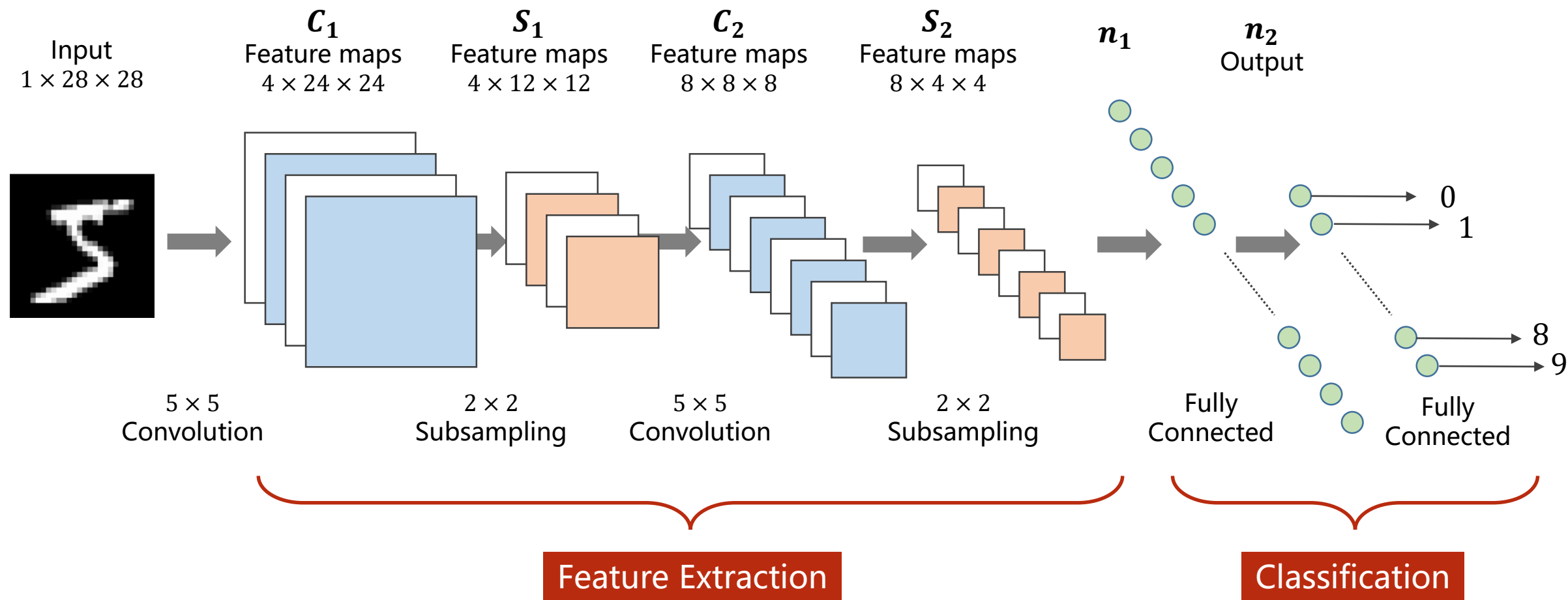




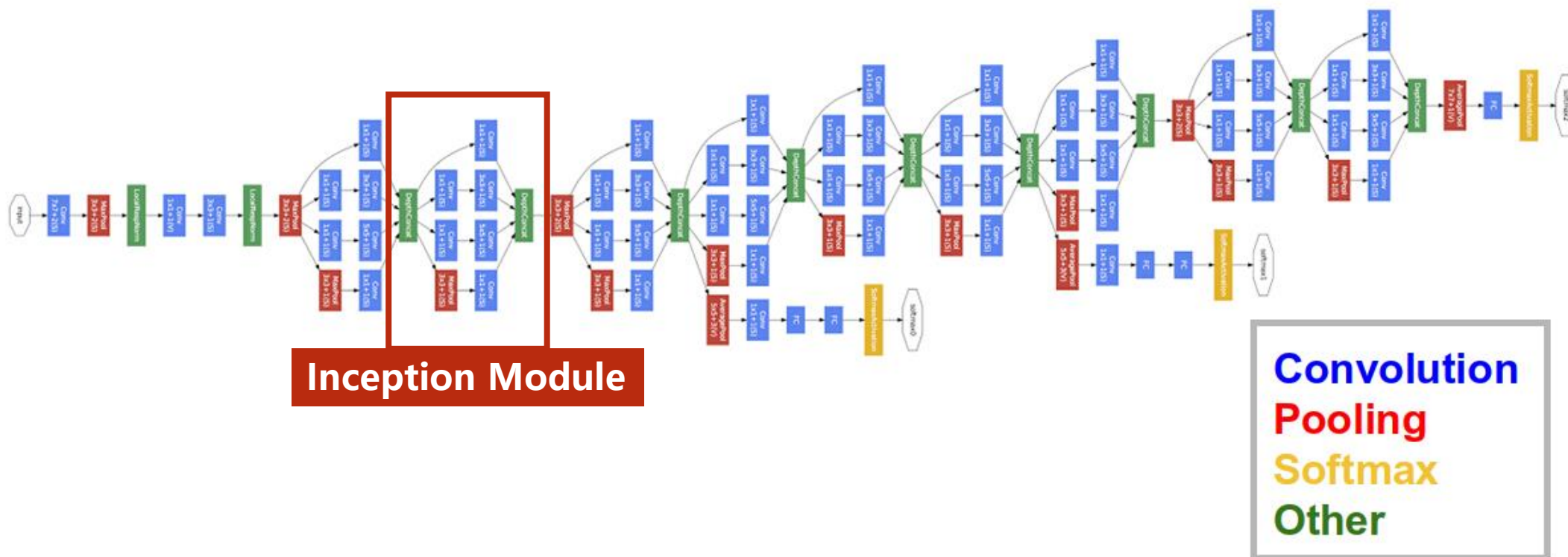
PyTorch Tutorial

11. Advanced CNN

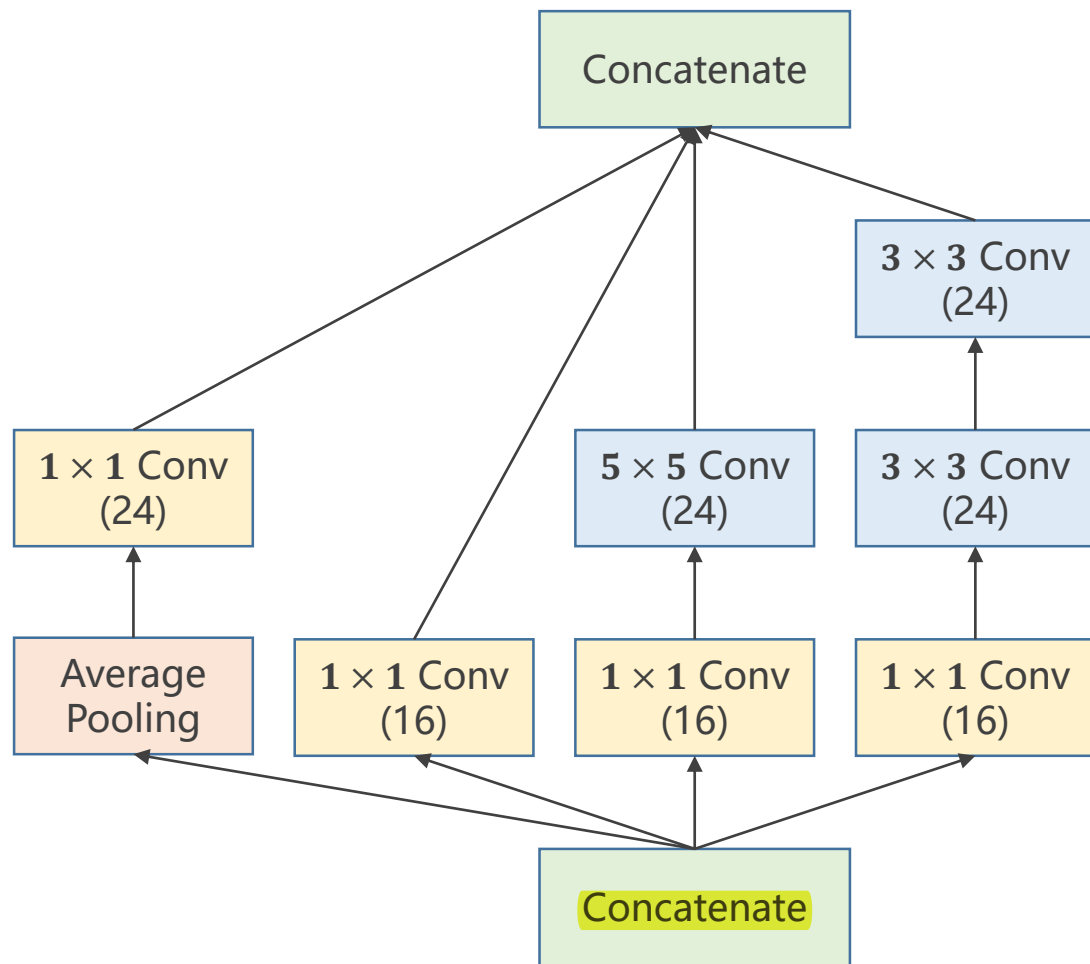
Revision



GoogLeNet



Inception Module



1×1 Conv
(16)

What is 1×1 convolution?

What is 1x1 convolution?

1	2	3
4	5	6
7	8	9

 \odot

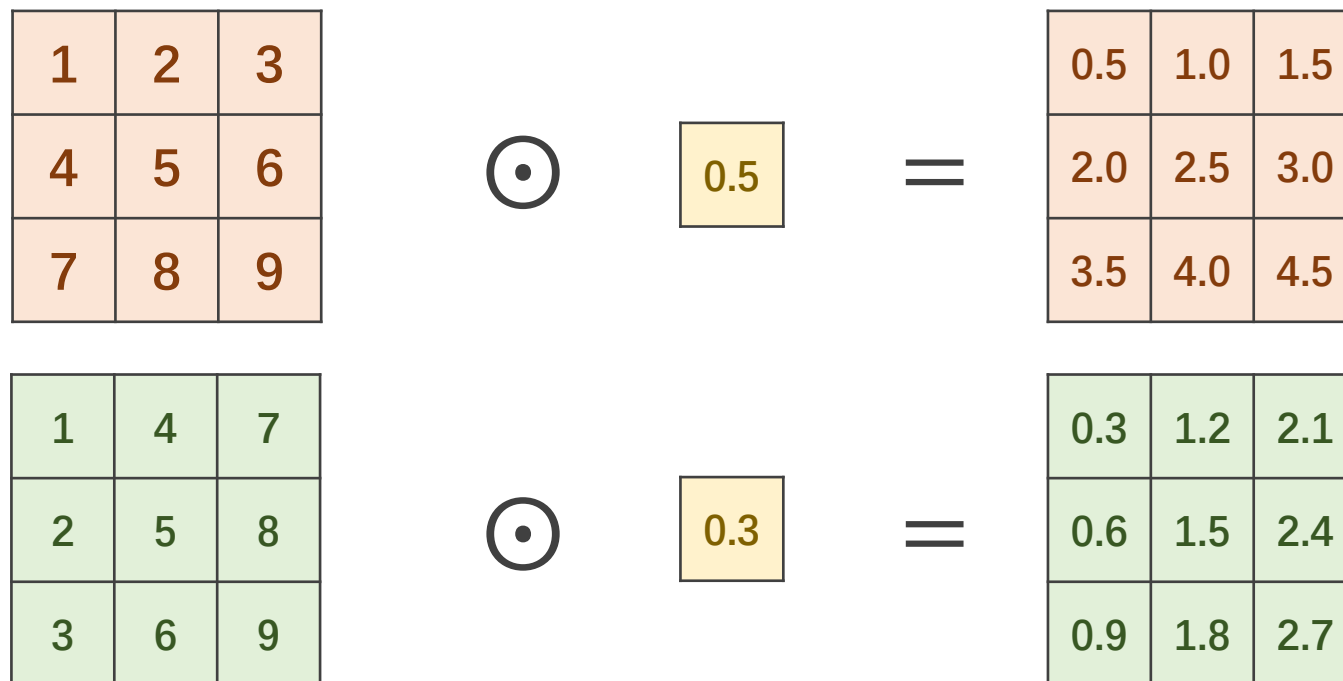
0.5

 $=$

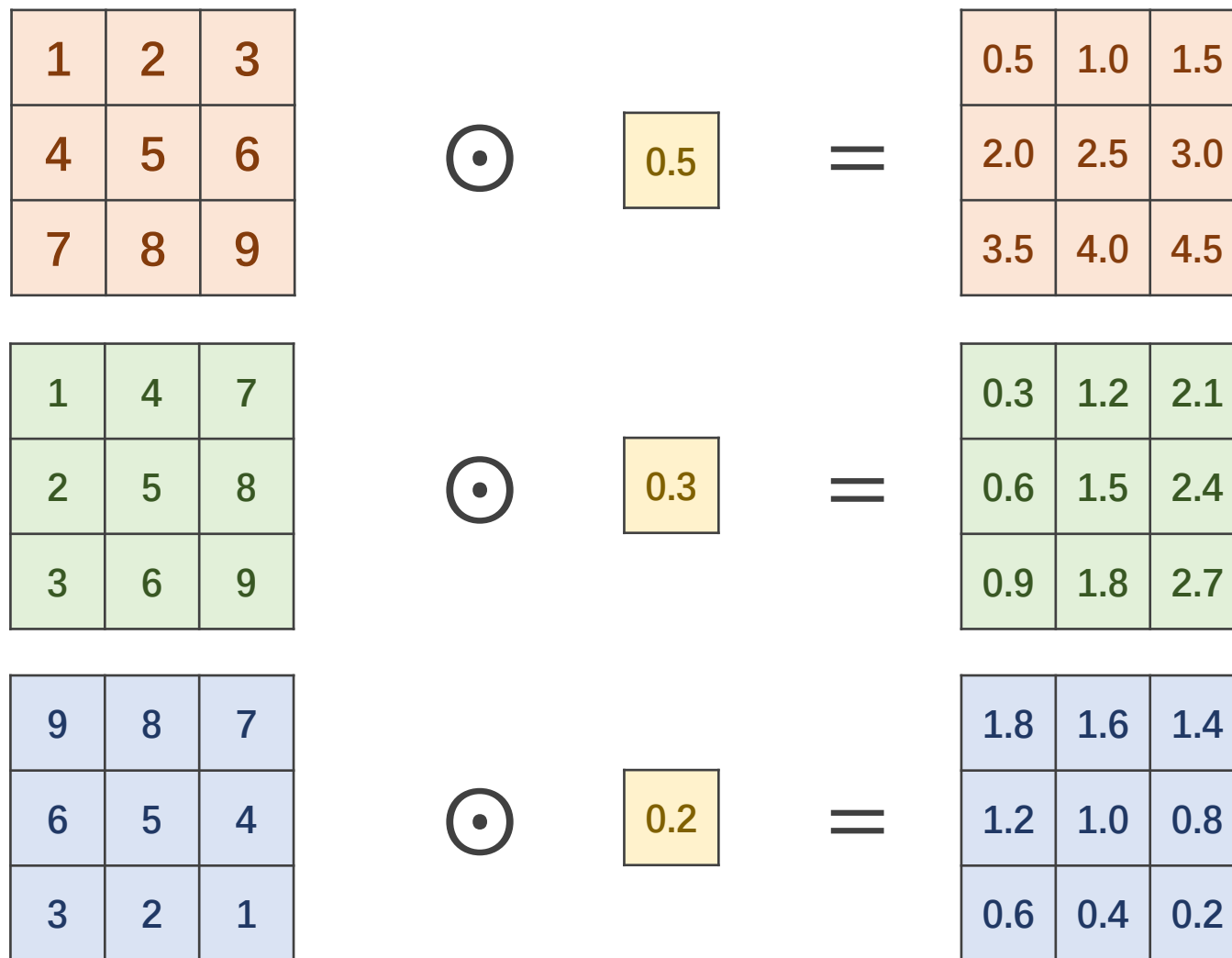
0.5	1.0	1.5
2.0	2.5	3.0
3.5	4.0	4.5

The diagram illustrates a 1x1 convolution operation. It shows a 3x3 input matrix of integers (1 to 9) being element-wise multiplied (indicated by the \odot symbol) by a 1x1 kernel containing the value 0.5. The result is a 3x3 output matrix where each element is 0.5 times the corresponding input element (e.g., 1 * 0.5 = 0.5, 9 * 0.5 = 4.5).

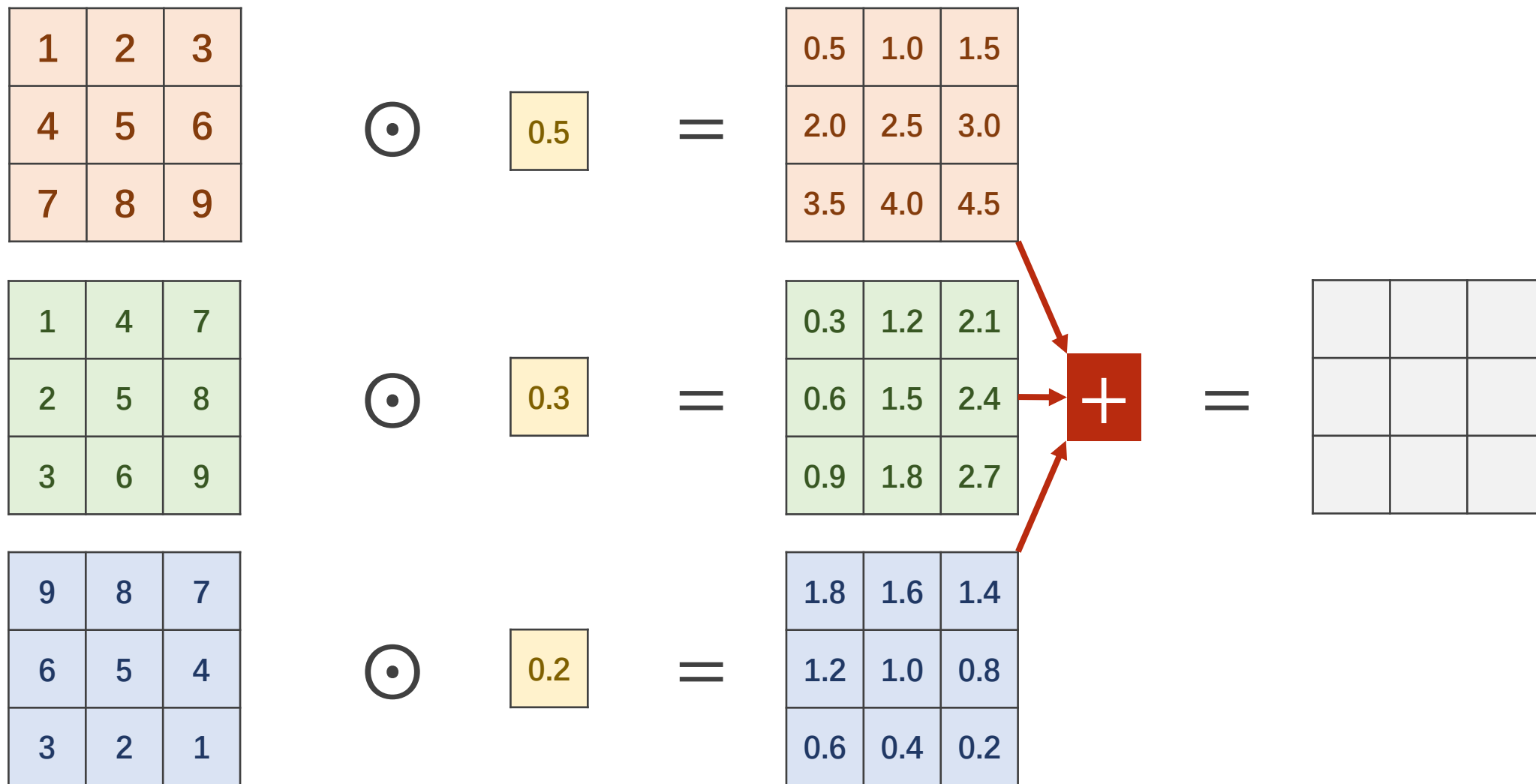
What is 1x1 convolution?



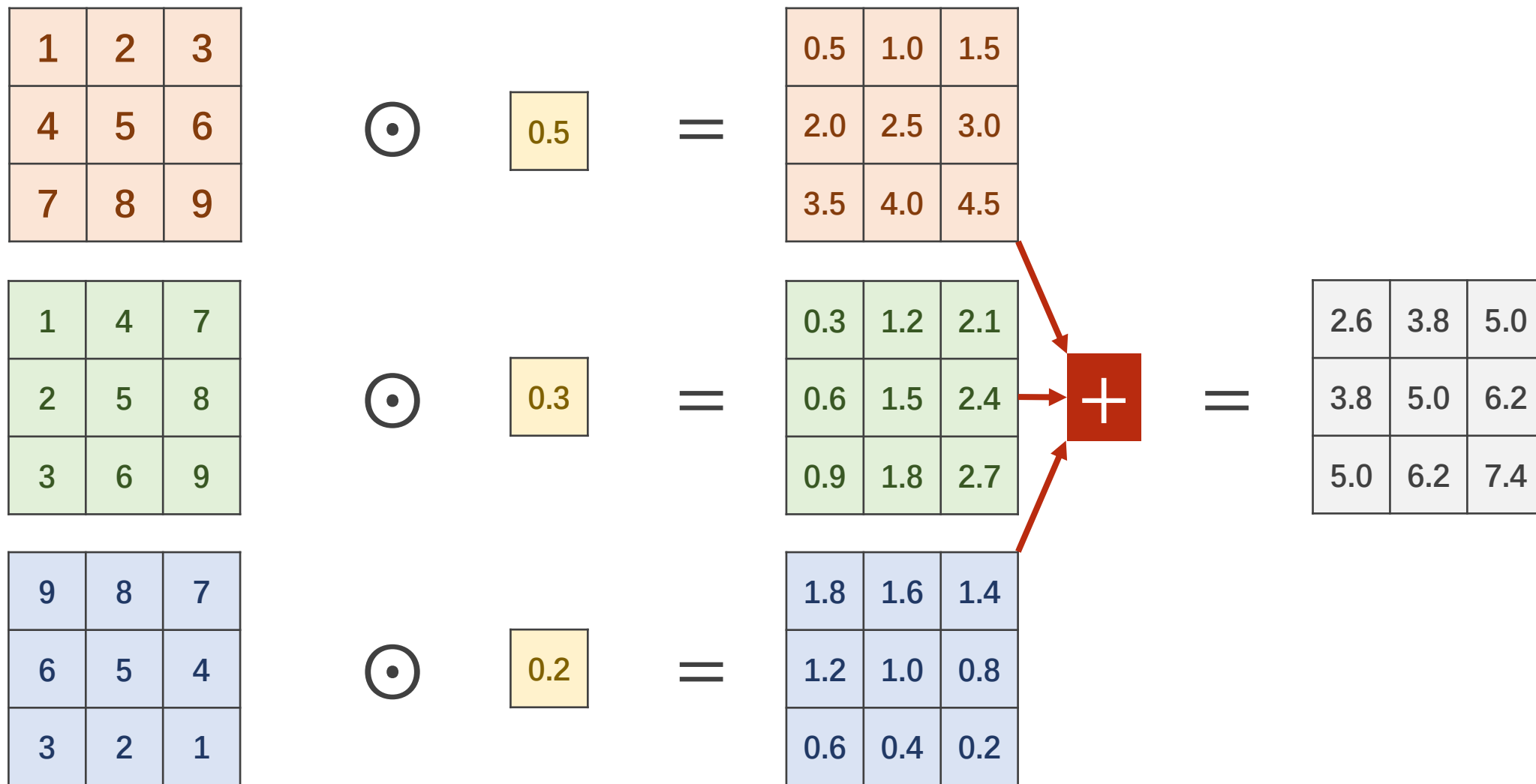
What is 1x1 convolution?



What is 1x1 convolution?



What is 1x1 convolution?



What is 1x1 convolution?

1	2	3
4	5	6
7	8	9

1	4	7
2	5	8
3	6	9

9	8	7
6	5	4
3	2	1



0.5

=

0.5	1.0	1.5
2.0	2.5	3.0
3.5	4.0	4.5



0.3

=

0.3	1.2	2.1
0.6	1.5	2.4
0.9	1.8	2.7



0.2

=

1.8	1.6	1.4
1.2	1.0	0.8
0.6	0.4	0.2



=

1x1 Convolution

2.6	3.8	5.0
3.8	5.0	6.2
5.0	6.2	7.4

What is 1x1 convolution?

1	2	3
4	5	6
7	8	9

1	4	7
2	5	8
3	6	9

9	8	7
6	5	4
3	2	1



0.5

=

0.5	1.0	1.5
2.0	2.5	3.0
3.5	4.0	4.5



0.3

=

0.3	1.2	2.1
0.6	1.5	2.4
0.9	1.8	2.7



0.2

=

1.8	1.6	1.4
1.2	1.0	0.8
0.6	0.4	0.2

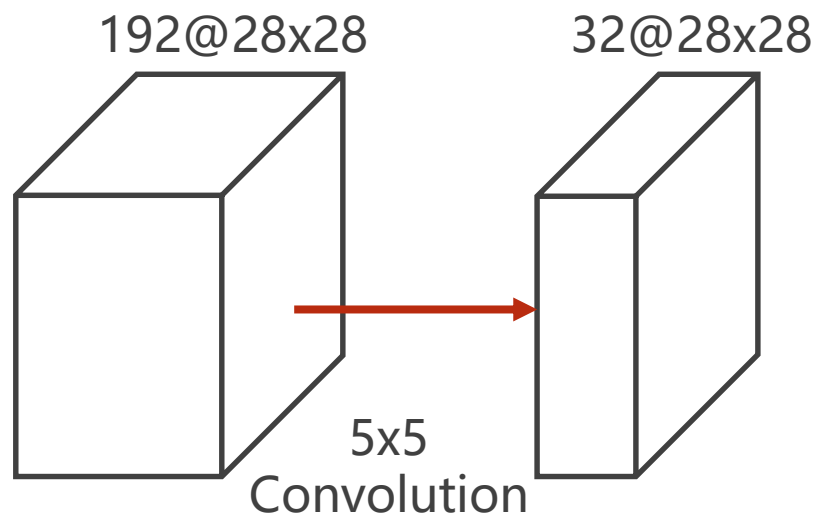


=

1x1 Convolution

2.6	3.8	5.0
3.8	5.0	6.2
5.0	6.2	7.4

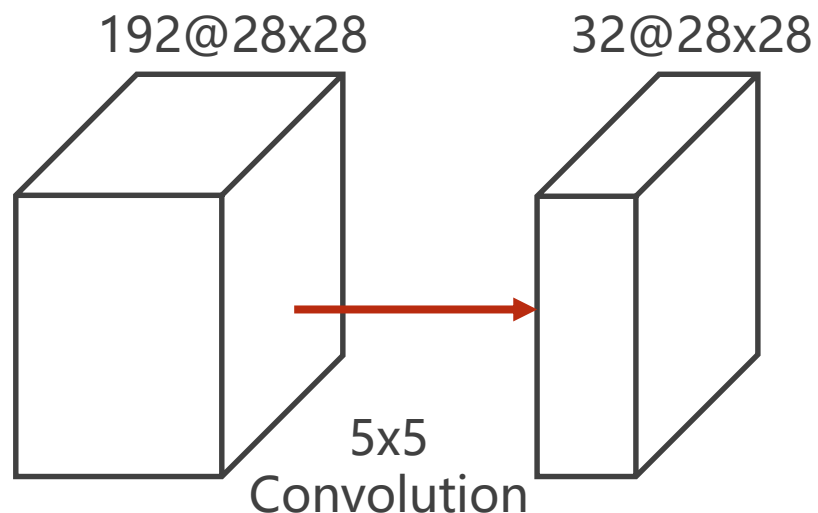
Why is 1x1 convolution?



Operations:

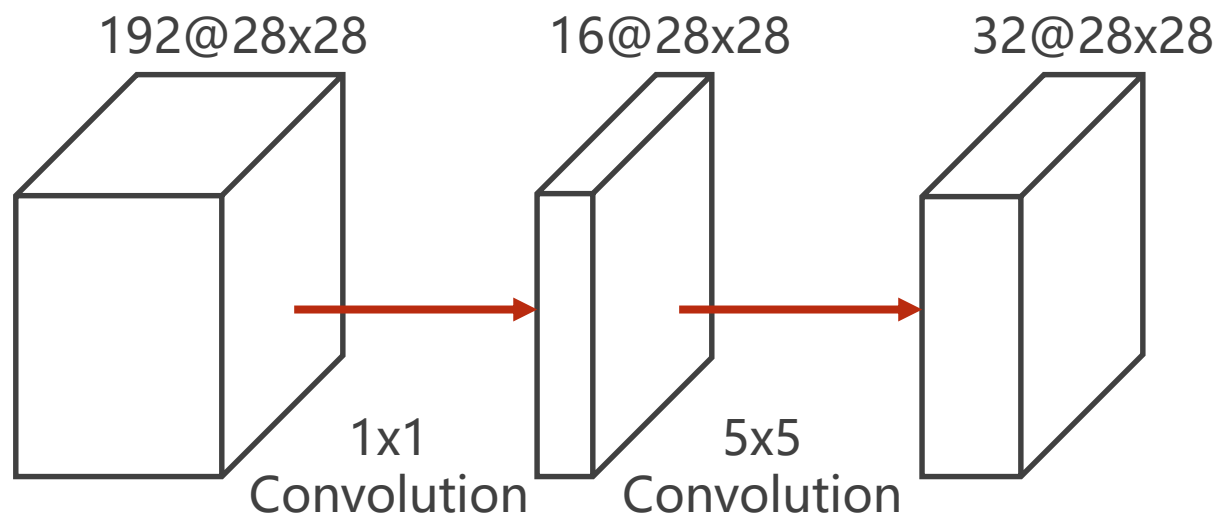
$$5^2 \times 28^2 \times 192 \times 32 = 120,422,400$$

Why is 1x1 convolution?



Operations:

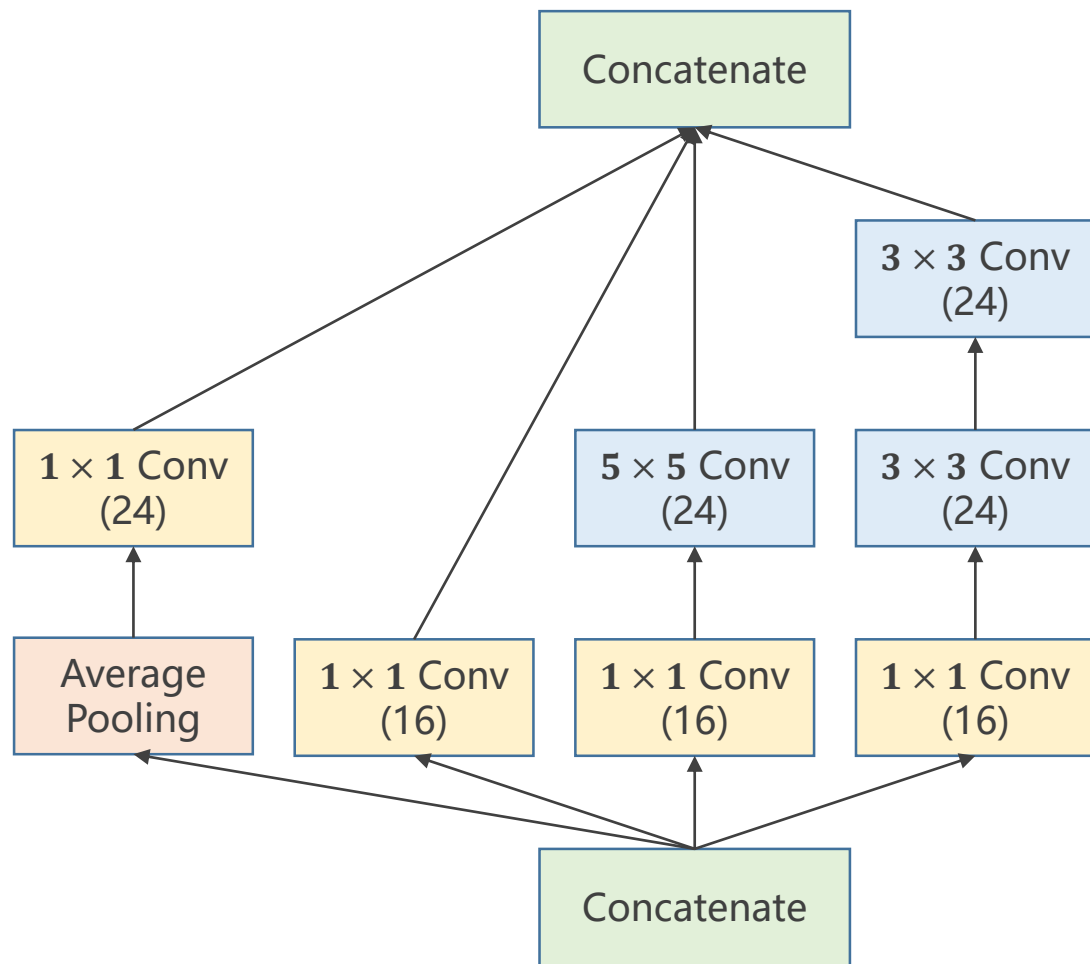
$$5^2 \times 28^2 \times 192 \times 32 = 120,422,400$$



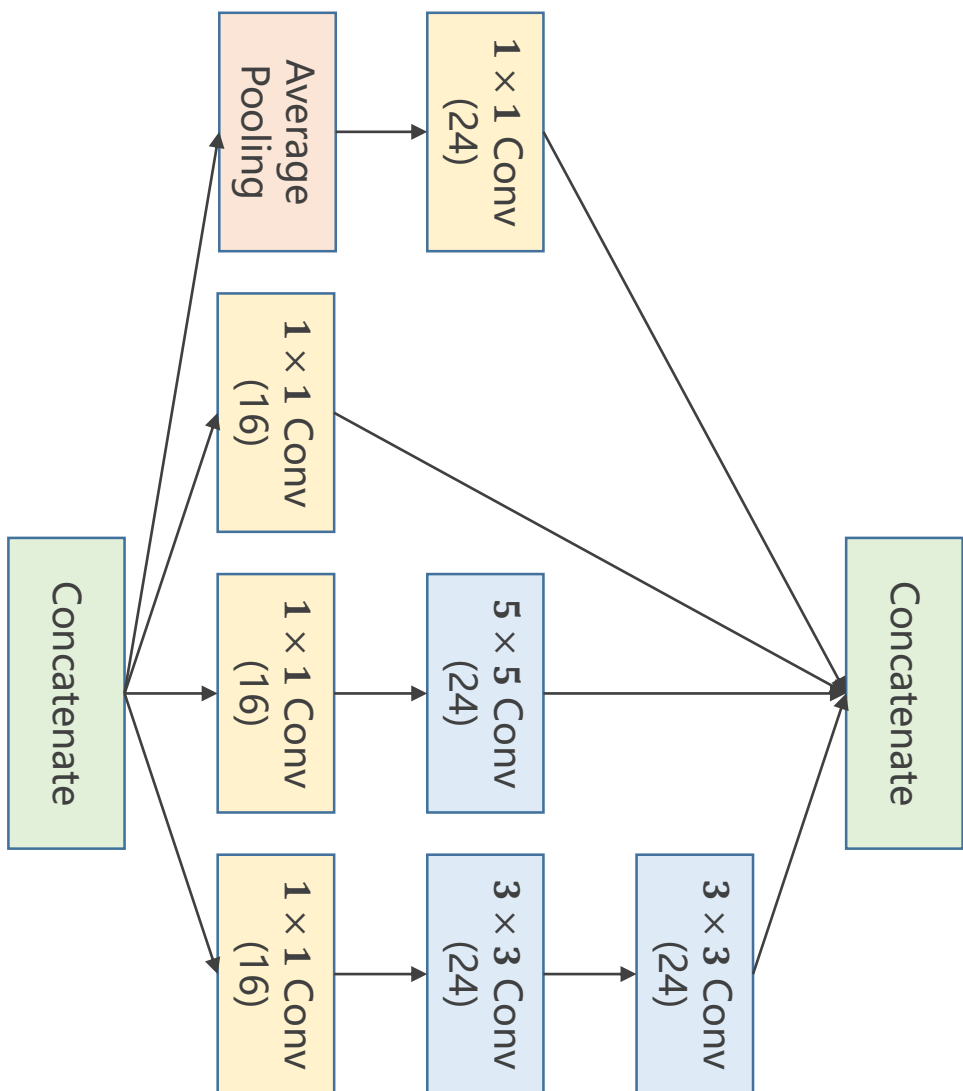
Operations:

$$1^2 \times 28^2 \times 192 \times 16 + 5^2 \times 28^2 \times 16 \times 32 = 12,433,648$$

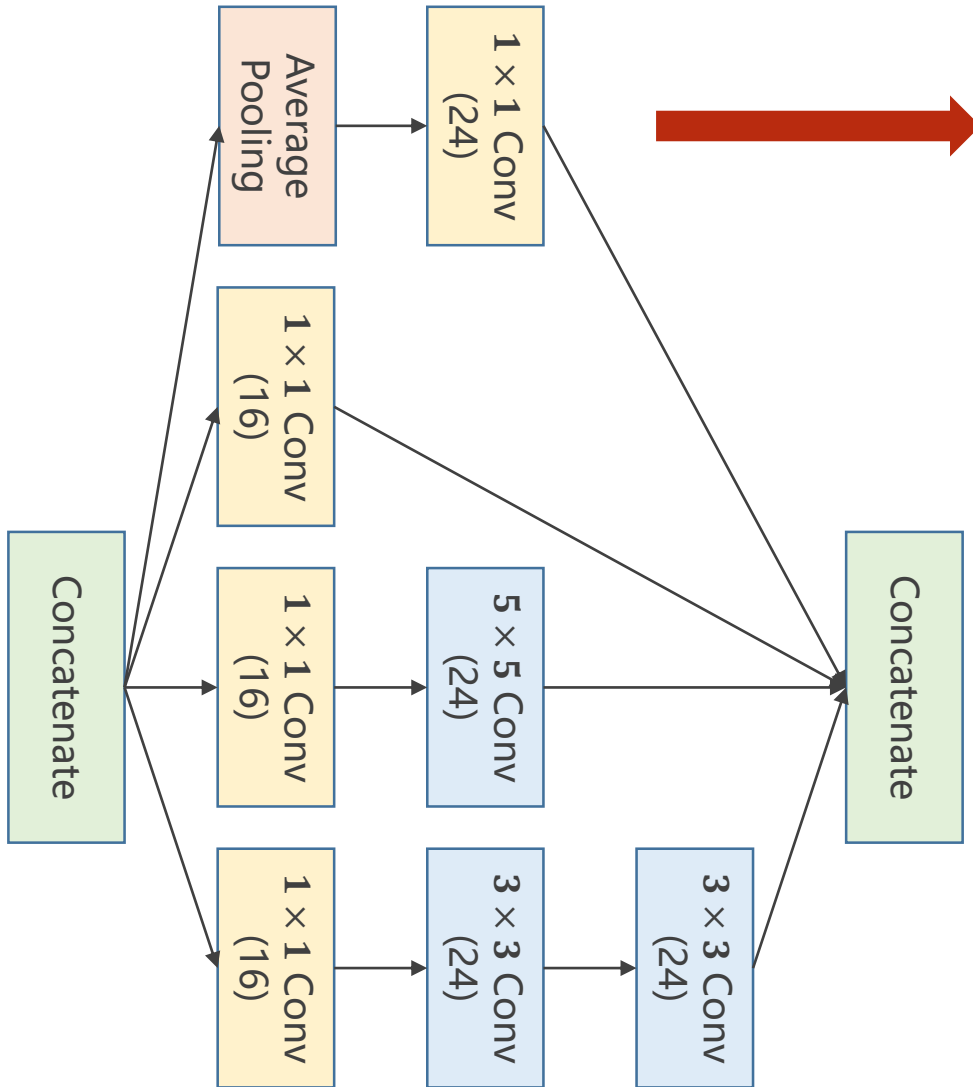
Implementation of Inception Module



Implementation of Inception Module



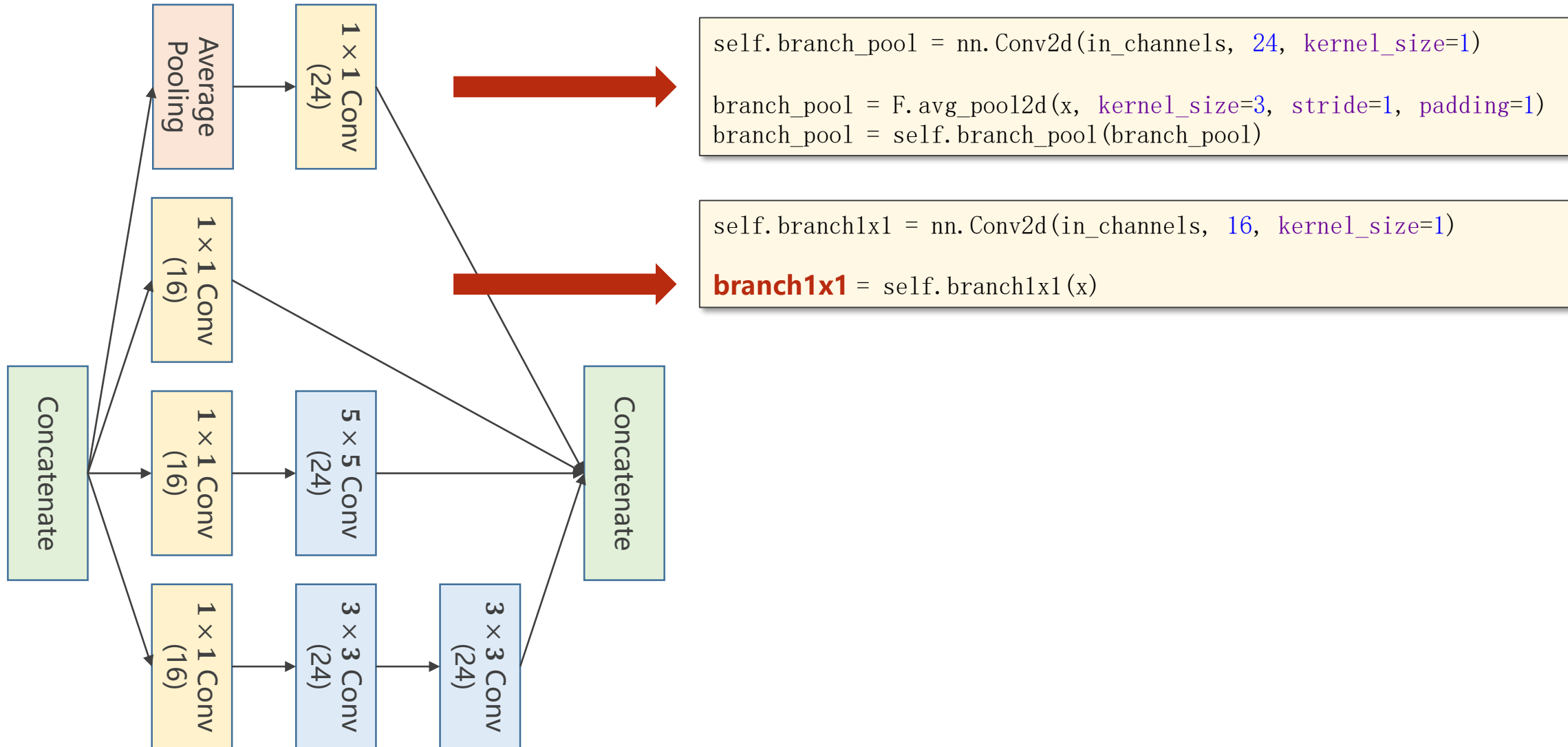
Implementation of Inception Module



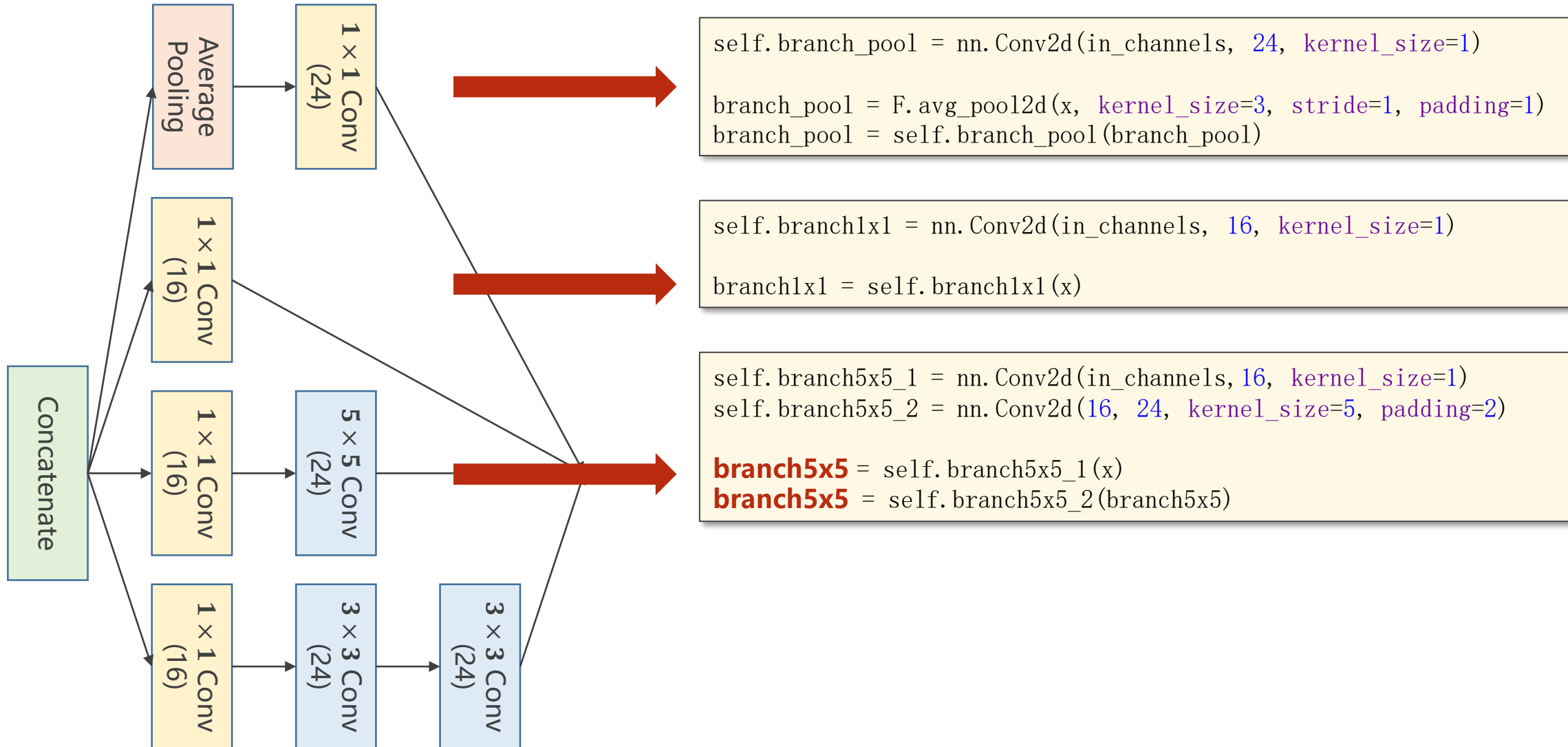
```
self.branch_pool = nn.Conv2d(in_channels, 24, kernel_size=1)
```

```
branch_pool = F.avg_pool2d(x, kernel_size=3, stride=1, padding=1)  
branch_pool = self.branch_pool(branch_pool)
```

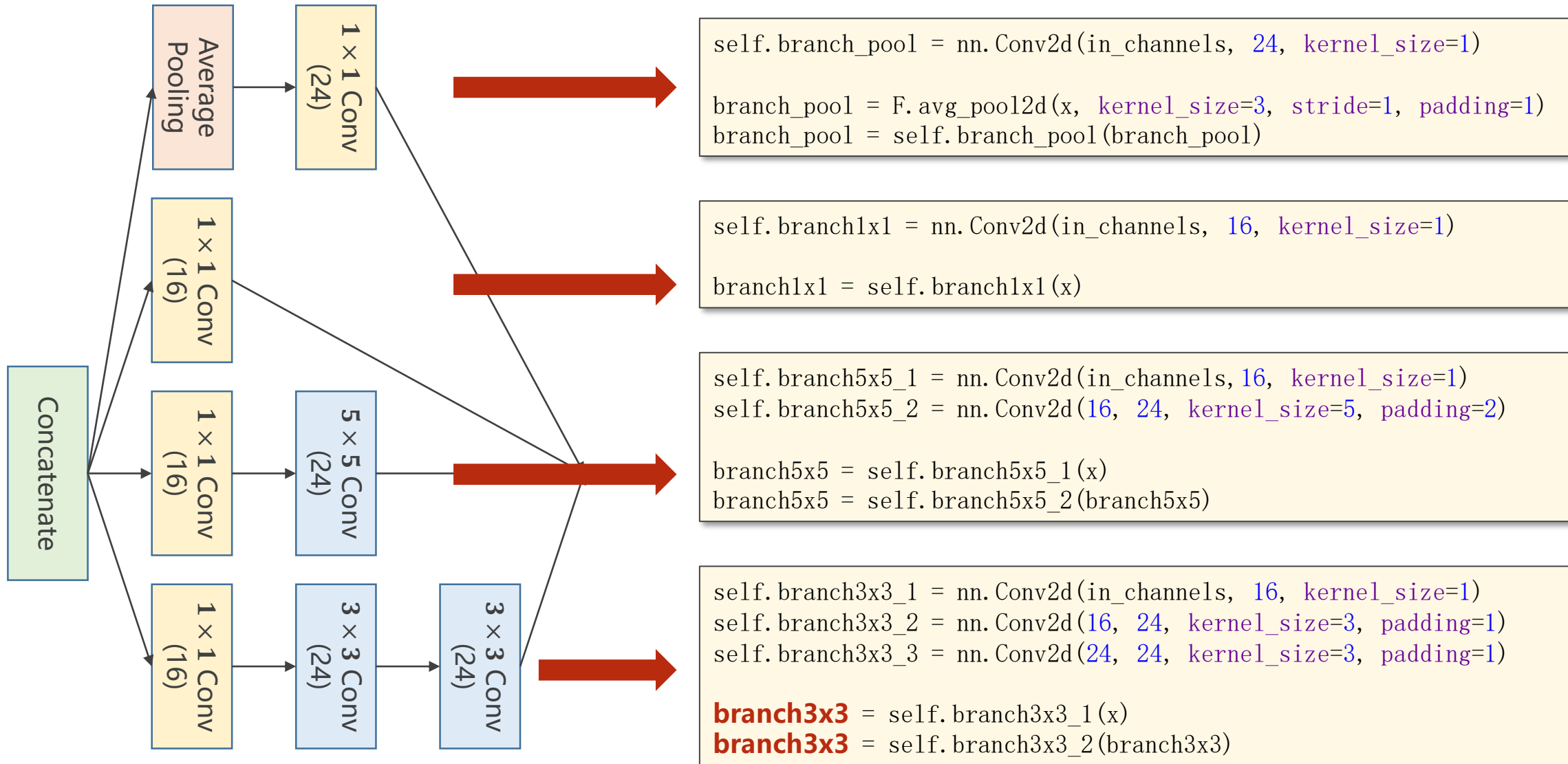

Implementation of Inception Module



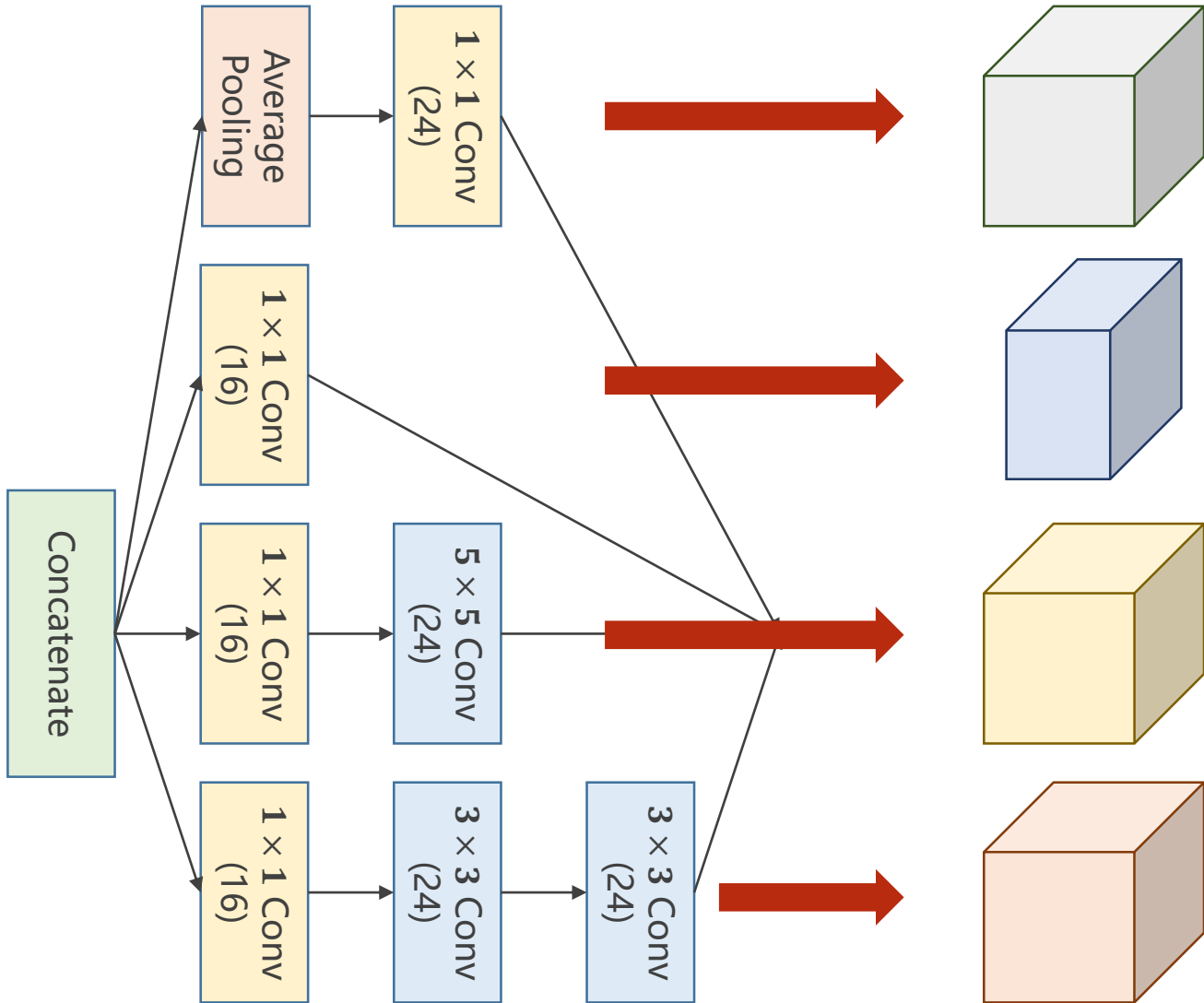
Implementation of Inception Module



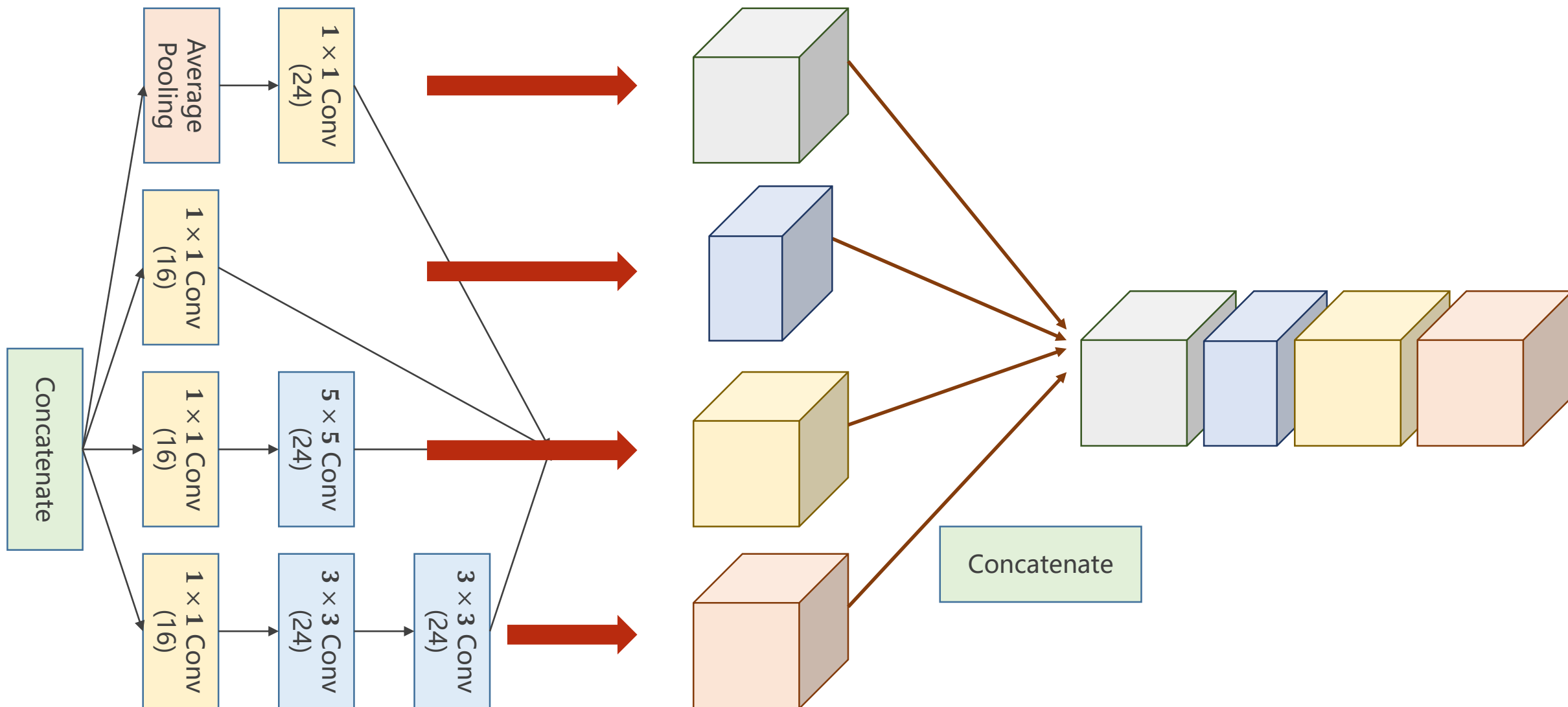
Implementation of Inception Module



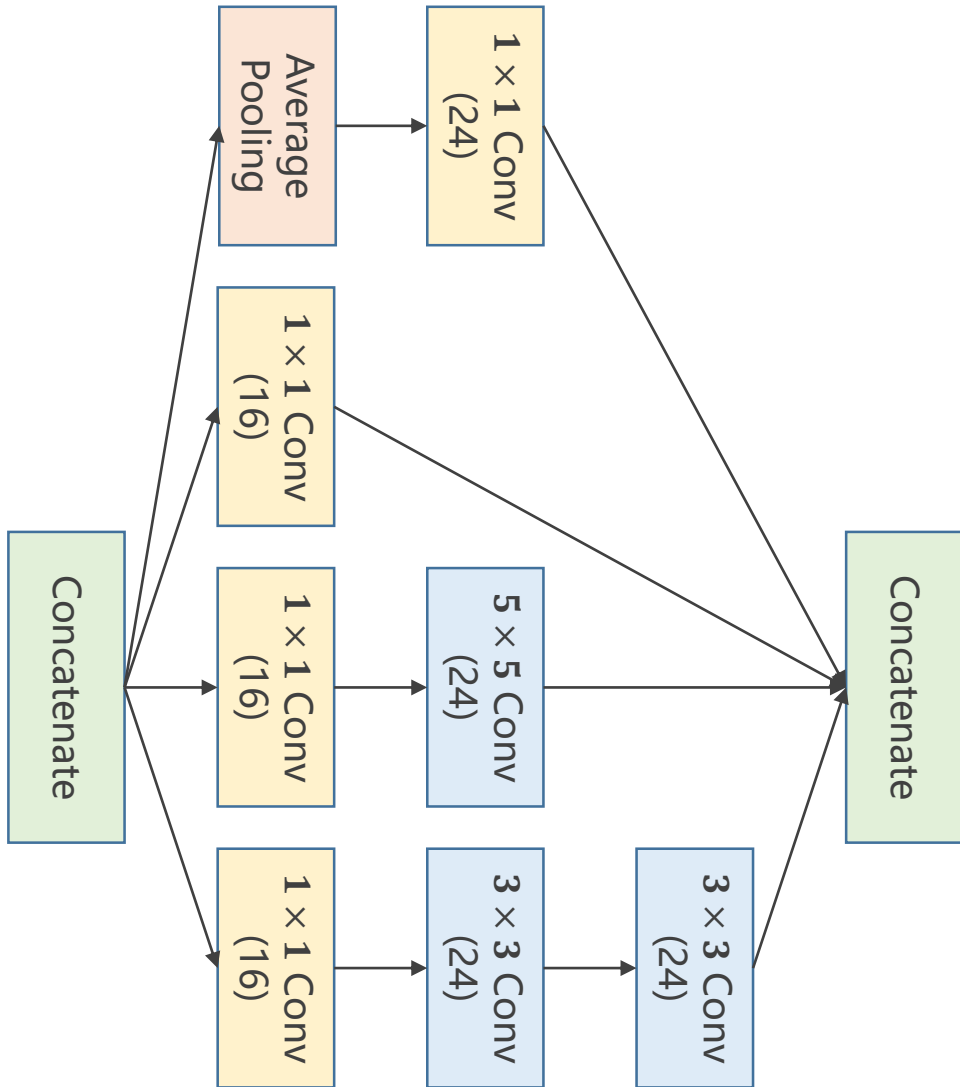
Implementation of Inception Module



Implementation of Inception Module



Implementation of Inception Module



```
outputs = [branch1x1, branch5x5, branch3x3, branch_pool]
return torch.cat(outputs, dim=1)
```

Implementation of Inception Module

```
class InceptionA(nn.Module):
    def __init__(self, in_channels):
        super(InceptionA, self).__init__()
        self.branch1x1 = nn.Conv2d(in_channels, 16, kernel_size=1)

        self.branch5x5_1 = nn.Conv2d(in_channels, 16, kernel_size=1)
        self.branch5x5_2 = nn.Conv2d(16, 24, kernel_size=5, padding=2)

        self.branch3x3_1 = nn.Conv2d(in_channels, 16, kernel_size=1)
        self.branch3x3_2 = nn.Conv2d(16, 24, kernel_size=3, padding=1)
        self.branch3x3_3 = nn.Conv2d(24, 24, kernel_size=3, padding=1)

        self.branch_pool = nn.Conv2d(in_channels, 24, kernel_size=1)

    def forward(self, x):
        branch1x1 = self.branch1x1(x)

        branch5x5 = self.branch5x5_1(x)
        branch5x5 = self.branch5x5_2(branch5x5)

        branch3x3 = self.branch3x3_1(x)
        branch3x3 = self.branch3x3_2(branch3x3)
        branch3x3 = self.branch3x3_3(branch3x3)

        branch_pool = F.avg_pool2d(x, kernel_size=3, stride=1, padding=1)
        branch_pool = self.branch_pool(branch_pool)

        outputs = [branch1x1, branch5x5, branch3x3, branch_pool]
        return torch.cat(outputs, dim=1)
```

Using Inception Module

```
class InceptionA(nn.Module):
    def __init__(self, in_channels):
        super(InceptionA, self).__init__()
        self.branch1x1 = nn.Conv2d(in_channels, 16, kernel_size=1)

        self.branch5x5_1 = nn.Conv2d(in_channels, 16, kernel_size=1)
        self.branch5x5_2 = nn.Conv2d(16, 24, kernel_size=5, padding=2)

        self.branch3x3_1 = nn.Conv2d(in_channels, 16, kernel_size=1)
        self.branch3x3_2 = nn.Conv2d(16, 24, kernel_size=3, padding=1)
        self.branch3x3_3 = nn.Conv2d(24, 24, kernel_size=3, padding=1)

        self.branch_pool = nn.Conv2d(in_channels, 24, kernel_size=1)

    def forward(self, x):
        branch1x1 = self.branch1x1(x)

        branch5x5 = self.branch5x5_1(x)
        branch5x5 = self.branch5x5_2(branch5x5)

        branch3x3 = self.branch3x3_1(x)
        branch3x3 = self.branch3x3_2(branch3x3)
        branch3x3 = self.branch3x3_3(branch3x3)

        branch_pool = F.avg_pool2d(x, kernel_size=3, stride=1, padding=1)
        branch_pool = self.branch_pool(branch_pool)

        outputs = [branch1x1, branch5x5, branch3x3, branch_pool]
        return torch.cat(outputs, dim=1)
```

```
class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(1, 10, kernel_size=5)
        self.conv2 = nn.Conv2d(88, 20, kernel_size=5)

        self.incep1 = InceptionA(in_channels=10)
        self.incep2 = InceptionA(in_channels=20)

        self.mp = nn.MaxPool2d(2)
        self.fc = nn.Linear(1408, 10)

    def forward(self, x):
        in_size = x.size(0)
        x = F.relu(self.mp(self.conv1(x)))
        x = self.incep1(x)
        x = F.relu(self.mp(self.conv2(x)))
        x = self.incep2(x)
        x = x.view(in_size, -1)
        x = self.fc(x)
        return x
```


Using Inception Module

```
class InceptionA(nn.Module):
    def __init__(self, in_channels):
        super(InceptionA, self).__init__()
        self.branch1x1 = nn.Conv2d(in_channels, 16, kernel_size=1)

        self.branch5x5_1 = nn.Conv2d(in_channels, 16, kernel_size=1)
        self.branch5x5_2 = nn.Conv2d(16, 24, kernel_size=5, padding=2)

        self.branch3x3_1 = nn.Conv2d(in_channels, 16, kernel_size=1)
        self.branch3x3_2 = nn.Conv2d(16, 24, kernel_size=3, padding=1)
        self.branch3x3_3 = nn.Conv2d(24, 24, kernel_size=3, padding=1)

        self.branch_pool = nn.Conv2d(in_channels, 24, kernel_size=1)

    def forward(self, x):
        branch1x1 = self.branch1x1(x)

        branch5x5 = self.branch5x5_1(x)
        branch5x5 = self.branch5x5_2(branch5x5)

        branch3x3 = self.branch3x3_1(x)
        branch3x3 = self.branch3x3_2(branch3x3)
        branch3x3 = self.branch3x3_3(branch3x3)

        branch_pool = F.avg_pool2d(x, kernel_size=3, stride=1, padding=1)
        branch_pool = self.branch_pool(branch_pool)

        outputs = [branch1x1, branch5x5, branch3x3, branch_pool]
        return torch.cat(outputs, dim=1)
```

```
class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(1, 10, kernel_size=5)
        self.conv2 = nn.Conv2d(88, 20, kernel_size=5)

        self.incep1 = InceptionA(in_channels=10)
        self.incep2 = InceptionA(in_channels=20)

        self.mp = nn.MaxPool2d(2)
        self.fc = nn.Linear(1408, 10)

    def forward(self, x):
        in_size = x.size(0)
        x = F.relu(self.mp(self.conv1(x)))
        x = self.incep1(x)
        x = F.relu(self.mp(self.conv2(x)))
        x = self.incep2(x)
        x = x.view(in_size, -1)
        x = self.fc(x)
        return x
```

Results of using Inception Module

Accuracy on test set: 9 % [982/10000]

[1, 300] loss: 0.141

[1, 600] loss: 0.031

[1, 900] loss: 0.020

Accuracy on test set: 95 % [9554/10000]

[2, 300] loss: 0.015

[2, 600] loss: 0.014

[2, 900] loss: 0.012

Accuracy on test set: 97 % [9793/10000]

.....

[9, 300] loss: 0.005

[9, 600] loss: 0.005

[9, 900] loss: 0.005

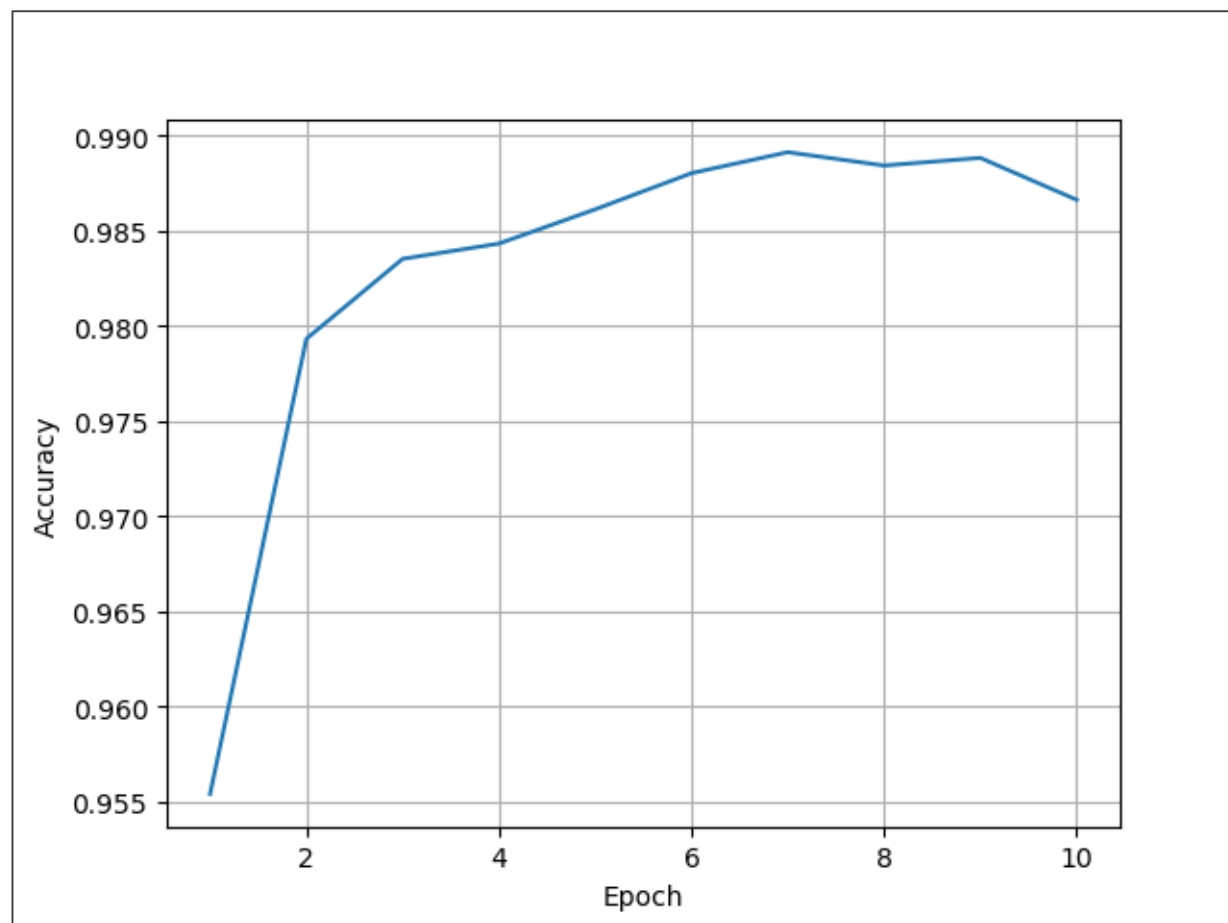
Accuracy on test set: 98 % [9888/10000]

[10, 300] loss: 0.005

[10, 600] loss: 0.005

[10, 900] loss: 0.005

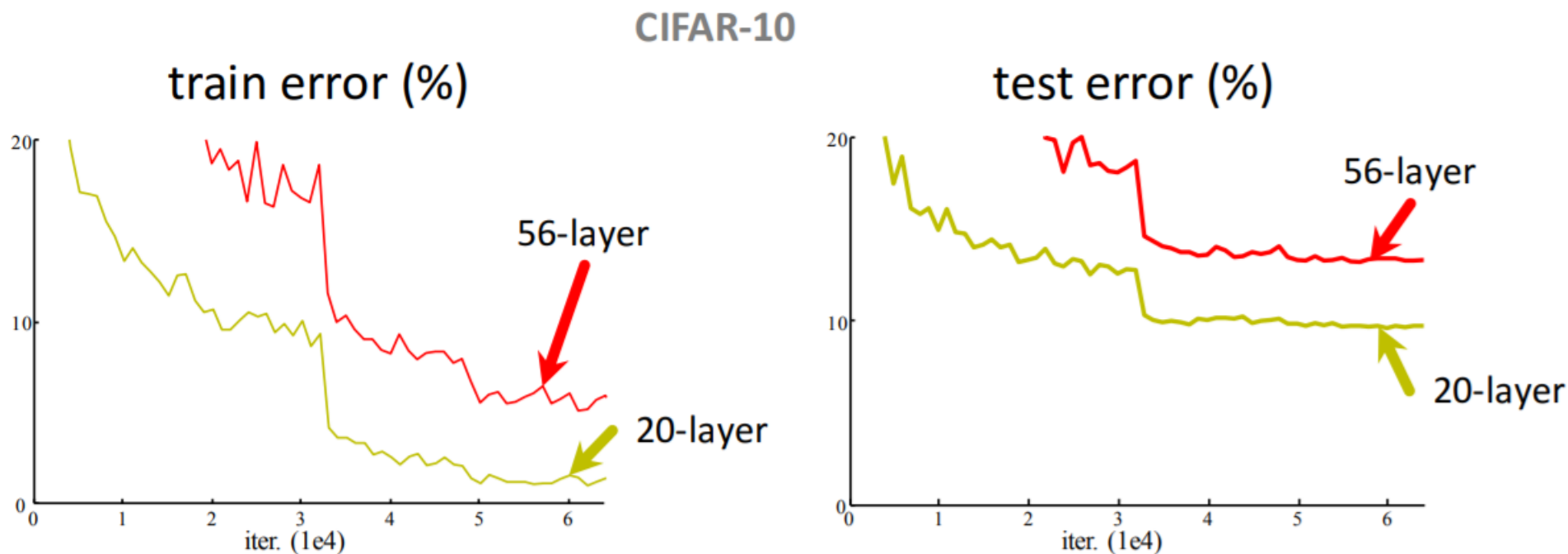
Accuracy on test set: 98 % [9866/10000]



Go Deeper



Can we stack layers to go deeper?

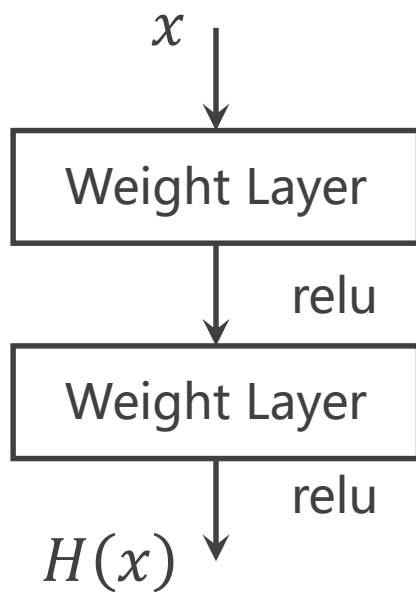


Plain nets: stacking 3x3 conv layers

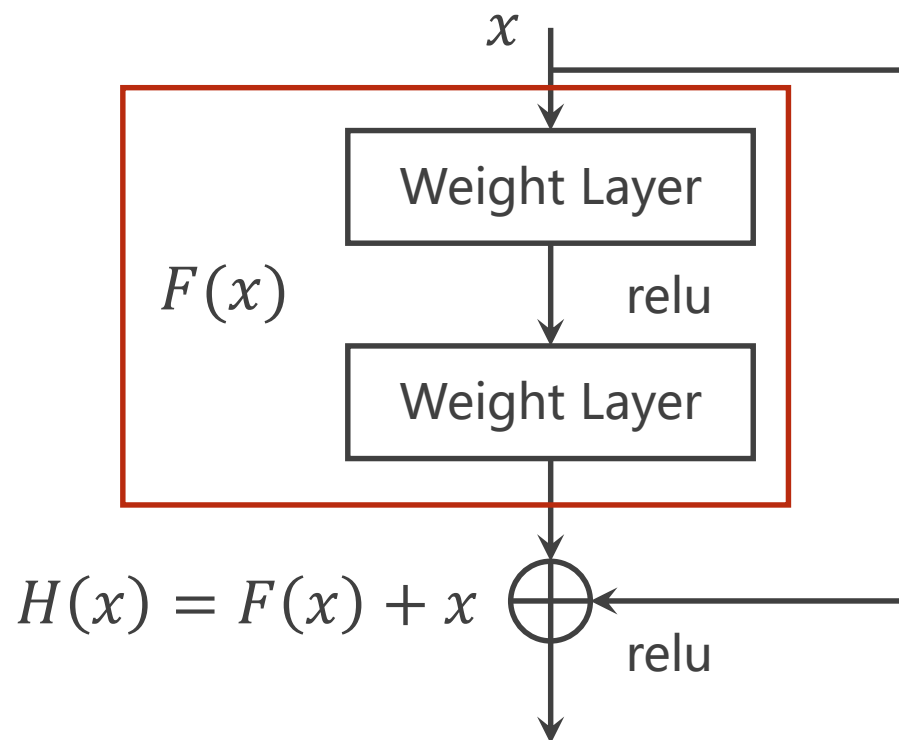
He K, Zhang X, Ren S, et al. Deep Residual Learning for Image Recognition[C]// IEEE Conference on Computer Vision and Pattern Recognition. IEEE Computer Society, 2016:770-778.

Deep Residual Learning

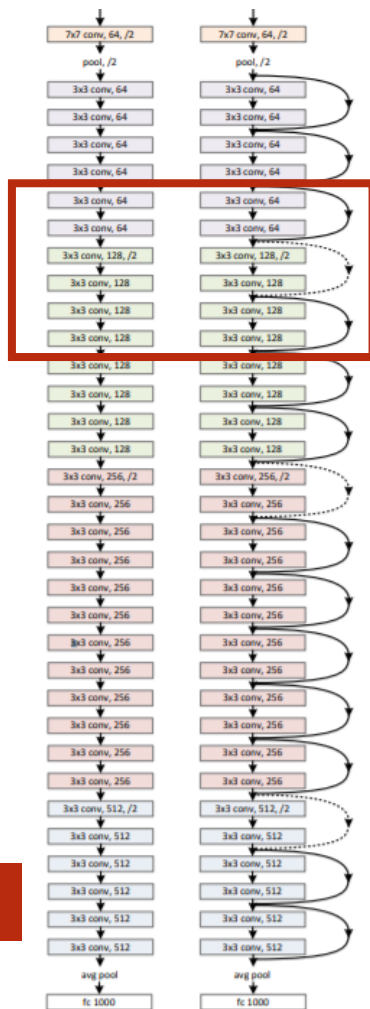
Plain net



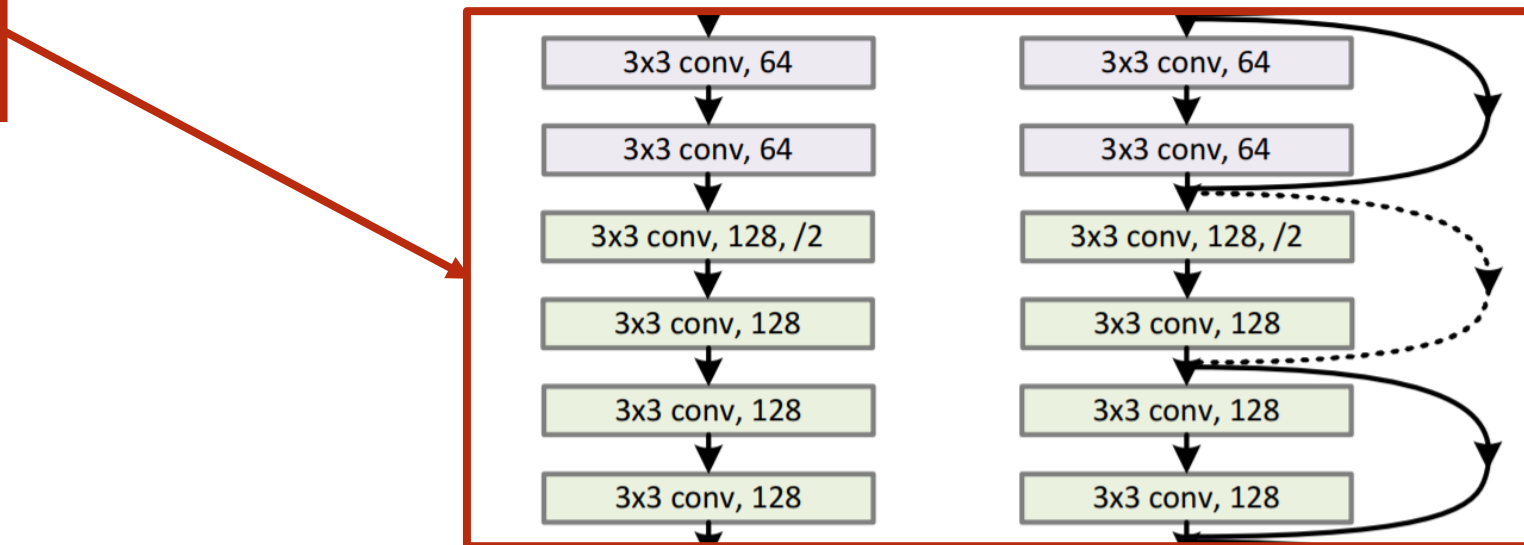
Residual net



Residual Network

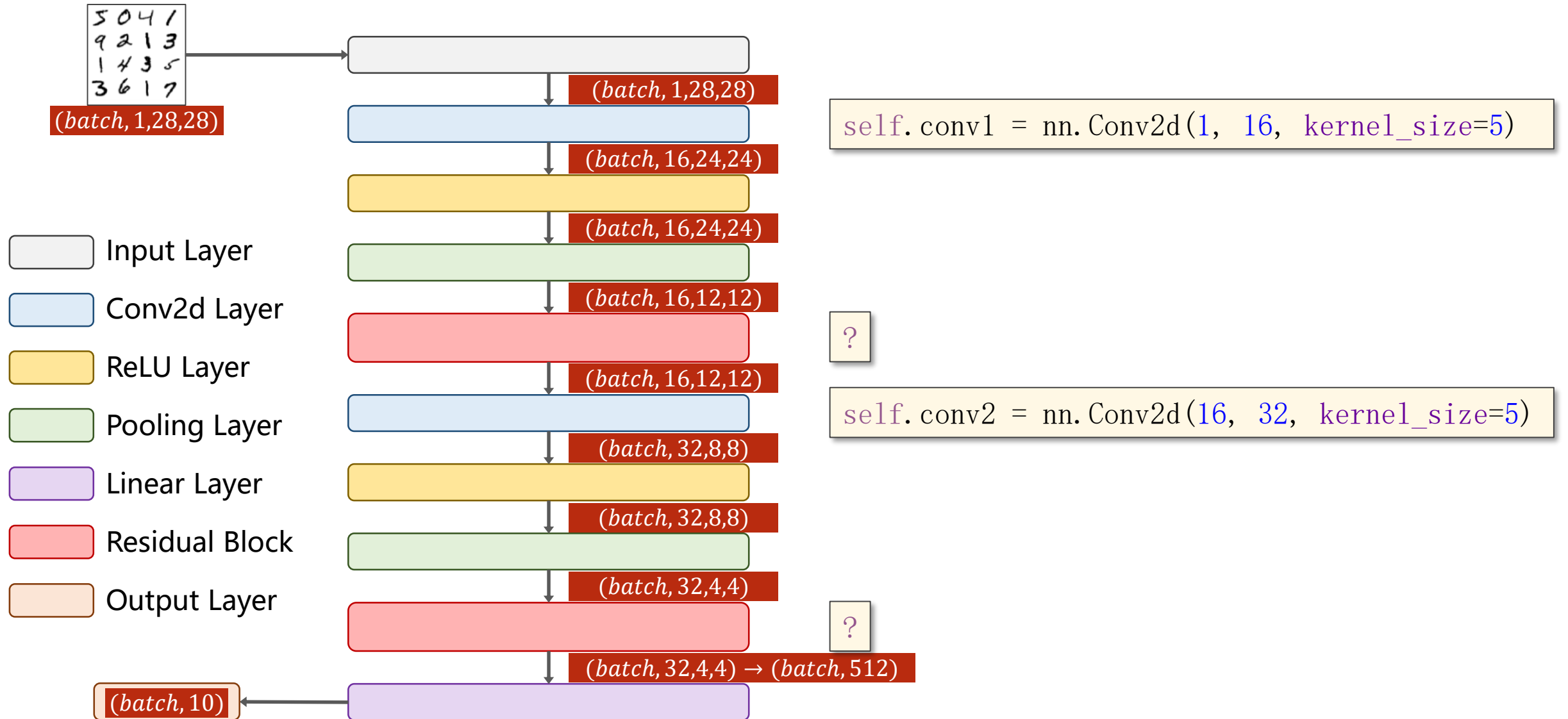


Plain net

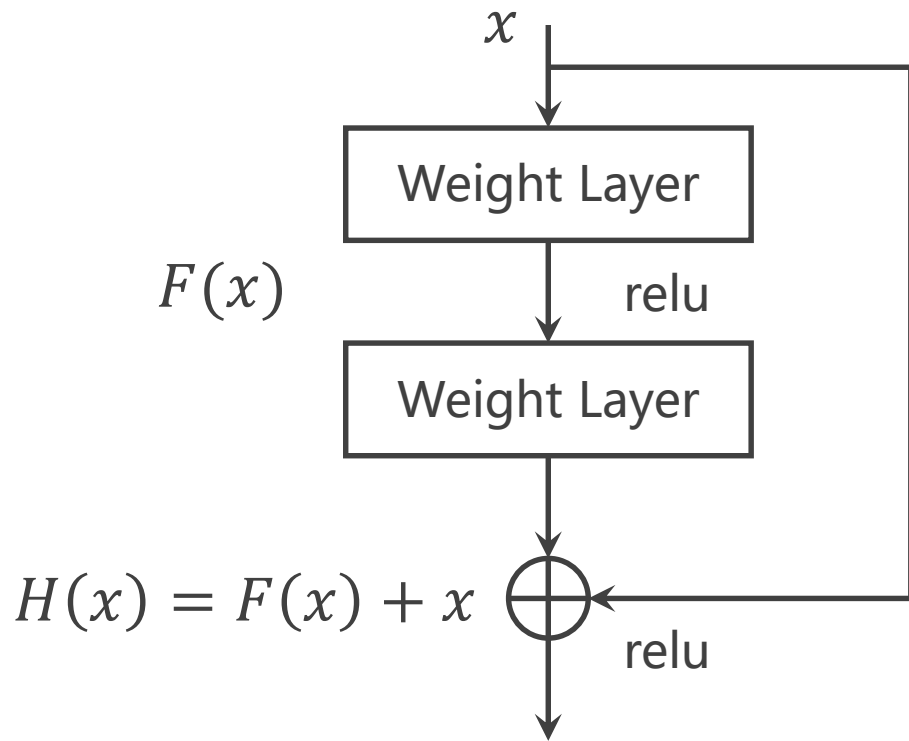


Residual net

Implementation of Simple Residual Network

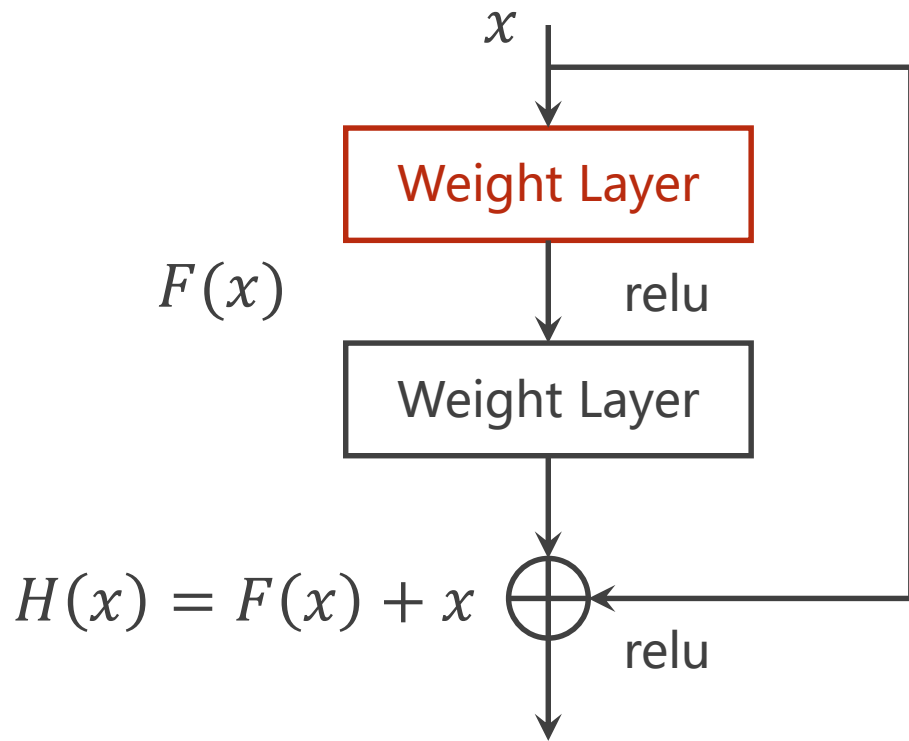


Implementation of Residual Block



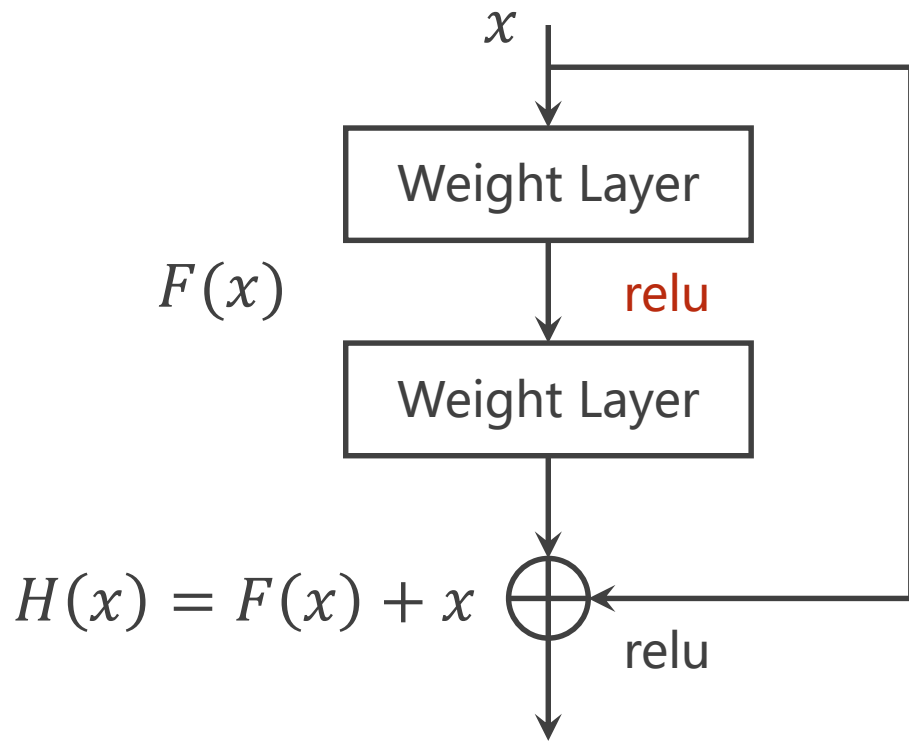
```
class ResidualBlock(nn.Module):  
    def __init__(self, channels):  
        super(ResidualBlock, self).__init__()  
        self.channels = channels  
        self.conv1 = nn.Conv2d(channels, channels,  
                                kernel_size=3, padding=1)  
        self.conv2 = nn.Conv2d(channels, channels,  
                                kernel_size=3, padding=1)  
  
    def forward(self, x):  
        y = F.relu(self.conv1(x))  
        y = self.conv2(y)  
        return F.relu(x + y)
```


Implementation of Residual Block



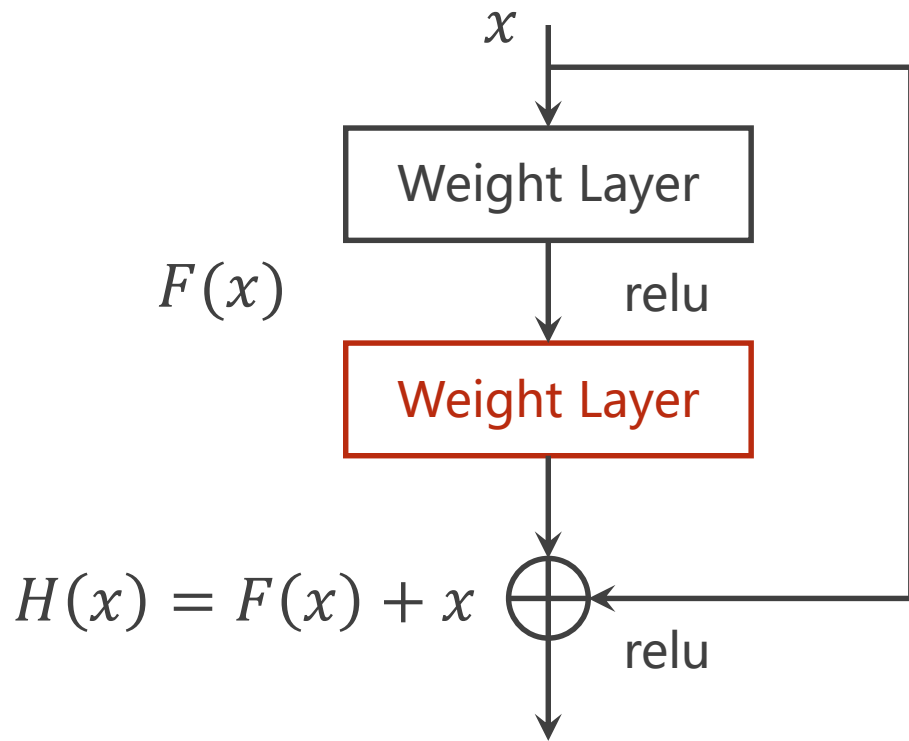
```
class ResidualBlock(nn.Module):  
    def __init__(self, channels):  
        super(ResidualBlock, self).__init__()  
        self.channels = channels  
        self.conv1 = nn.Conv2d(channels, channels,  
                                kernel_size=3, padding=1)  
        self.conv2 = nn.Conv2d(channels, channels,  
                                kernel_size=3, padding=1)  
  
    def forward(self, x):  
        y = F.relu(self.conv1(x))  
        y = self.conv2(y)  
        return F.relu(x + y)
```

Implementation of Residual Block



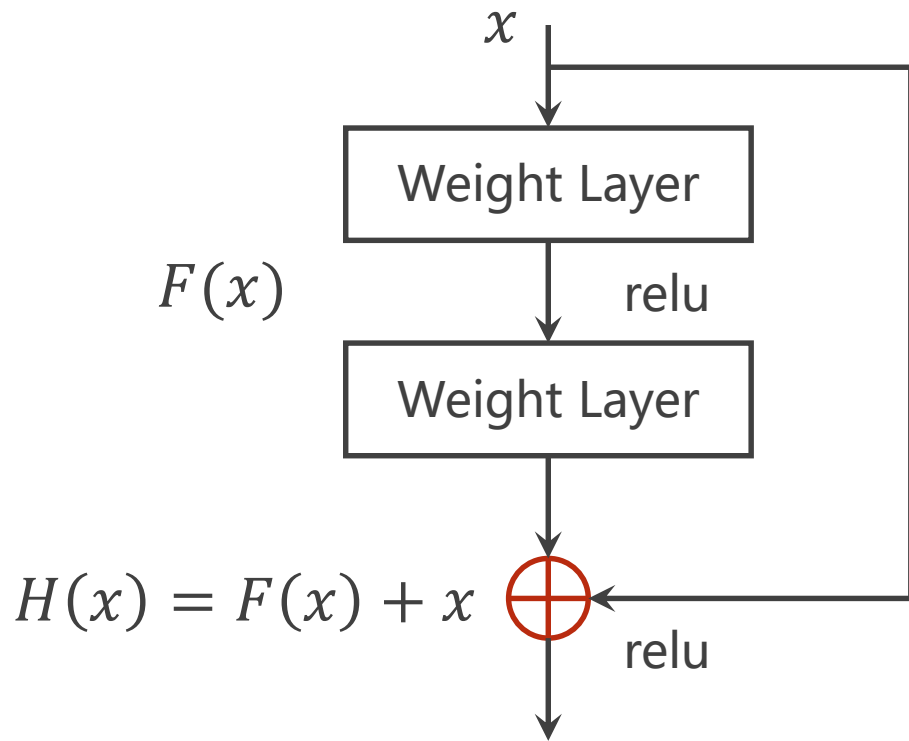
```
class ResidualBlock(nn.Module):  
    def __init__(self, channels):  
        super(ResidualBlock, self).__init__()  
        self.channels = channels  
        self.conv1 = nn.Conv2d(channels, channels,  
                                kernel_size=3, padding=1)  
        self.conv2 = nn.Conv2d(channels, channels,  
                                kernel_size=3, padding=1)  
  
    def forward(self, x):  
        y = F.relu(self.conv1(x))  
        y = self.conv2(y)  
        return F.relu(x + y)
```

Implementation of Residual Block



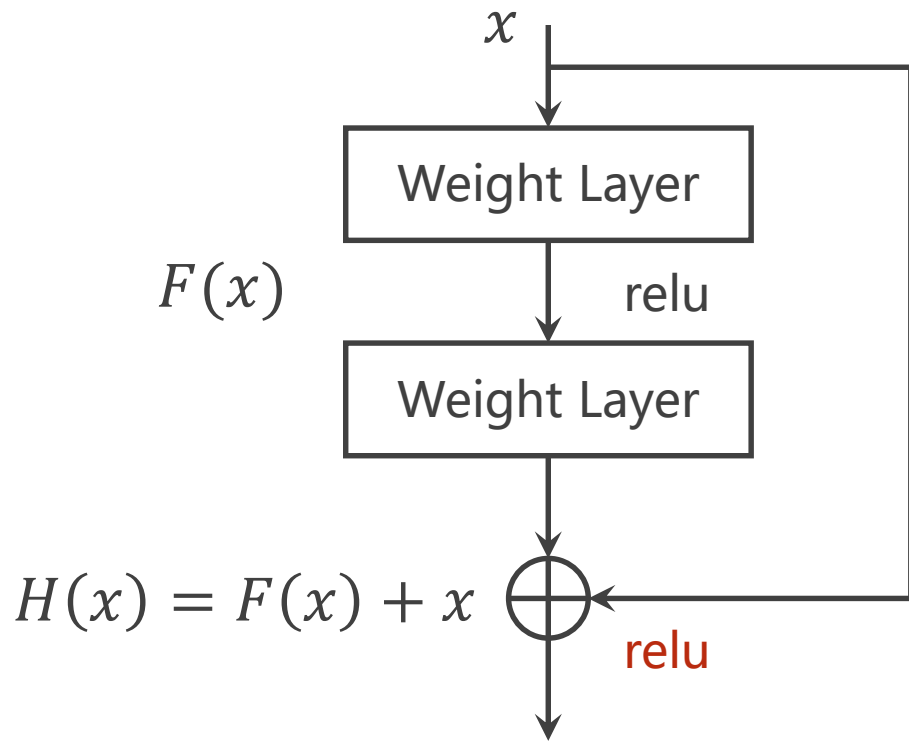
```
class ResidualBlock(nn.Module):  
    def __init__(self, channels):  
        super(ResidualBlock, self).__init__()  
        self.channels = channels  
        self.conv1 = nn.Conv2d(channels, channels,  
                                kernel_size=3, padding=1)  
        self.conv2 = nn.Conv2d(channels, channels,  
                                kernel_size=3, padding=1)  
  
    def forward(self, x):  
        y = F.relu(self.conv1(x))  
        y = self.conv2(y)  
        return F.relu(x + y)
```

Implementation of Residual Block



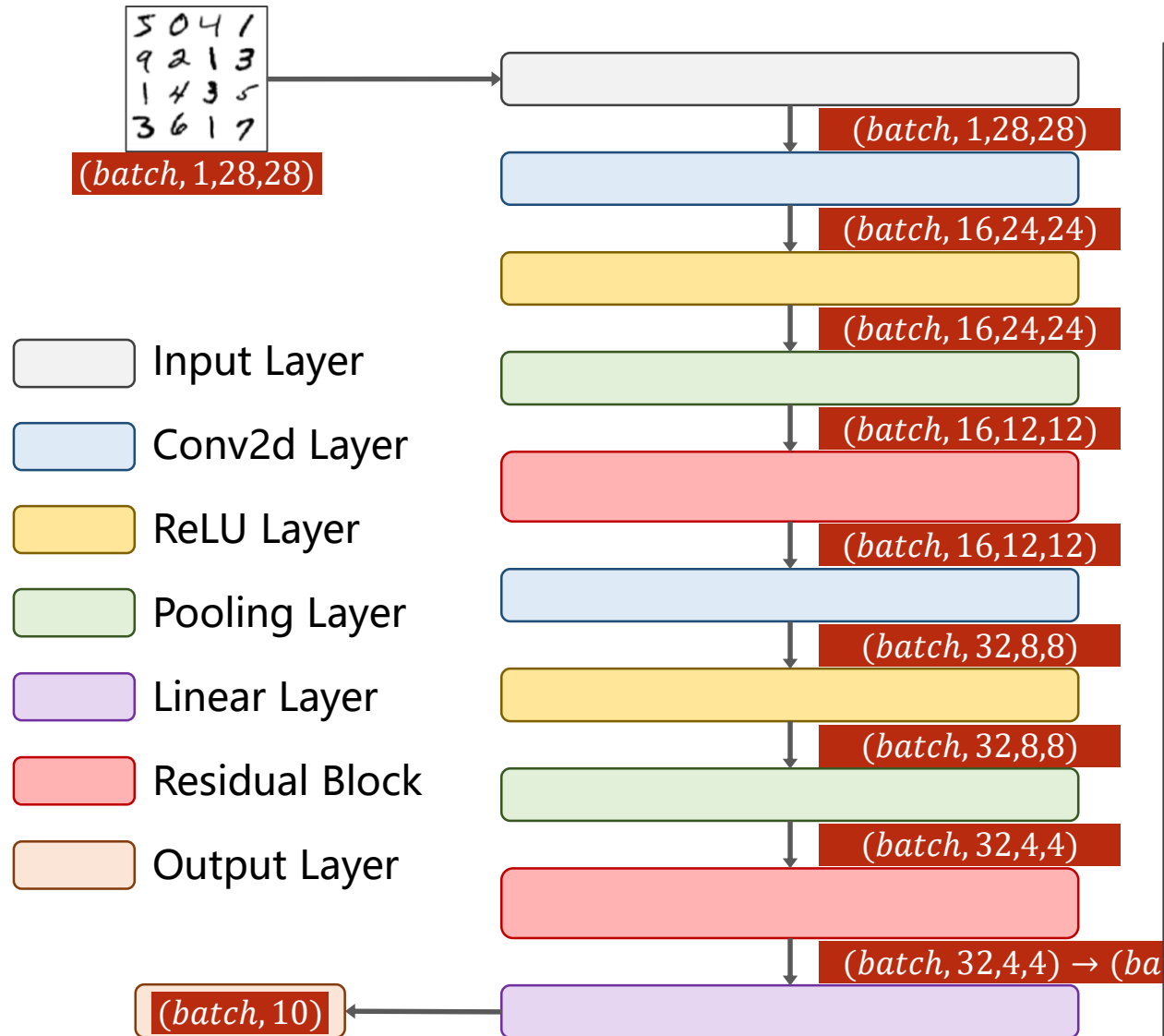
```
class ResidualBlock(nn.Module):  
    def __init__(self, channels):  
        super(ResidualBlock, self).__init__()  
        self.channels = channels  
        self.conv1 = nn.Conv2d(channels, channels,  
                                kernel_size=3, padding=1)  
        self.conv2 = nn.Conv2d(channels, channels,  
                                kernel_size=3, padding=1)  
  
    def forward(self, x):  
        y = F.relu(self.conv1(x))  
        y = self.conv2(y)  
        return F.relu(x + y)
```

Implementation of Residual Block



```
class ResidualBlock(nn.Module):  
    def __init__(self, channels):  
        super(ResidualBlock, self).__init__()  
        self.channels = channels  
        self.conv1 = nn.Conv2d(channels, channels,  
                                kernel_size=3, padding=1)  
        self.conv2 = nn.Conv2d(channels, channels,  
                                kernel_size=3, padding=1)  
  
    def forward(self, x):  
        y = F.relu(self.conv1(x))  
        y = self.conv2(y)  
        return F.relu(x + y)
```

Implementation of Simple Residual Network



```
class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(1, 16, kernel_size=5)
        self.conv2 = nn.Conv2d(16, 32, kernel_size=5)
        self.mp = nn.MaxPool2d(2)

        self.rblock1 = ResidualBlock(16)
        self.rblock2 = ResidualBlock(32)

        self.fc = nn.Linear(512, 10)

    def forward(self, x):
        in_size = x.size(0)
        x = self.mp(F.relu(self.conv1(x)))
        x = self.rblock1(x)
        x = self.mp(F.relu(self.conv2(x)))
        x = self.rblock2(x)
        x = x.view(in_size, -1)
        x = self.fc(x)
        return x
```

Accuracy on test set: 9 % [916/10000]

[1, 300] loss: 0.074

[1, 600] loss: 0.021

[1, 900] loss: 0.017

Accuracy on test set: 97 % [9736/10000]

[2, 300] loss: 0.013

[2, 600] loss: 0.011

[2, 900] loss: 0.011

Accuracy on test set: 98 % [9831/10000]

.....

[9, 300] loss: 0.003

[9, 600] loss: 0.004

[9, 900] loss: 0.004

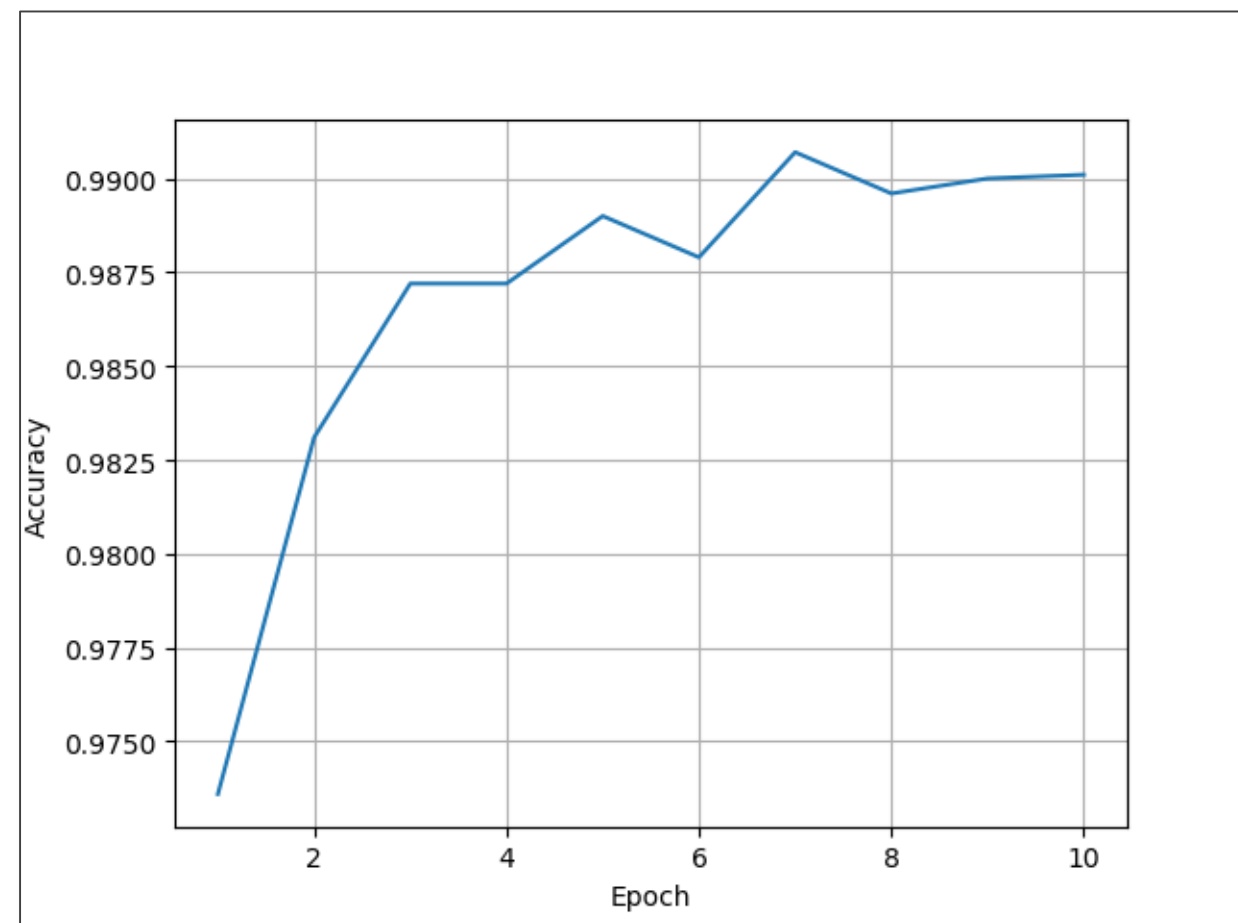
Accuracy on test set: 99 % [9900/10000]

[10, 300] loss: 0.003

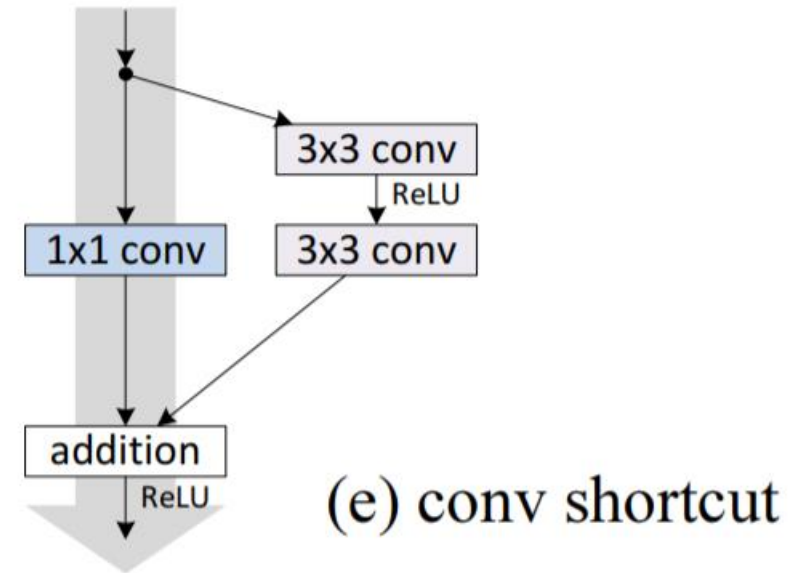
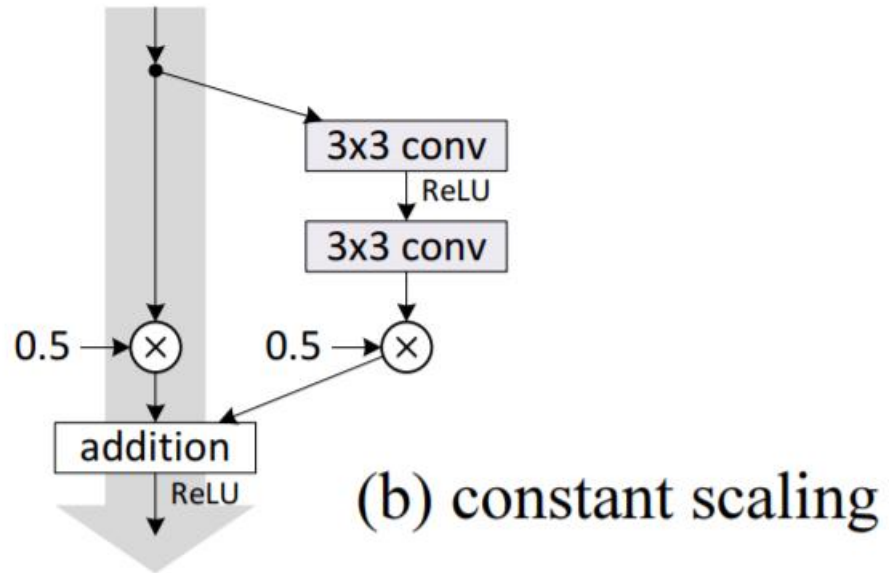
[10, 600] loss: 0.003

[10, 900] loss: 0.004

Accuracy on test set: 99 % [9901/10000]

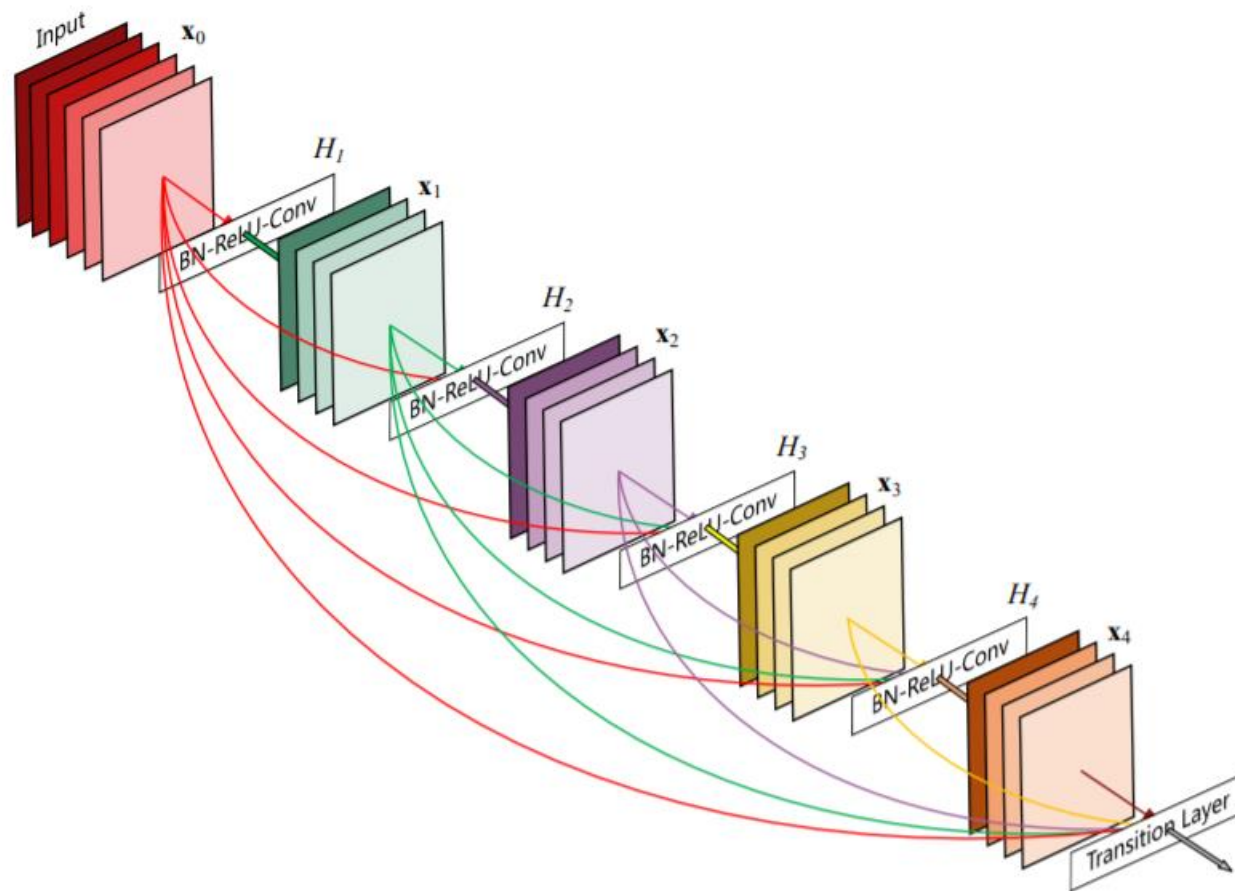


Exercise 11-1: Reading Paper and Implementing



He K, Zhang X, Ren S, et al. Identity Mappings in Deep Residual Networks[C]

Exercise 11-2: Reading and Implementing DenseNet



Huang G, Liu Z, Laurens V D M, et al. Densely Connected Convolutional Networks[J]. 2016:2261-2269.



PyTorch Tutorial

11. Advanced CNN