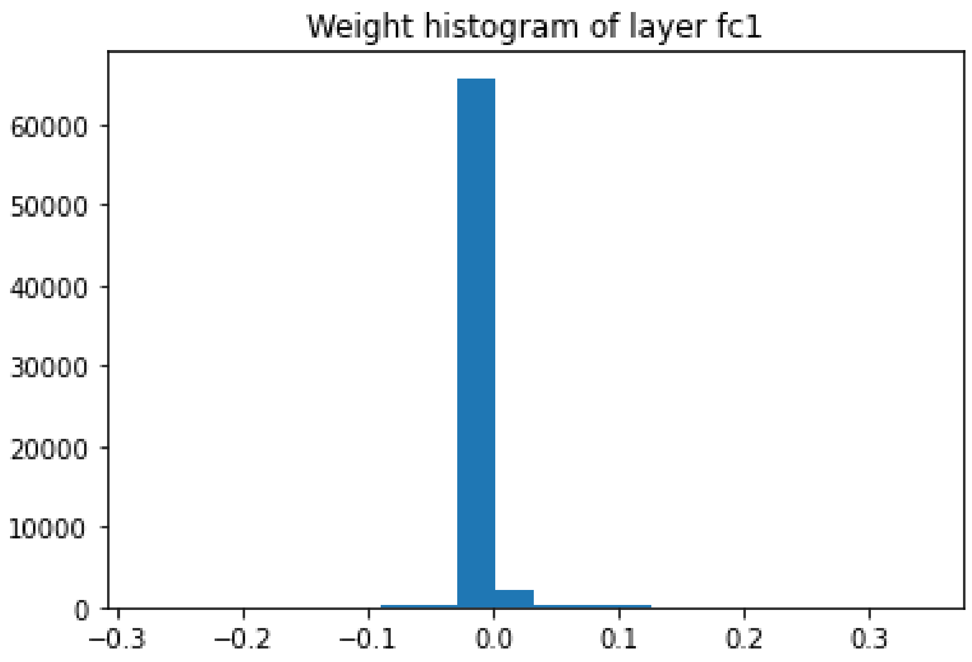

Weight histogram of layer fc2
1750
1500
1250
1000
750
500
250
0
−0.3
−0.2
−0.1
0.0
0.1
0.2
0.3

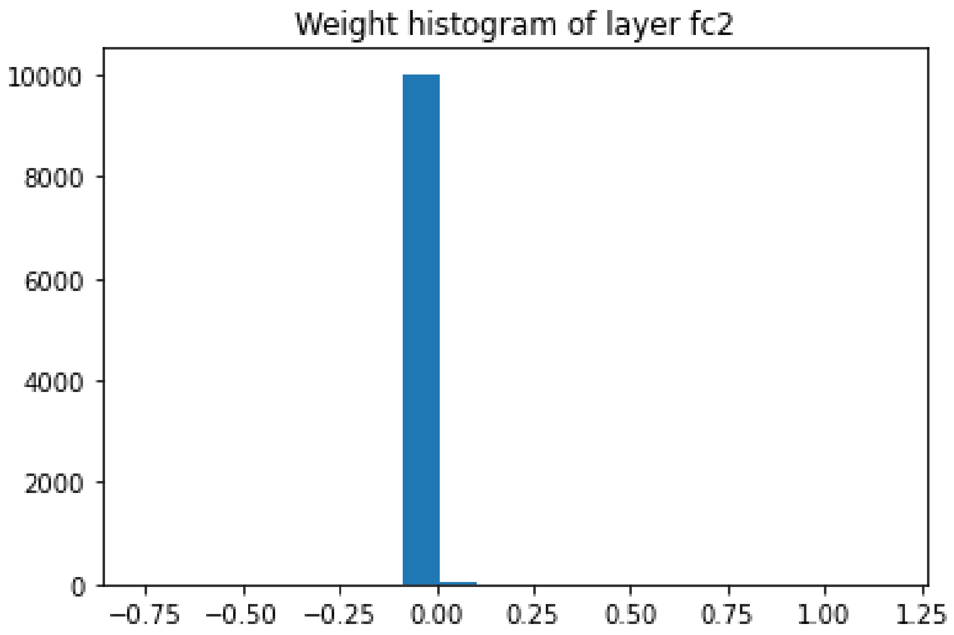

Weight histogram of layer fc3
120
100
80
60
40
20
0
−0.4
−0.2
0.0
0.2
0.4
0.6

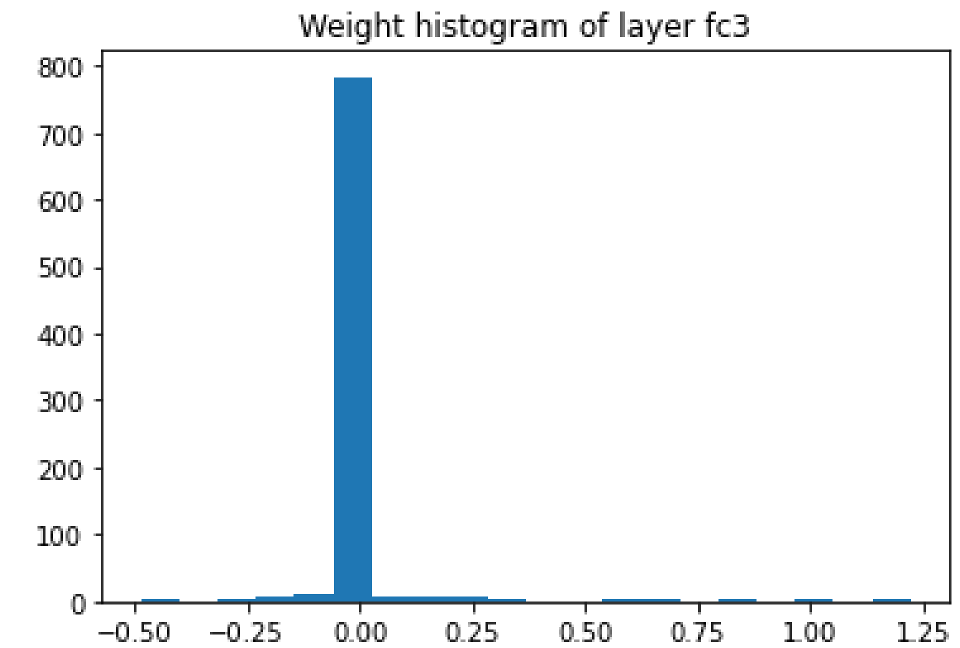
I also decided to set the L1 regularization value as 0.001. After going through the same training protocol as the above L2 regularization, the L1 regularization model's best validation accuracy is 63.00%, which is relatively bad. However, since in this problem we focus on the difference of weight distribution between L1 and L2 regularization, I will not try to optimize the L1 regularization hyperparameter. Below are five weight histogram figures for my SimpleNN given L1 regularization value is 0.001.






Weight histogram of layer fc1
60000
50000
40000
30000
20000
10000
0
−0.3
−0.2
−0.1
0.0
0.1
0.2
0.3


Weight histogram of layer fc2
10000
8000
6000
4000
2000
0
−0.75
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00
1.25

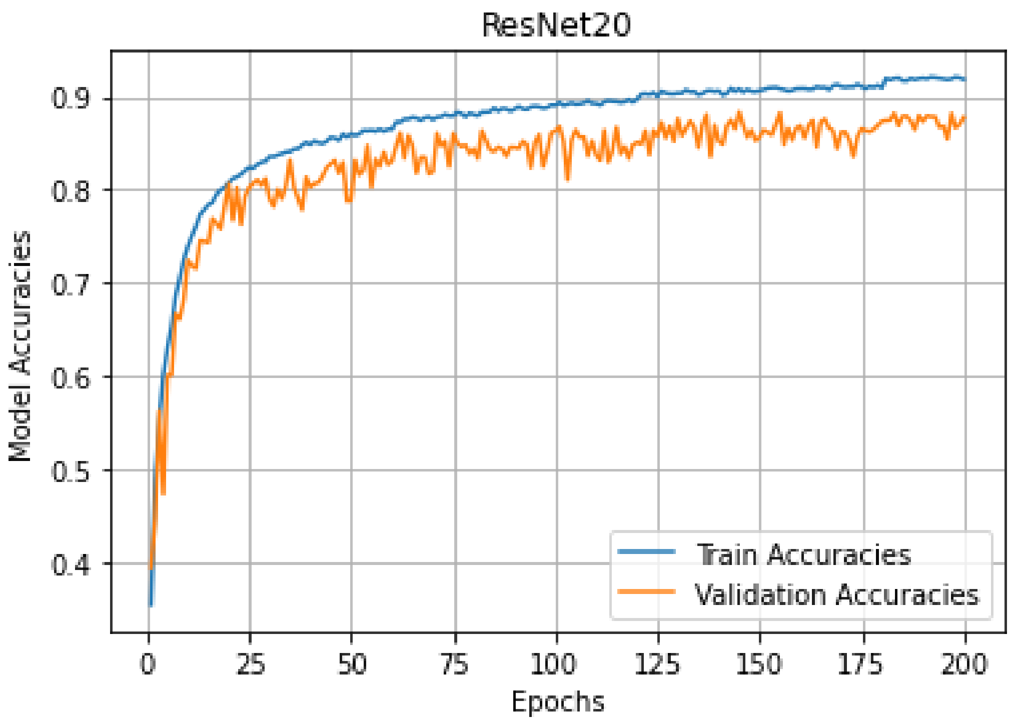

Weight histogram of layer fc3
800
700
600
500
400
300
200
100
0
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00
1.25

Given the above ten figures, it is noticeable that for L2 regularization, weight values of each layer tend to have a normal distribution. There are many small weight values between -0.5 and 0.5, but a relatively large portion of them is not 0, so the weights of a model with L2 regularization are not sparse. As for L1 regularization, there are a very large portion of weights which are 0s, and this applies to all 5 convolutional and fully connected layers in my SimpleNN model. Therefore, the weights of my SimpleNN model with L1 regularization are very sparse.

4 Lab (3): Advanced CNN architectures (20 pts)

After building the ResNet-20 model in "resnet-cifar10.ipynb" file, I trained my model with the hyperparameters provided in the ResNet paper. I also added the learning rate decay and defined the maximum number of epochs as 200. The initial learning rate, 0.1, would decay to its 90% every 60 epochs.

However, the best validation accuracy of my ResNet-20 model is 88.38%, which is less than 90%.


ResNet20
Model Accuracies
Epochs
Train Accuracies
Validation Accuracies