

# Assignment 1 CNN for image recognition

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2 Create your own ResNet work shown in Table 1 (19p)

2.2 Create this model in Table 1 (8p)

See my model in [MyResnet.py](#)

2.4 Use the downloaded training dataset (see Section 1) to train your created model

Since the size of images from CIFAR-10 is 32x32, I resized the size of images to 224x224.  
See the details in [test.py](#).

2.5 Report the final accuracy (10,000 steps) of training and testing for the CIFAR-10 dataset  
(2x1=2p).

The final accuracy of training is [100%](#), and the final accuracy of testing is [86.33%](#).  
The results are based on 9765 iterations (25 epoch times, 128 batch sizes).  
See the details in [test.py](#).

2.6 Visualize the learning progress. Accuracy (1p) and Cross\_entropy (or loss function) (1p).

See the details in [test.py](#) and [Myvisdom.py](#).

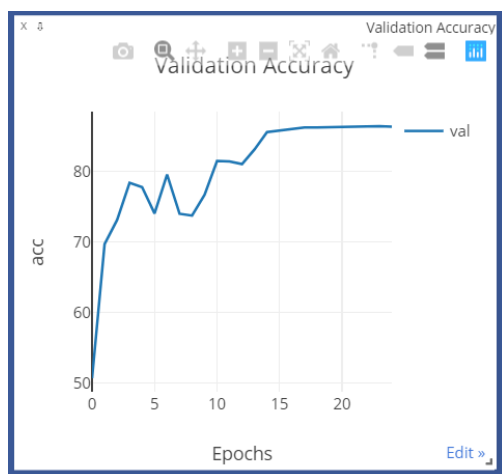


Figure.6.1 Validation Accuracy

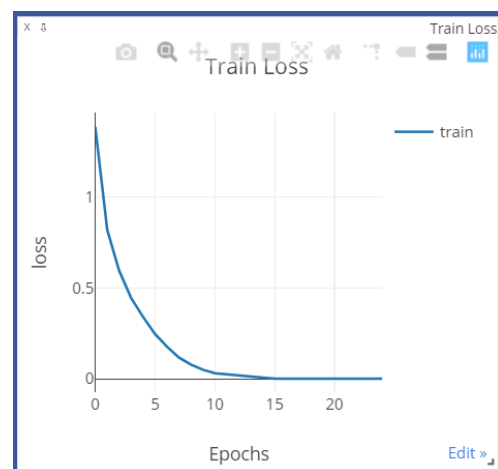


Figure.6.2 Train Loss

## 2.7 Filter visualization (3p).

See the details in [test\\_filter.py](#)

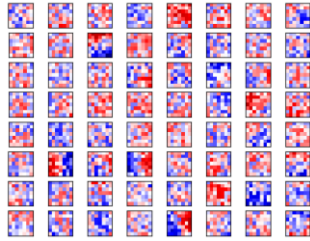


Figure.7.1. Channel\_0

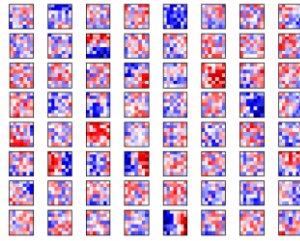


Figure.7.2. Channel\_1

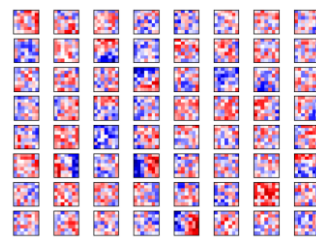


Figure.7.3 Channel\_2

## 2.8 Feature mapping visualization (4p).



Figure.8.1. An image from validation set

Firstly, I choosed an image(Figure.8.1.) from the validation set, and get the feature maps of the layer 'Conv1'(Figure.8.2.) and the last layer in the block Conv5\_x(Figure.8.3.).

See the details in [test\\_reply.py](#).

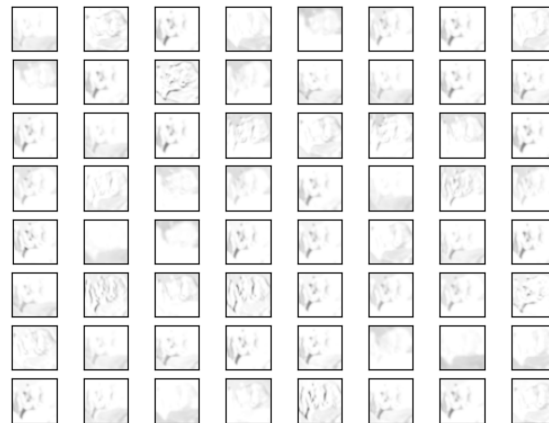
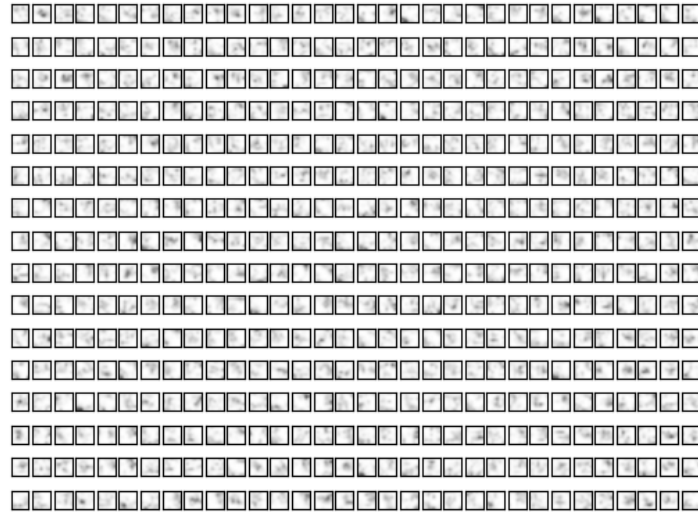
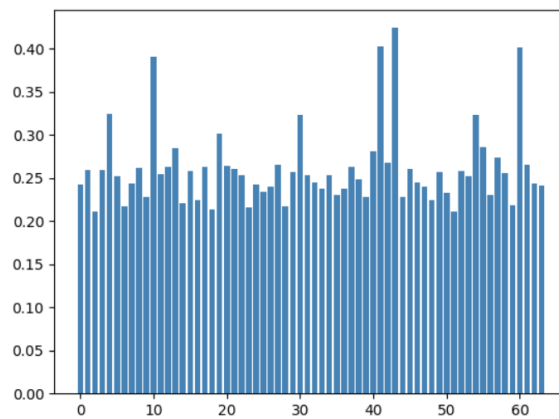


Figure.8.2. Feature maps of the layer 'Con1'

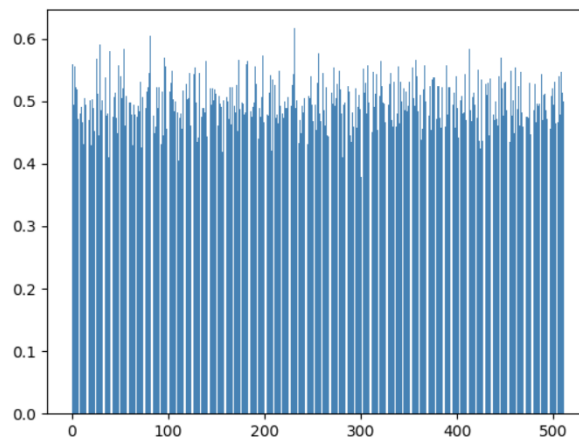


**Figure.8.3. Feature maps of the layer 'Conv5\_x'**

In order to choose a feature map which had the highest activations in each layer, I showed activations of each layer through column charts(Figure.8.4.1. and Figure.8.4.2.). See the details in [test\\_image.py](#).



**Figure.8.4.1. Column chart of the layer 'Con1'**

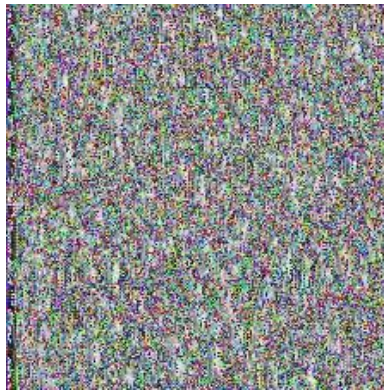


**Figure.8.4.2. Column chart of the layer 'Conv5\_x'**

Since the Resnet has the shortcut operation, it's hard to get reconstructed patterns by deconvolution for a feature map. Essentially, the deconvolution operation is a part of the processes of backpropagation. Therefore, the patterns can be reconstructed directly by backpropagation.

Finally, I choosed the 43th feature map in 'Conv1' layer and the 231th feature map in the last layer and get the reconstructed patterns of both feature maps(Figure.8.5.1. and Figure.8.5.2.).

See the details in [test\\_reconimage\\_conv1.py](#) and [test\\_reconimage\\_conv5.py](#).



**Figure.8.5.1 The reconstructed patterns of the layer 'Con1'(the 43th feature map)**



**Figure.8.5.2 The reconstructed patterns of the layer 'Conv5\_x'(the 231th feature map)**

### 3 Feedback (1p)

- I spent more than 48 hours for this assignment.
- This course is pretty cool, but I am not so familiar with deep learning. So it will take me much time to preview some basic knowledge.
- Emmm...this assignment really helped me develop some skills of deep learning. Since I am not familiar with some basic knowledge of image processing, it really took me a lot of time to learn some basic skills of image processing.
- Well, maybe we should pay more attention on some basic principles of AI. And I'd also like to hear about the history of AI and what we can learn from it.

## Reference

MyResnet.py and test.py

[1] <https://github.com/pytorch/vision/blob/master/torchvision/models/resnet.py>

[2] [https://pytorch.org/tutorials/beginner/blitz/cifar10\\_tutorial.html](https://pytorch.org/tutorials/beginner/blitz/cifar10_tutorial.html)

test\_filter.py and test\_reply.py

[3] <https://github.com/grishasergei/conviz>

test\_reconimage\_conv1.py and test\_reconimage\_conv5.py

[4] <https://github.com/utkuozbulak/pytorch-cnn-visualizations>

[5] <https://mathpretty.com/10475.html>