

Assignment 1 CNN for image recognition (20p)

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Environment: Ubuntu, 1080 Titan, Pytorch, tensorboardX

Set up: EPOCH = 40, Batch Size = 64,

Learning Rate = 0.01, momentum=0.9, weight_decay=5e-4

Step1. Dataset download

Load and resize the data with torchvision and transform.

Remember to resize the image from 32*32 to 224*224, for the sake of not only align the network with the output size in homework description, but also improving the training accuracy.

Train: Test = 50000: 10000

```
def transform(x):  
    x = x.resize((224, 224), 2) # resize the image from 32*32 to 224*224  
    x = np.array(x, dtype='float32') / 255  
    x = (x - 0.5) / 0.5 # Normalize  
    x = x.transpose((2, 0, 1)) # reshape, put the channel to 1-d; input = {channel, size, size}  
    x = torch.from_numpy(x)  
    return x  
  
trainset = torchvision.datasets.CIFAR10(root='./data', train=True,  
                                         download=False, transform=transform)  
trainloader = torch.utils.data.DataLoader(trainset, batch_size=64,  
                                           shuffle=True, num_workers=2)  
testset = torchvision.datasets.CIFAR10(root='./data', train=False,  
                                         download=False, transform=transform)  
testloader = torch.utils.data.DataLoader(testset, batch_size=64,  
                                          shuffle=False, num_workers=2)
```

Fig 1. Data loading

Step2. Create ResNet18 shown in Table 1 (19p)+

layer name	output size	18-layer
conv1	112×112	
conv2_x	56×56	$\begin{bmatrix} 3 \times 3, 64 \\ 3 \times 3, 64 \end{bmatrix} \times 2$
conv3_x	28×28	$\begin{bmatrix} 3 \times 3, 128 \\ 3 \times 3, 128 \end{bmatrix} \times 2$
conv4_x	14×14	$\begin{bmatrix} 3 \times 3, 256 \\ 3 \times 3, 256 \end{bmatrix} \times 2$
conv5_x	7×7	$\begin{bmatrix} 3 \times 3, 512 \\ 3 \times 3, 512 \end{bmatrix} \times 2$
	1×1	
FLOPs		1.8×10^9

Table 1. Architectures for ResNet18

First, define a ResidualBlock according to the ResNet paper^[1].

```
class ResidualBlock(nn.Module):
    def __init__(self, inchannel, outchannel, stride=1):
        super(ResidualBlock, self).__init__()
        self.left = nn.Sequential(
            nn.Conv2d(inchannel, outchannel, kernel_size=3, stride=stride, padding=1, bias=False),
            nn.BatchNorm2d(outchannel),
            nn.ReLU(inplace=True), # inplace = True
            nn.Conv2d(outchannel, outchannel, kernel_size=3, stride=1, padding=1, bias=False),
            nn.BatchNorm2d(outchannel)
        )
        if stride == 1 and inchannel == outchannel:
            self.shortcut = nn.Sequential()
        else:
            self.shortcut = nn.Sequential(
                nn.Conv2d(inchannel, outchannel, kernel_size=1, stride=stride, bias=False),
                nn.BatchNorm2d(outchannel)
            )
    def forward(self, x):
        return F.relu(self.left(x) + self.shortcut(x))
```

Fig 2. ResidualBlock with shortcut

Then define ResNet18 with above ResidualBlock.

```
class ResNet18(nn.Module):
    def __init__(self, ResidualBlock, num_class=10):
        super(ResNet18, self).__init__()
        # First Conv Layer: kernel=7, channel=64, stride=2, and feature map size is halved
        self.conv1 = nn.Sequential(
            nn.Conv2d(3, 64, kernel_size=7, stride=2, padding=3, bias=False),
            nn.BatchNorm2d(64),
            nn.ReLU(),
        )
        self.layer1 = nn.Sequential(
            ResidualBlock(64, 64, stride=1),
            ResidualBlock(64, 64, stride=1)
        )
        self.layer2 = nn.Sequential(
            ResidualBlock(64, 128, stride=2),
            ResidualBlock(128, 128, stride=1)
        )
        self.layer3 = nn.Sequential(
            ResidualBlock(128, 256, stride=2),
            ResidualBlock(256, 256, stride=1)
        )
        self.layer4 = nn.Sequential(
            ResidualBlock(256, 512, stride=2),
            ResidualBlock(512, 512, stride=1)
        )
        self.fc = nn.Linear(512, num_class)

    def forward(self, x):
        out = self.conv1(x)
        out = self.layer1(out)
        out = F.max_pool2d(out, 3, stride=2, padding=1)
        out = self.layer2(out)
        out = self.layer3(out)
        out = self.layer4(out)
        out = F.avg_pool2d(out, 7) ####
        out = out.view(out.size(0), -1) # 1, 4608
        out = self.fc(out)
        return out
```

Fig 3. Architecture for ResNet18

```

(conv1): Sequential(
  (0): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
  (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (2): ReLU()
)
(layer1): Sequential(
  (0): ResidualBlock(
    (left): Sequential(
      (0): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (2): ReLU(inplace)
      (3): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (4): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
    (shortcut): Sequential()
  )
  (1): ResidualBlock(
    (left): Sequential(
      (0): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (2): ReLU(inplace)
      (3): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (4): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
    (shortcut): Sequential()
  )
)

```

Fig 4. Layer of ‘Conv1’ and ‘Layer1’

In order to ensure the computation complexity in each layer is the same, while the feature map size halved, channel size will double.

Step3. Final accuracy of training and testing for the CIFAR-10

In the training, I set the batch size 64, thus one epoch finish with 784 iterations gradient update. And 15,680 steps were executed after I train the model for 20 epochs, and I use this model for testing the CIFAR-10 test set.

The final training accuracy: 99.0%

And the final test result is: 88.0%

Step4. Visualize the learning progress (tensorboardX)

Then, I use tensorboardX to visualize the train loss train accuracy, which are showed on the following picture:

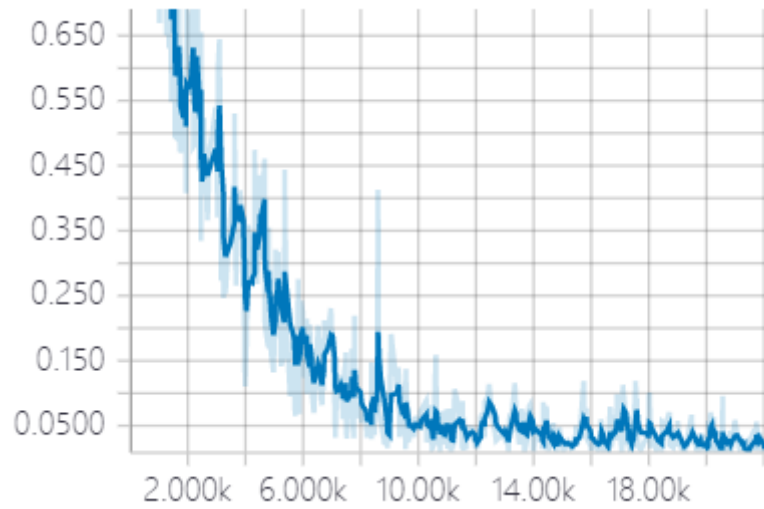


Fig 4. Variations of training loss(cross entropy)

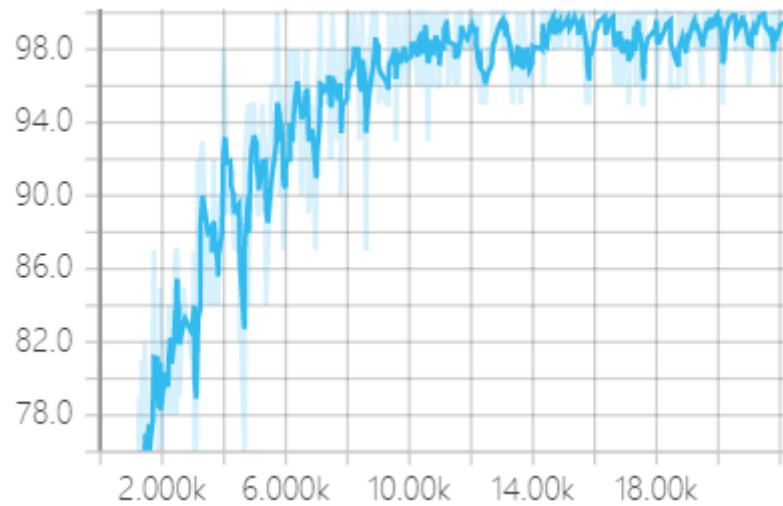


Fig 5. Accuracy for training dataset

Step5. Filter Visualization

Visualization is carried out according to a GitHub Repo: `pytorch-cnn-visualizations`^[3].

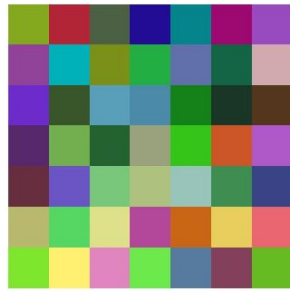


Fig 6. One of the filter in the layer Conv1



Fig 7. Visualization the 64 filters in the layer Conv1 (7*7*64)

Step6. Feature mapping Visualization

Visualize the feature maps of the layer Conv1 and also the last layer in the block Conv5_x in Table 1.



Fig 8. The Original Image (224*224*3 after resize)



Fig 9. Feature maps of layer Conv1 (112*112*64)

Note that because of the space limitation, there are 512 channel in feature maps of layer Conv5_x and I just show 220 of them.

If it is essential to submit all the pictures, please contact with me through 1901213121@pku.edu.cn.

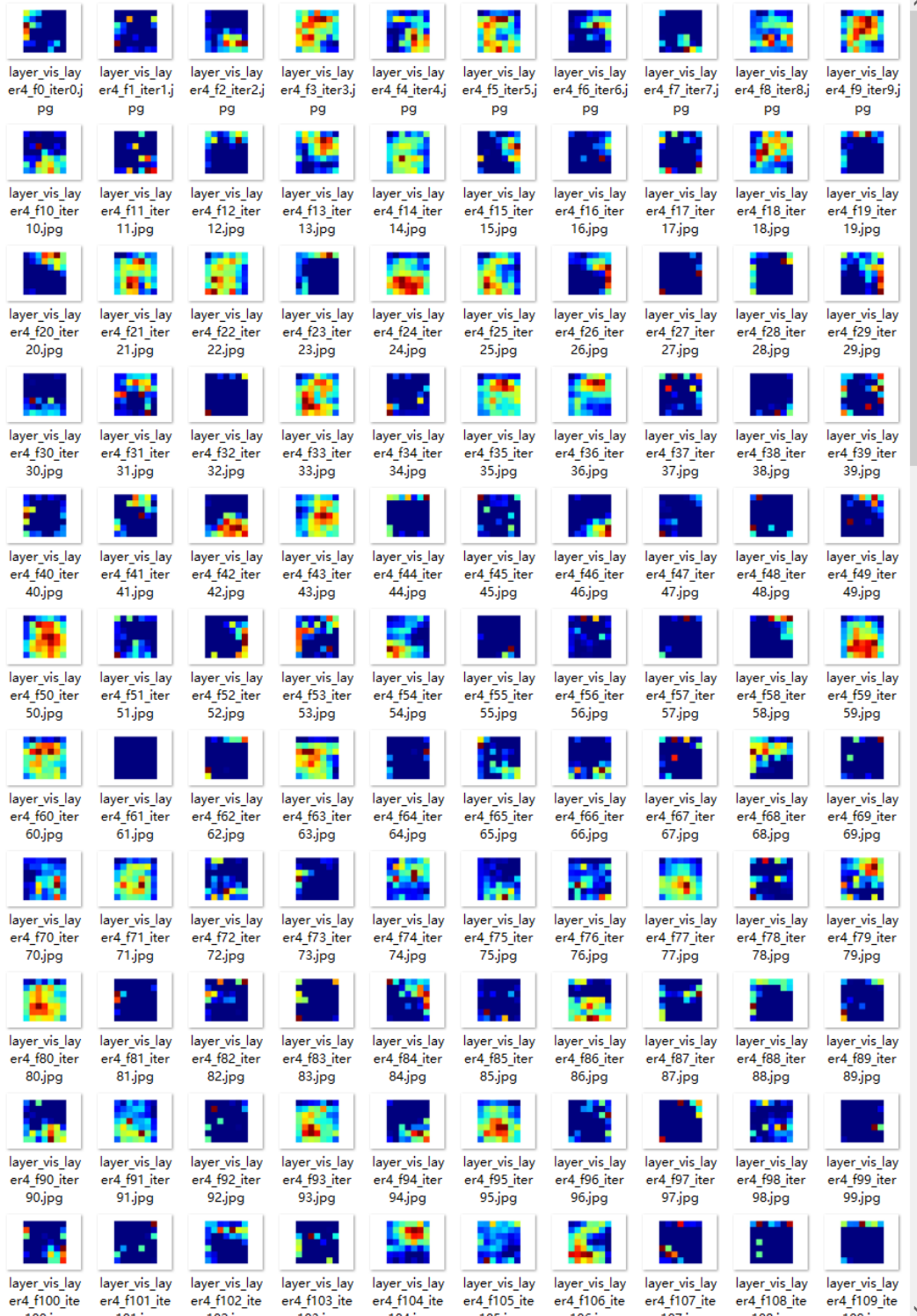


Fig 10(1). Feature maps of layer Conv5_x (7*7*512)

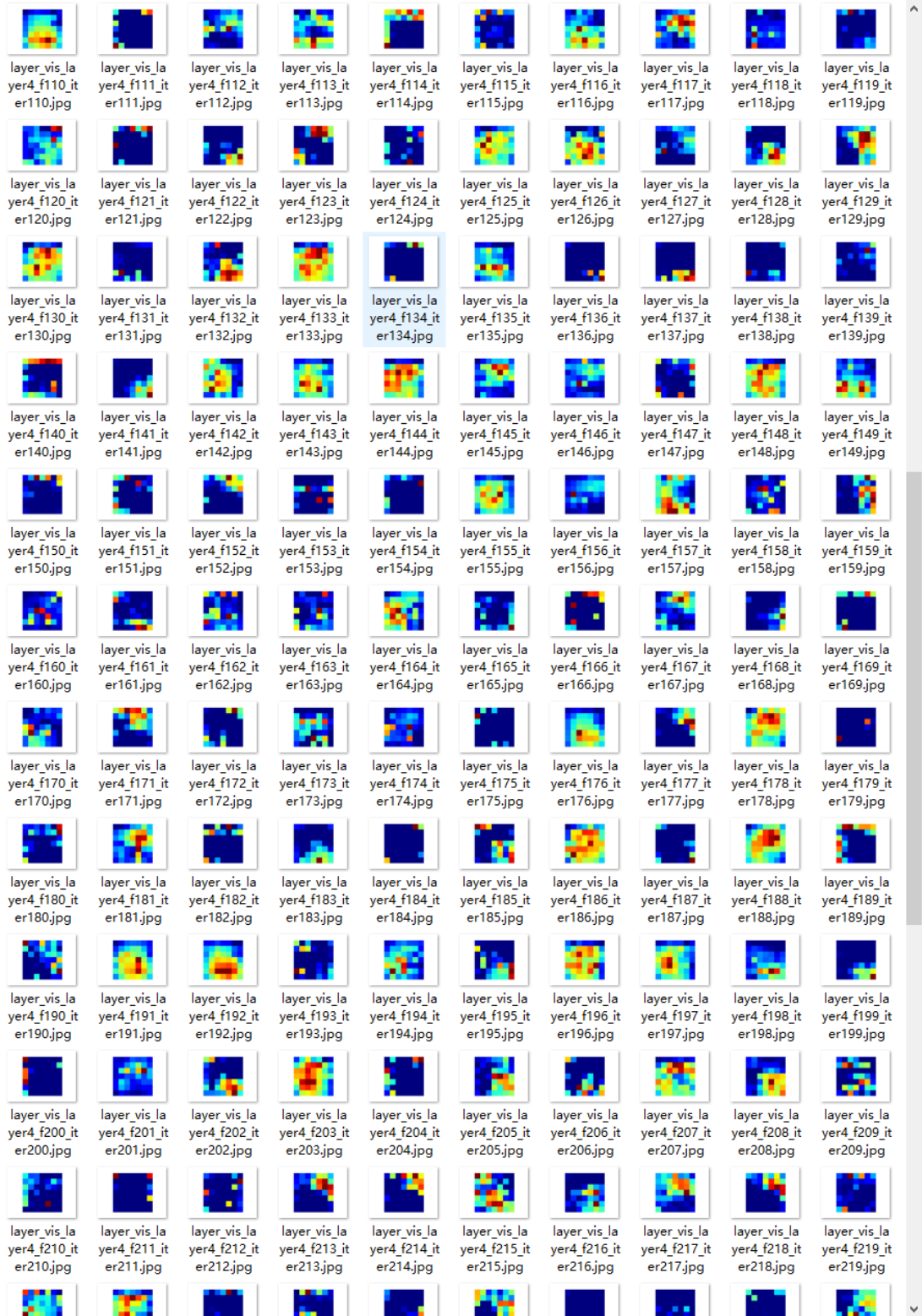


Fig 10(2). Feature maps of layer Conv5_x (7*7*512)



Fig 11. The reconstructed patterns from the validation set

Feedback (1p)

- 1) Time you spend for this assignment, i.e., how many hours?

Half of a month, nearly 30 hours.

- 2) Comments for this course?

Useful, meaningful, and interesting.

However, it is more like a computer vision class. I think Artificial Intelligence should not only contain CV. It has many other fields such as NLP, Robotics, Autonomous Vehicles. It will be better if we can learning things about such filed from this course.

- 3) Comments for this assignment?

Helpful. I learn some useful skills from this assignment that will do good help to my further research work.

And the most important is it gives us a chance to combat, not only stay in the book, we can learn how to build a model from scratch, how to adjust the parameter, how to use tensorboardX to get an accurate picture, how to visualize the feature map.

All this experience is meaningful.

4) Suggestion for the following lectures?

I think this lecture focus too much on the computer vision field. As we all know, artificial intelligence is not only for CV, it has many subfields. And for me, I major in Natural Language Processing, so I would like to know more about NLP pioneer, such as Transformer, XL-Net, etc.

To sum up, I think it should be an Introduction Class for us to enter the field of Artificial Intelligence, containing a wide and comprehensive field of AI, just like lecture on Computer Introduction for a computer newbie.

Reference:

- [1] <https://arxiv.org/abs/1512.03385>
- [2] <https://blog.csdn.net/sunqiande88/article/details/80100891>
- [3] <https://github.com/utkuozbulak/pytorch-cnn-visualizations>
- [4] <https://github.com/kvfrans/feature-visualization>
- [5] <http://kvfrans.com/visualizing-features-from-a-convolutional-neural-network/>