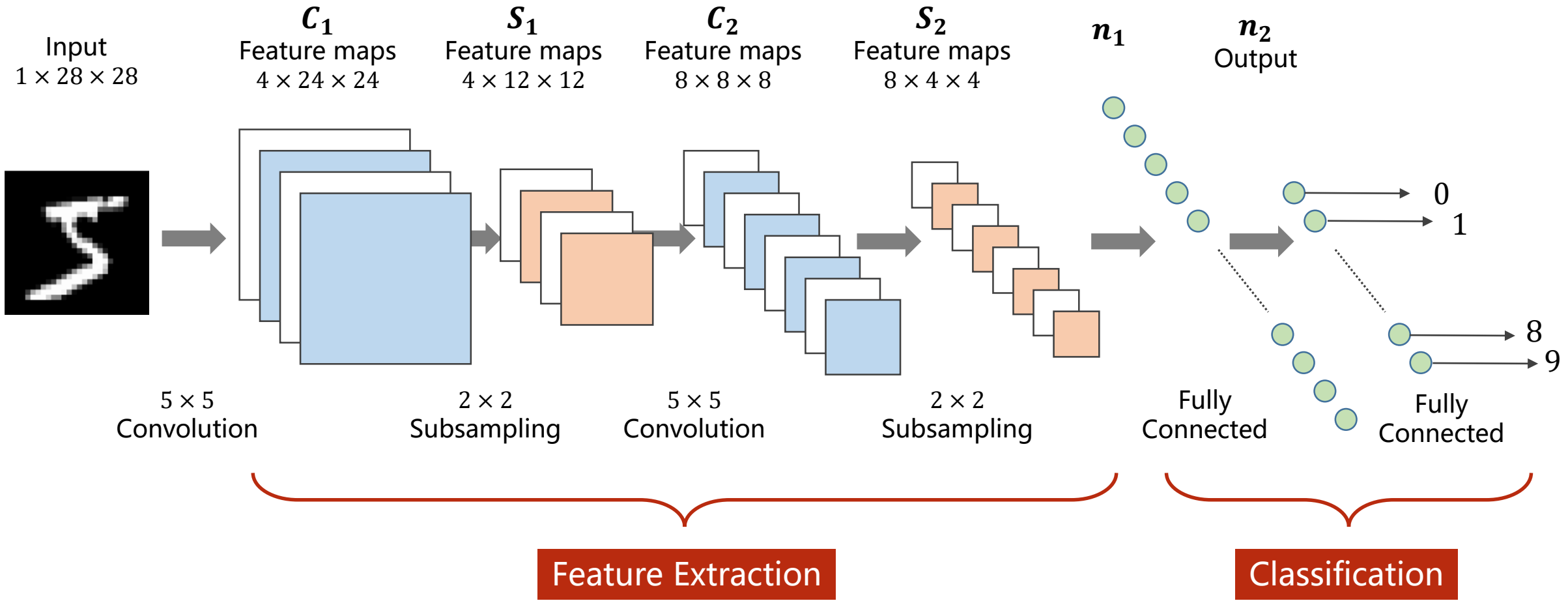
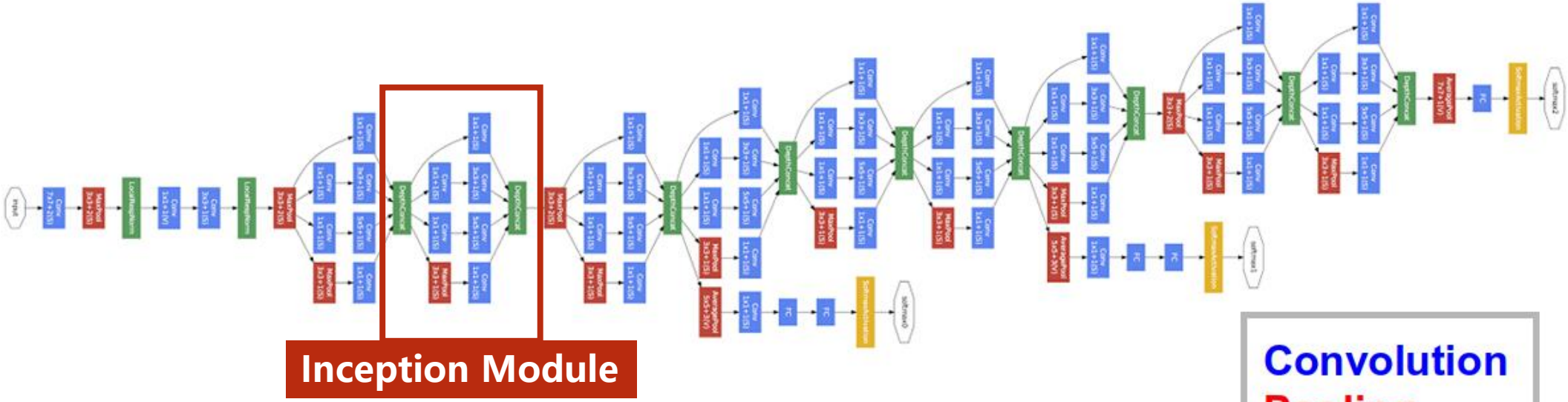
PyTorch Tutorial

11. Advanced CNN

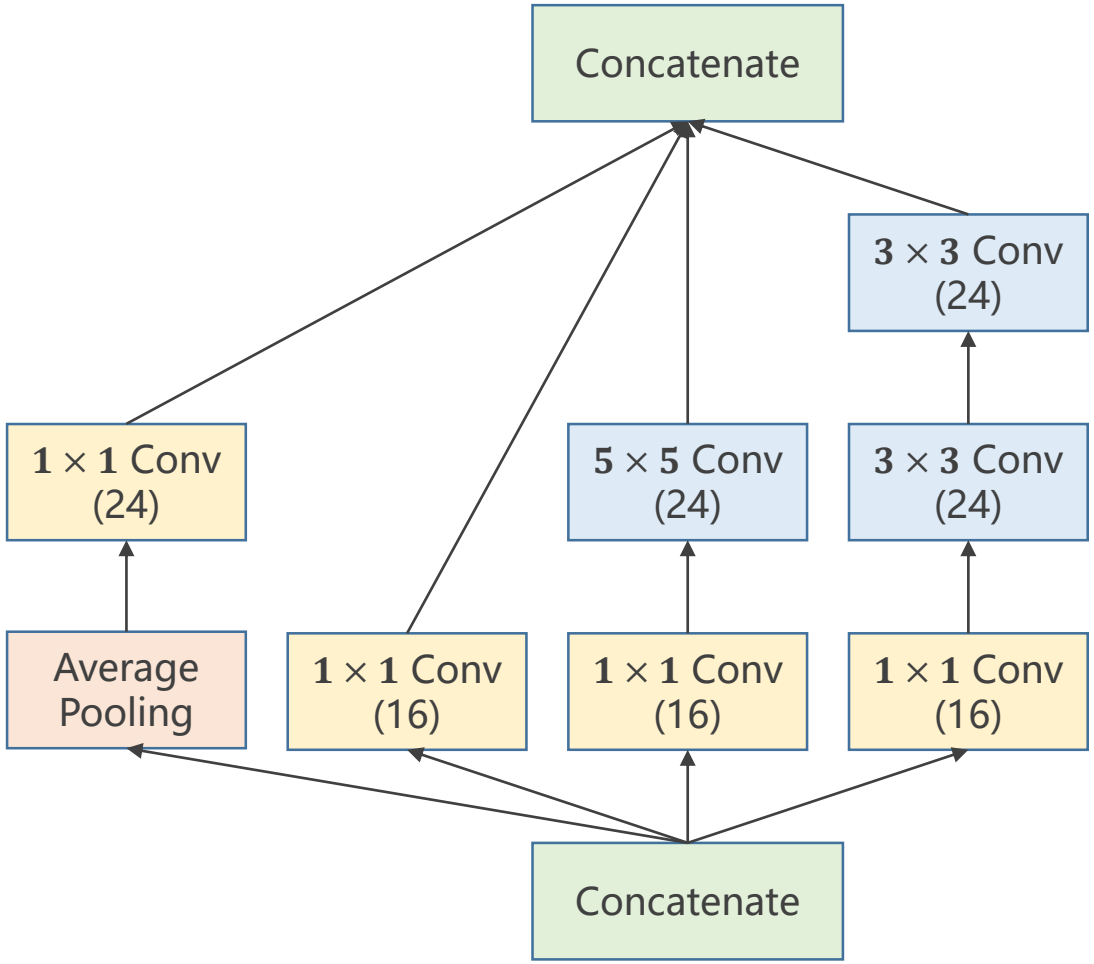
Revision

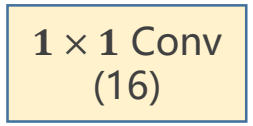

Input
1 × 28 × 28
C_1
Feature maps
4 × 24 × 24
S_1
Feature maps
4 × 12 × 12
C_2
Feature maps
8 × 8 × 8
S_2
Feature maps
8 × 4 × 4
n_1
n_2
Output
0
1
8
9
5 × 5
Convolution
2 × 2
Subsampling
5 × 5
Convolution
2 × 2
Subsampling
Fully
Connected
Fully
Connected
Feature Extraction
Classification

GoogLeNet



Inception Module





What is 1×1 convolution?

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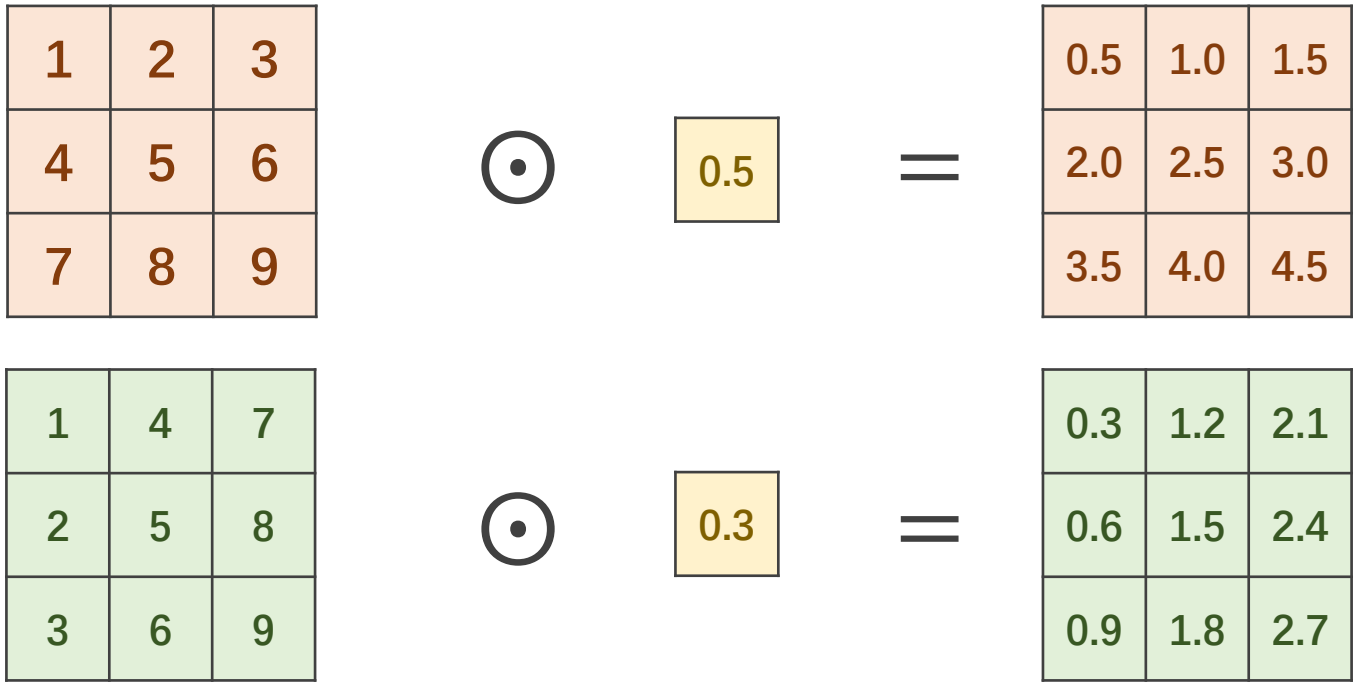

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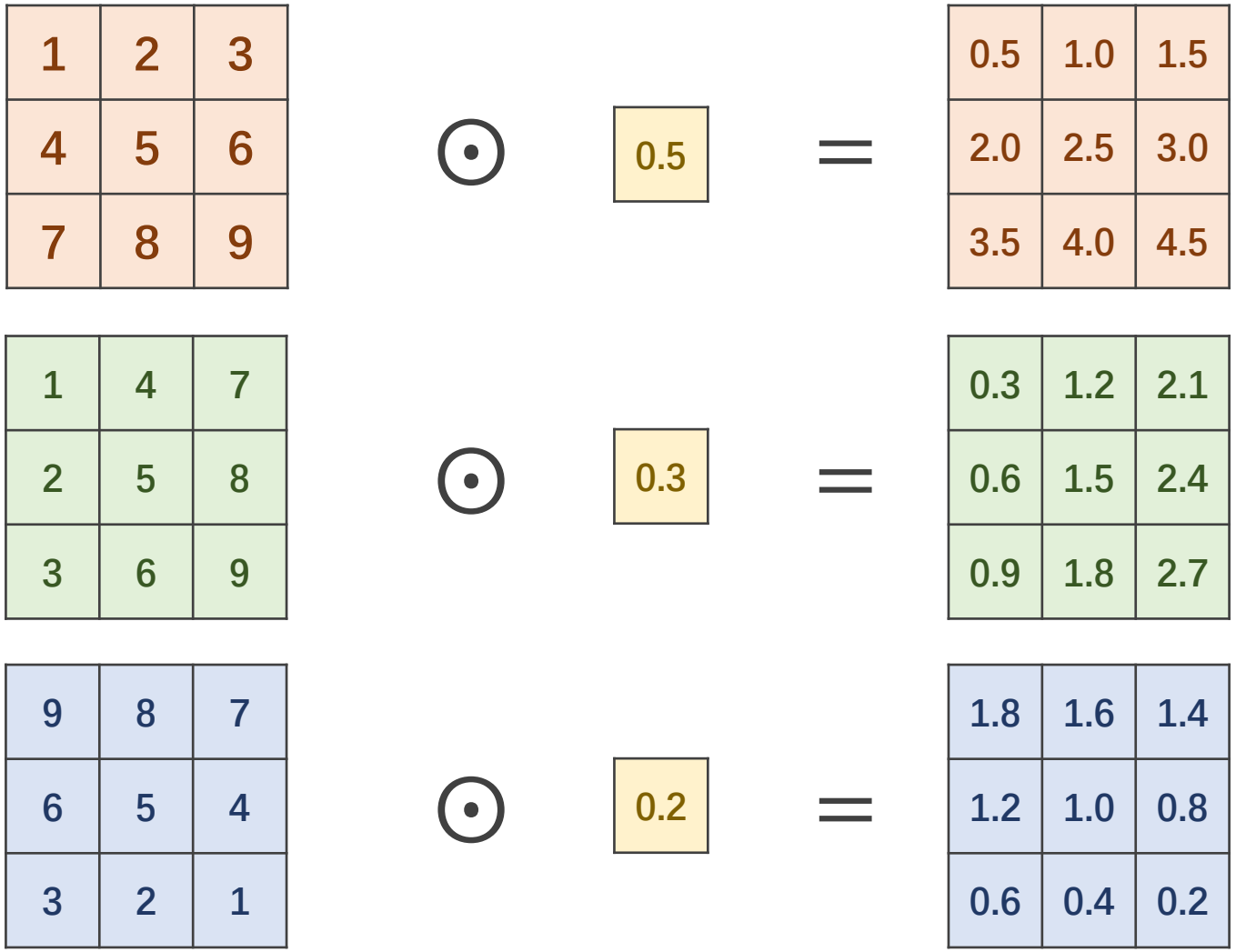

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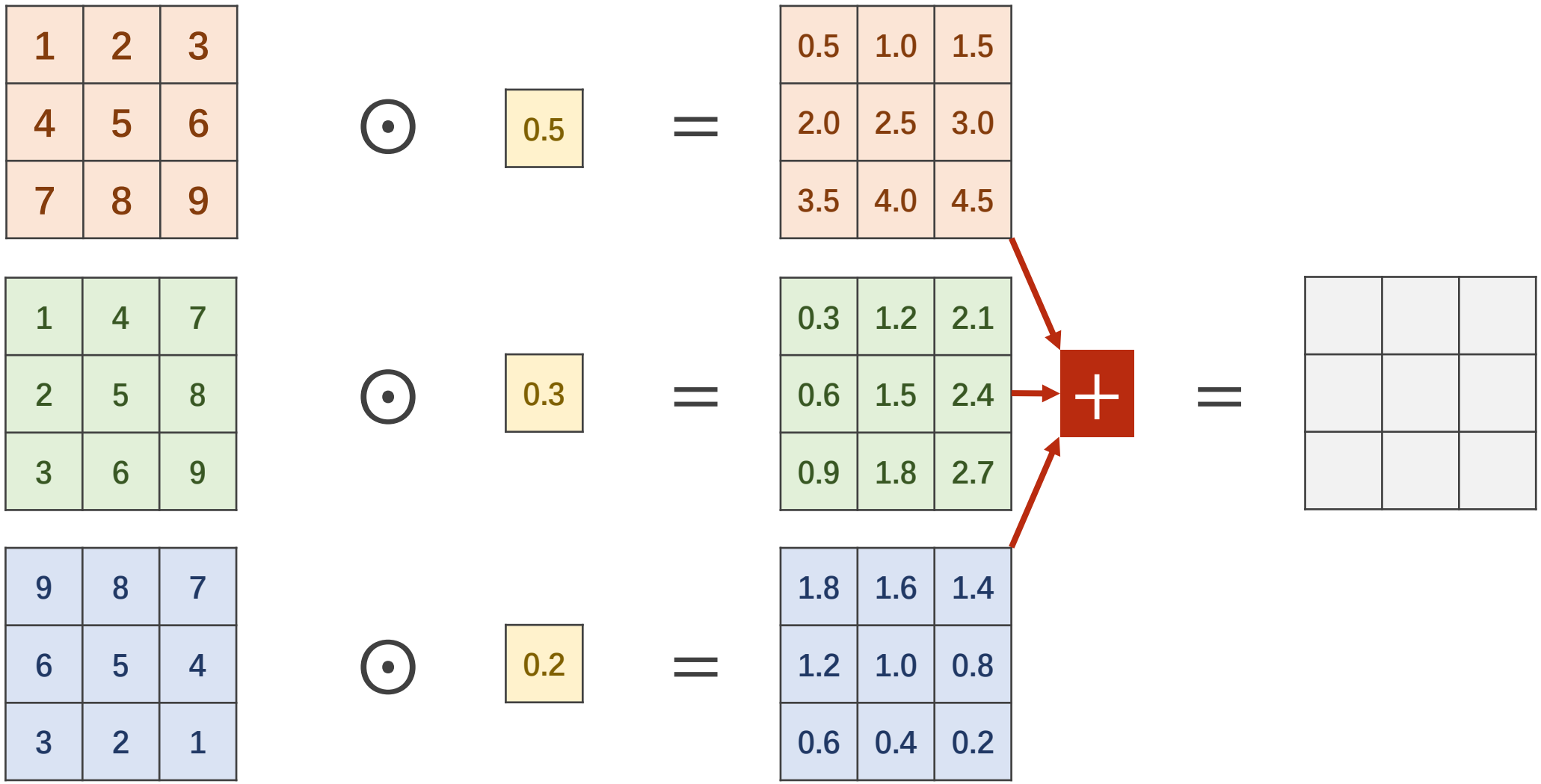

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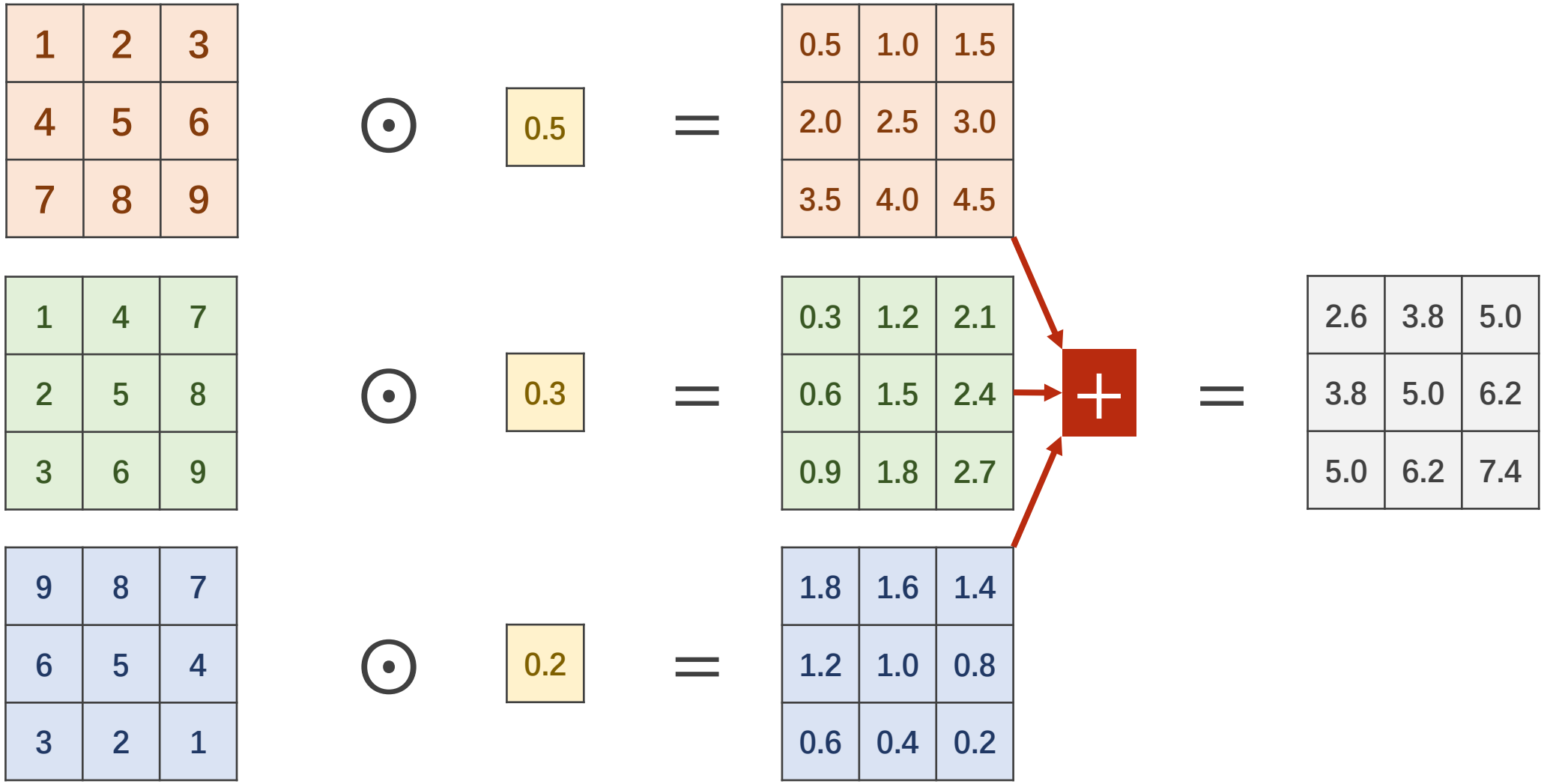

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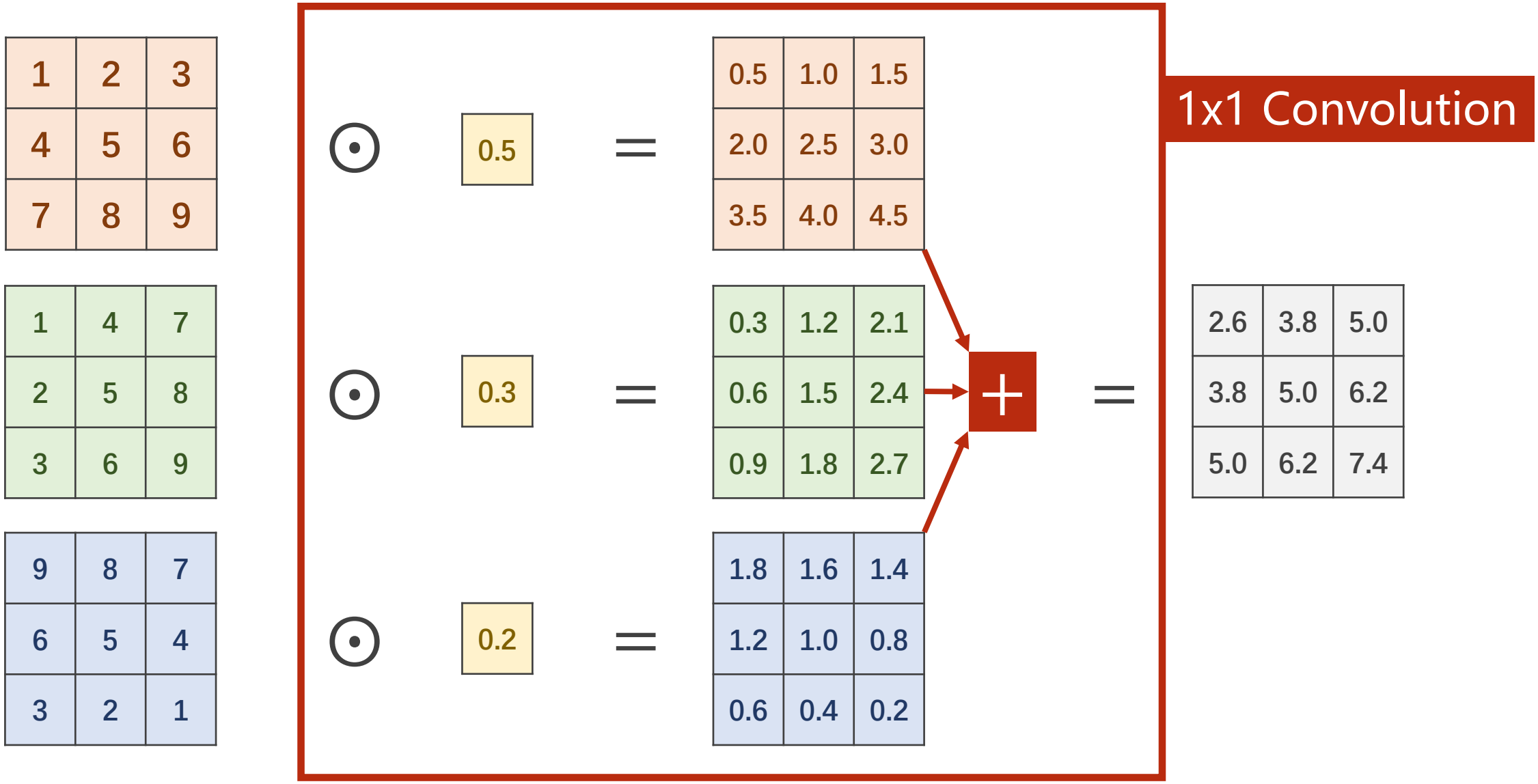
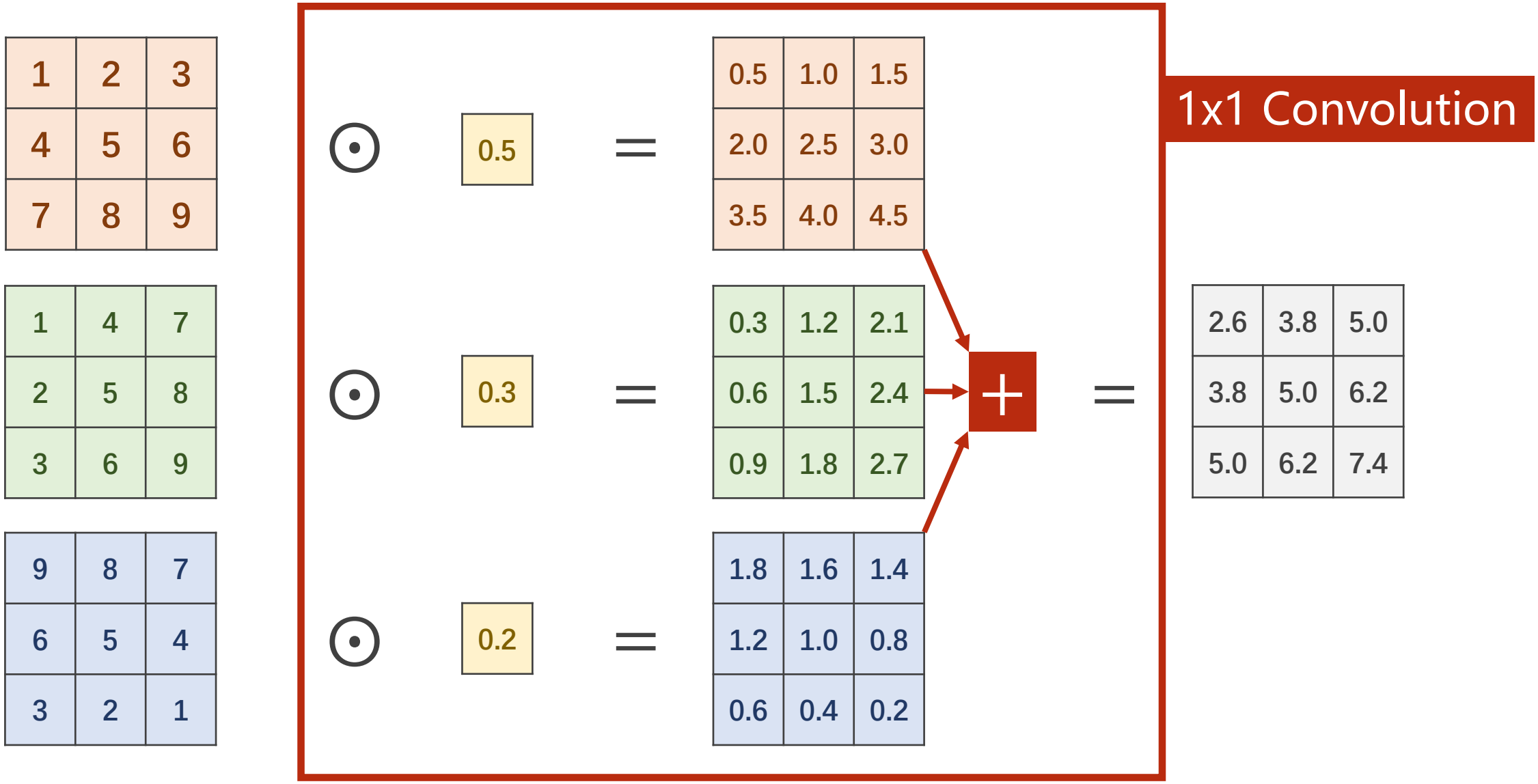
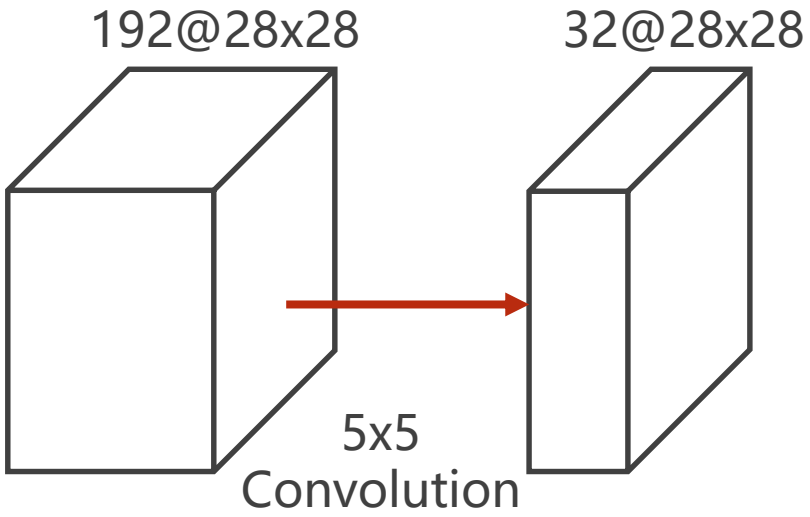


What is 1x1 convolution?



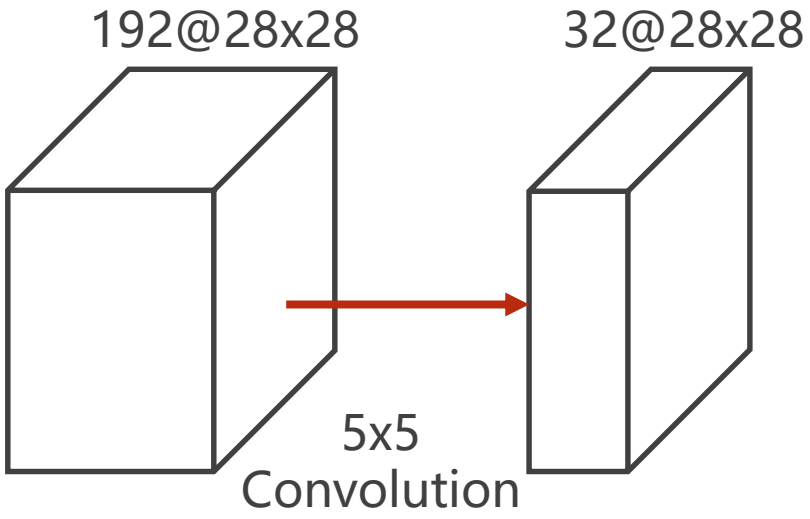
Why is 1x1 convolution?



Operations:

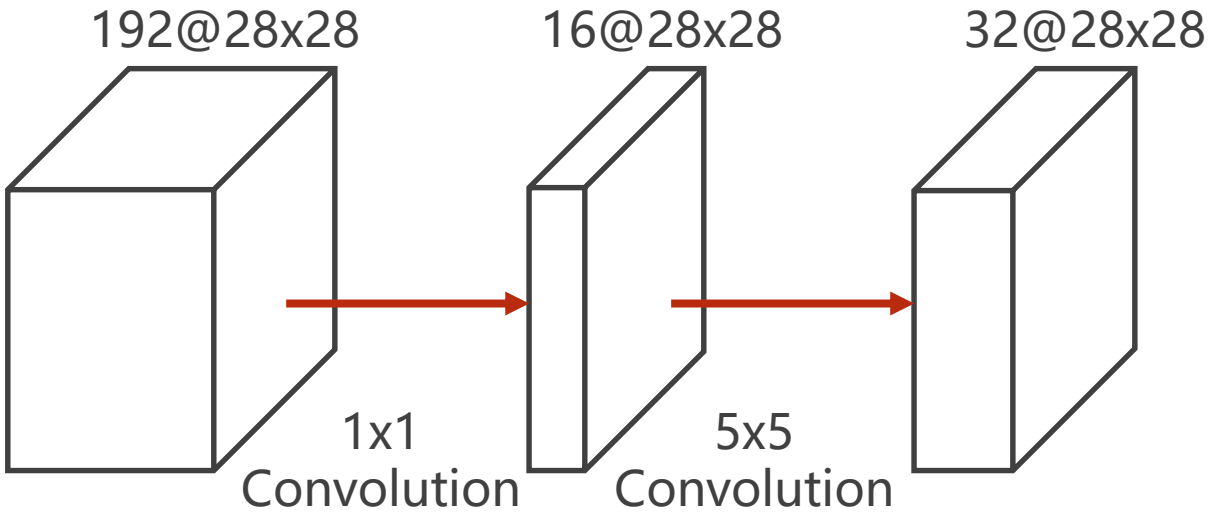
$5^2 \times 28^2 \times 192 \times 32 = 120{,}422{,}400$

Why is 1x1 convolution?



Operations:

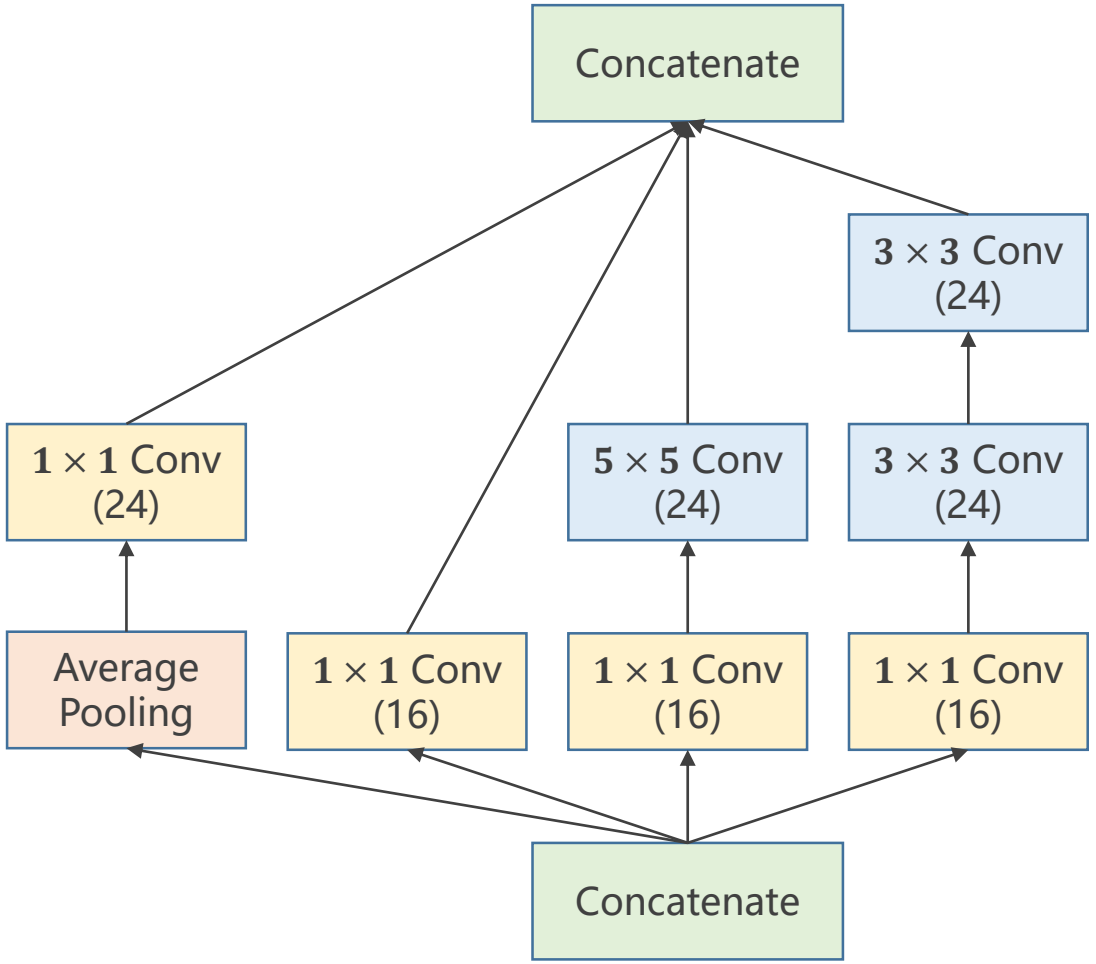
$5^2 \times 28^2 \times 192 \times 32 =$
$120{,}422{,}400$



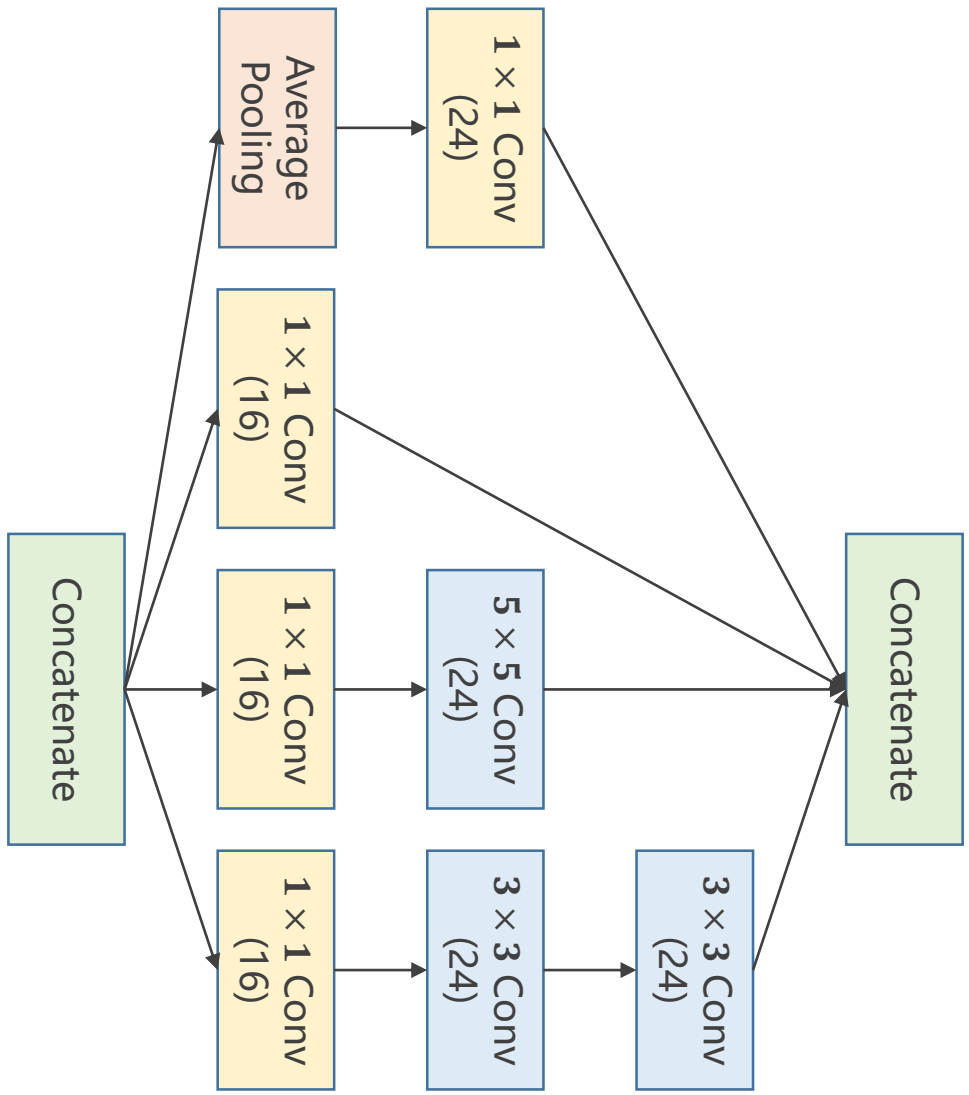
Operations:

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

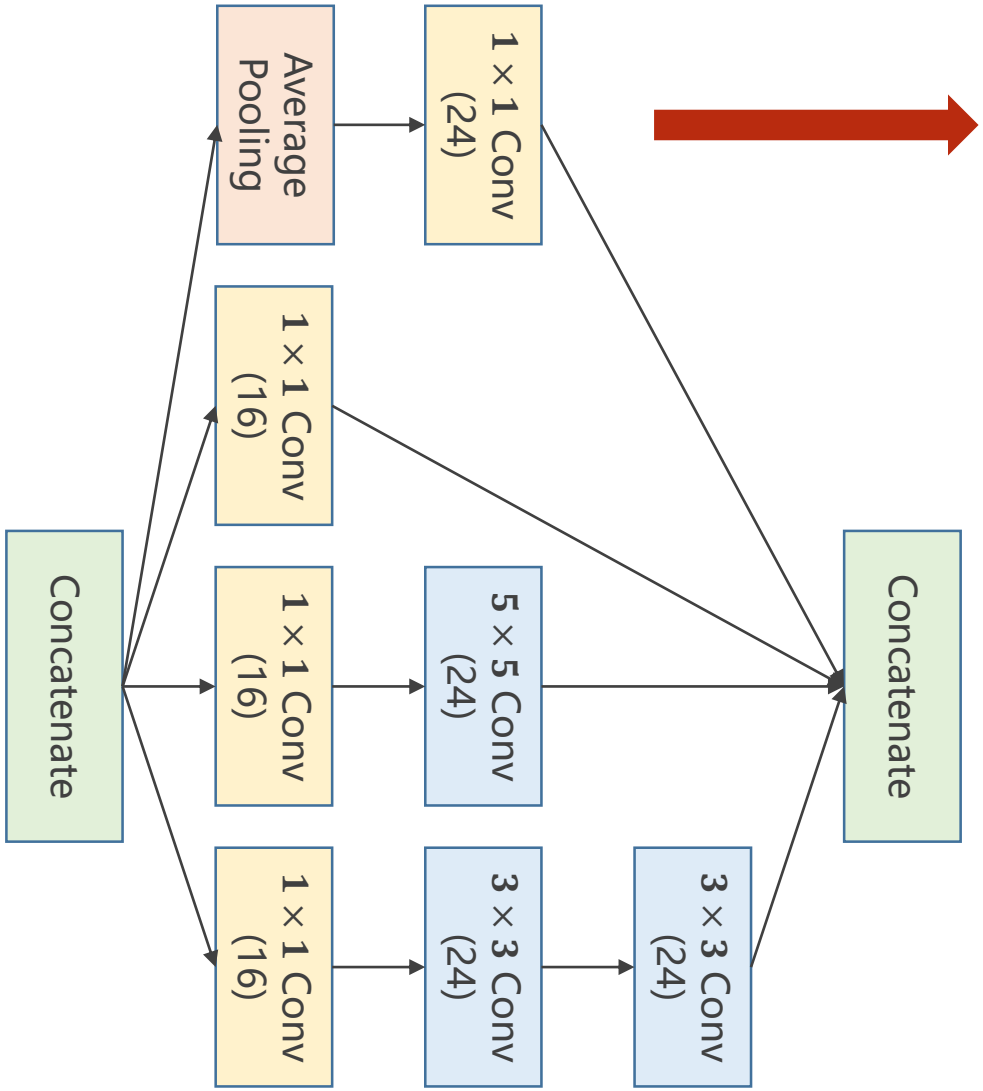
Implementation of Inception Module



Implementation of Inception Module

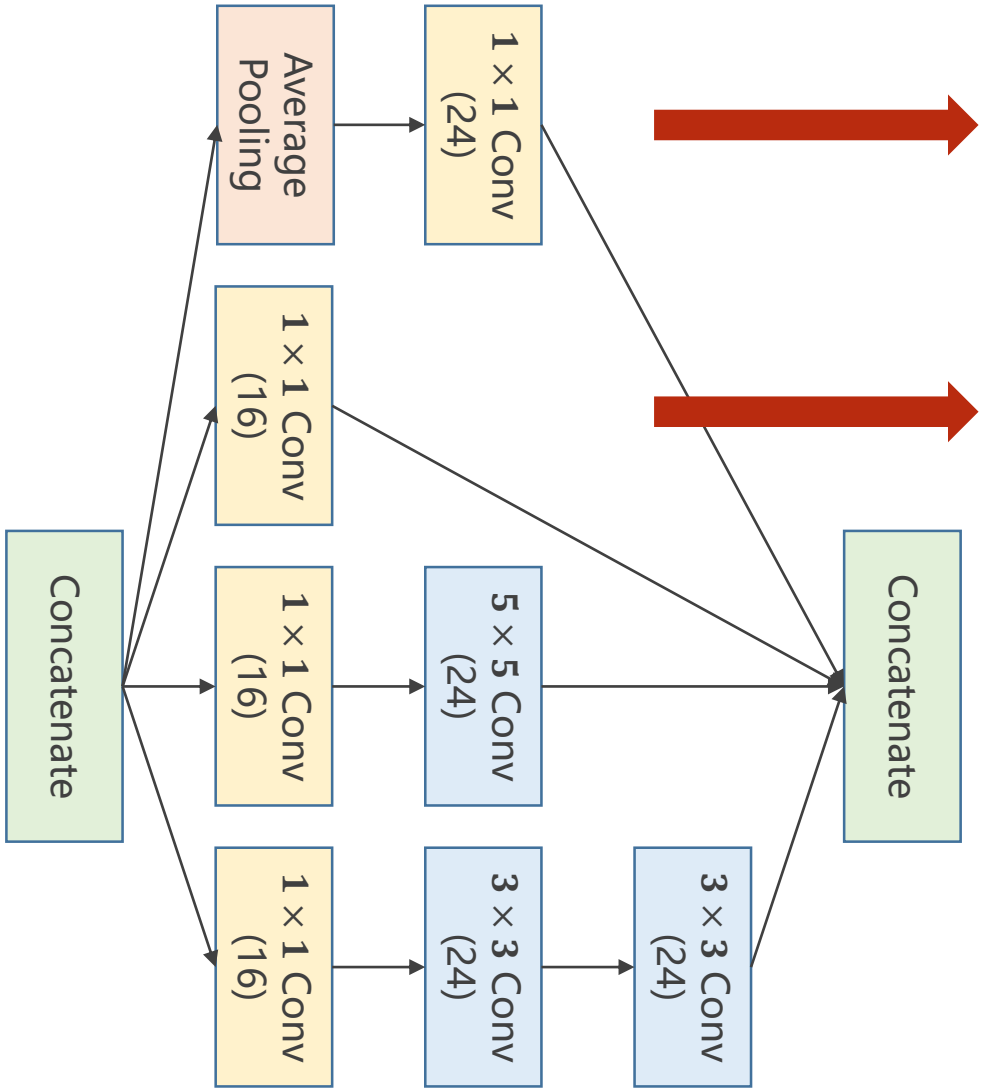


Implementation of Inception Module




```
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)
```

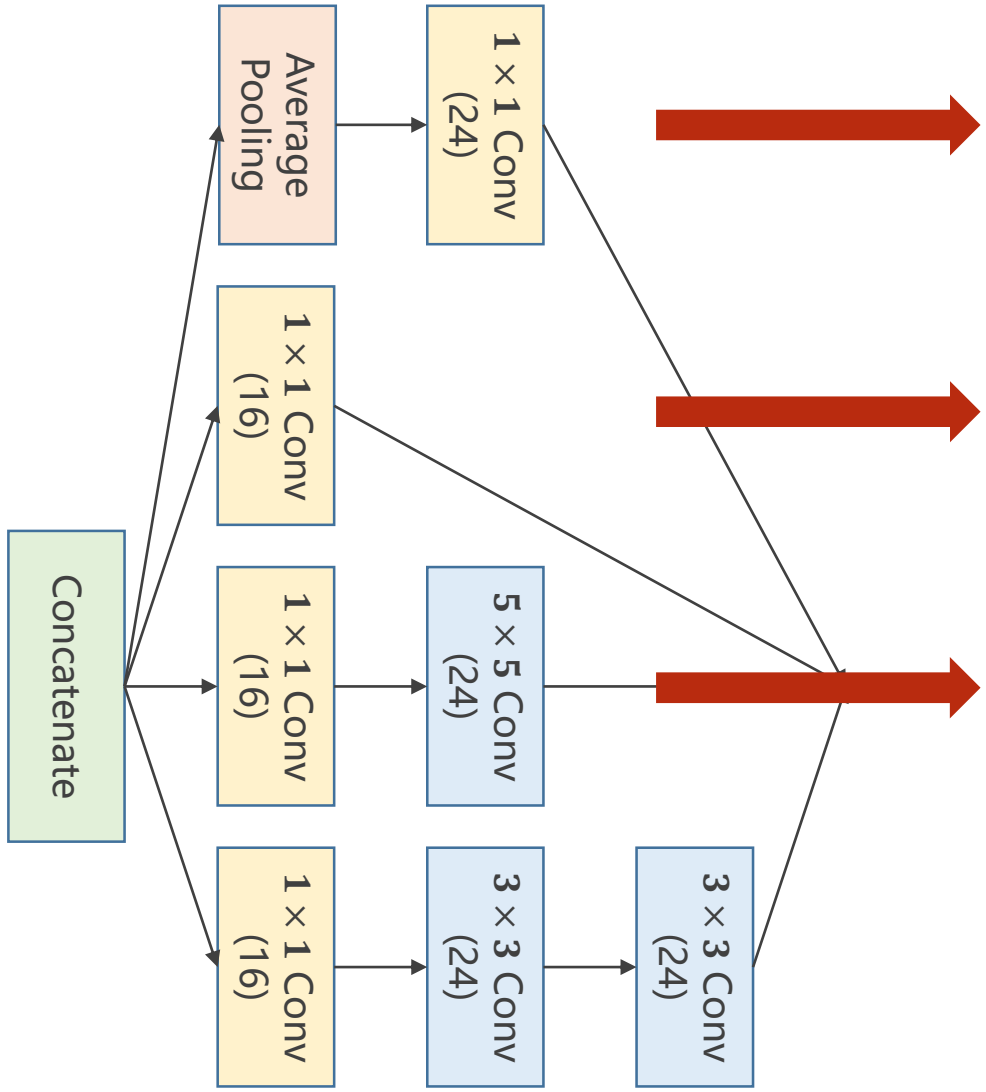
Implementation of Inception Module




```
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)
```

```
self.branch1x1 = nn.Conv2d(in_channels, 16, kernel_size=1)

branch1x1 = self.branch1x1(x)
```

Implementation of Inception Module

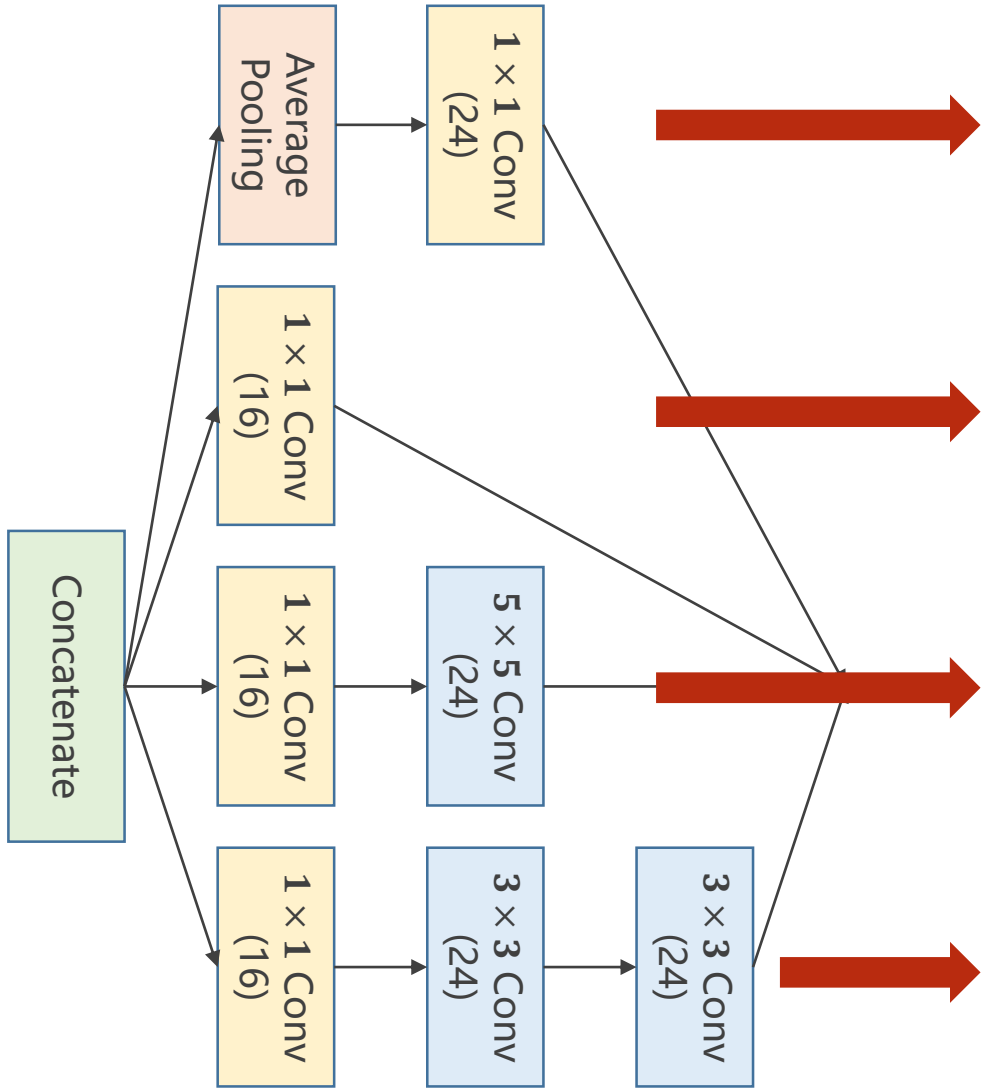



```
self.branch_pool = nn.Conv2d(in_channels, 24, kernel_size=1)

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

```
self.branch1x1 = nn.Conv2d(in_channels, 16, kernel_size=1)

branch1x1 = self.branch1x1(x)
```

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

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

Implementation of Inception Module



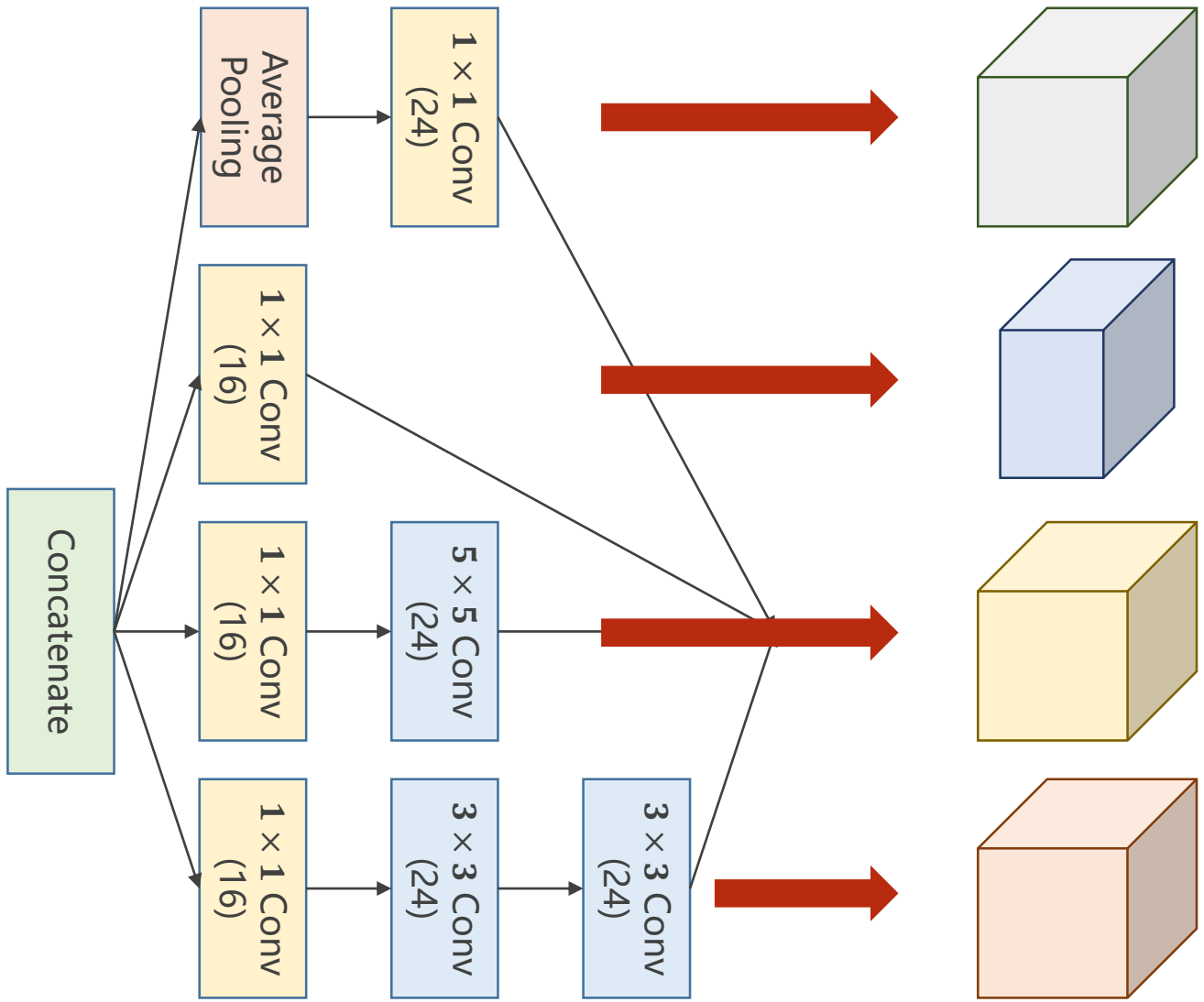

```
self.branch_pool = nn.Conv2d(in_channels, 24, kernel_size=1)

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

```
self.branch1x1 = nn.Conv2d(in_channels, 16, kernel_size=1)

branch1x1 = self.branch1x1(x)
```

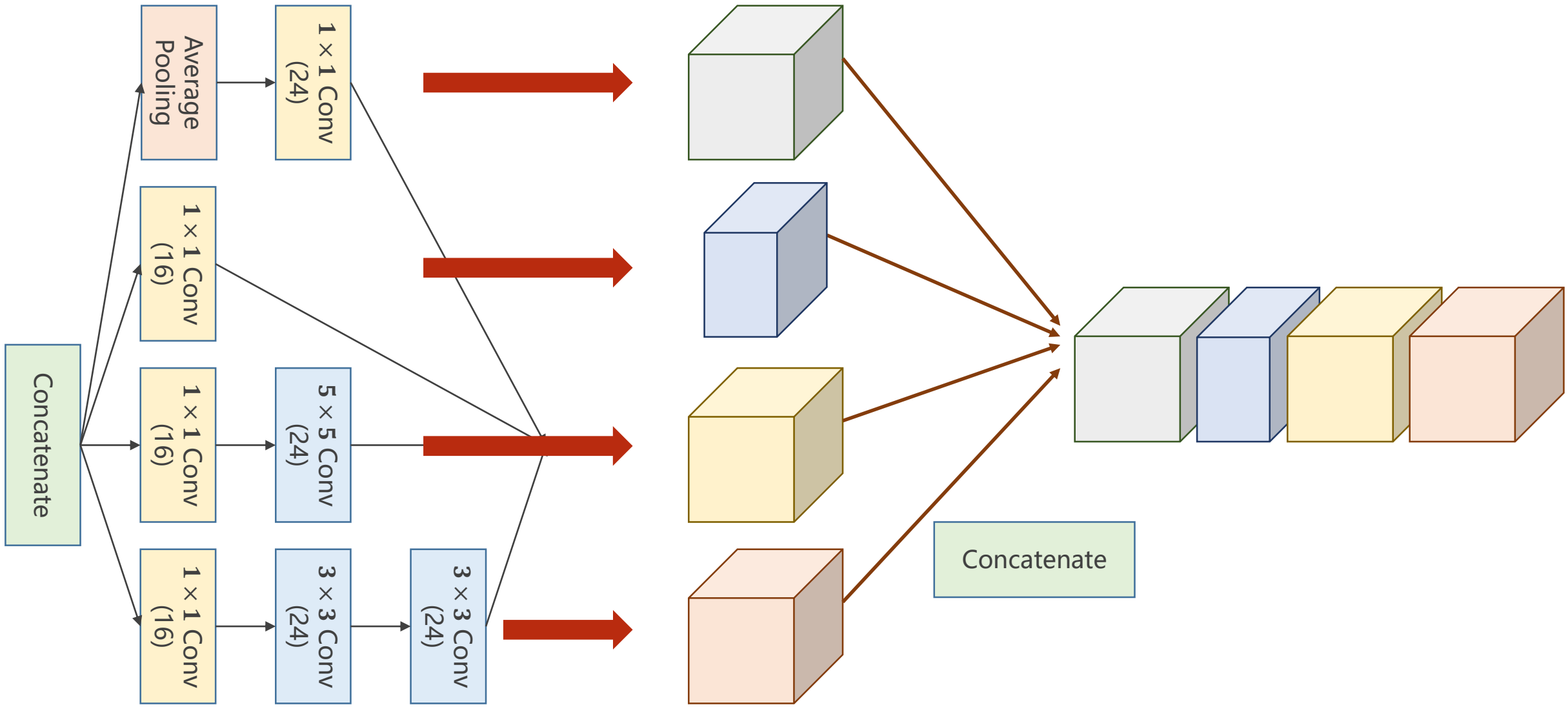
```
self.branch5x5_1 = nn.Conv2d(in_channels,16, kernel_size=1)
self.branch5x5_2 = nn.Conv2d(16, 24, kernel_size=5, padding=2)

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

```
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)

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

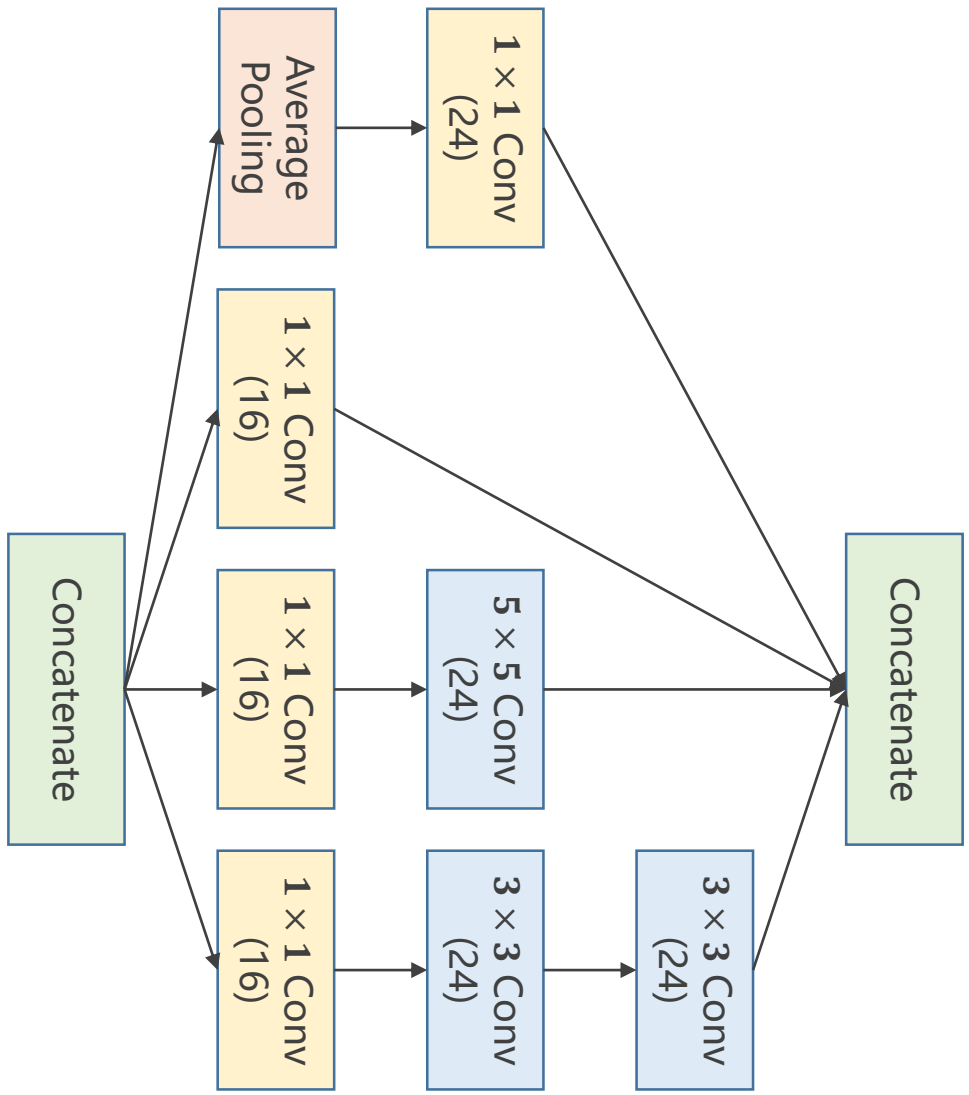
Implementation of Inception Module



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

```python
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)
```

```python
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
```

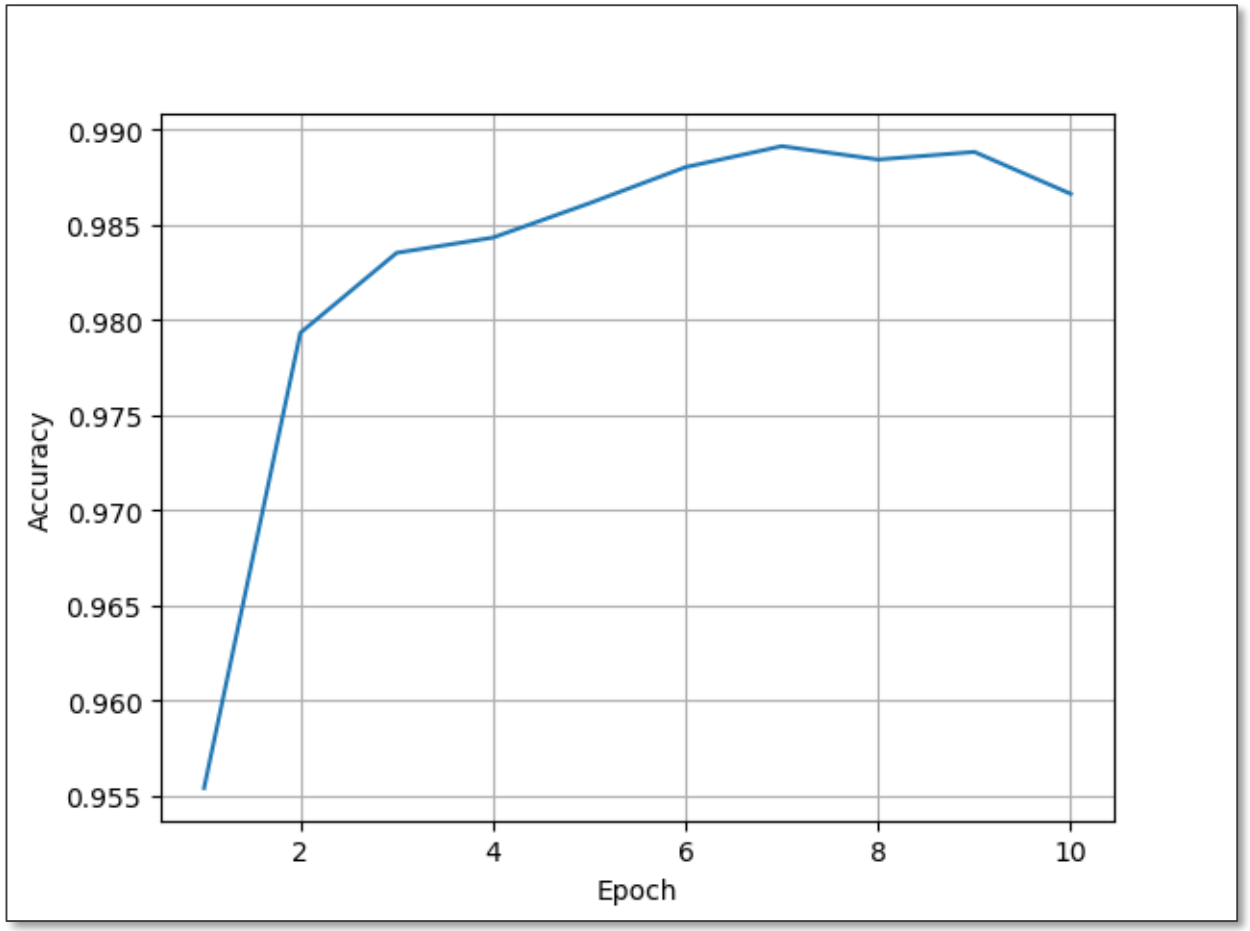
Using Inception Module

```python
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)
```

```python
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
```

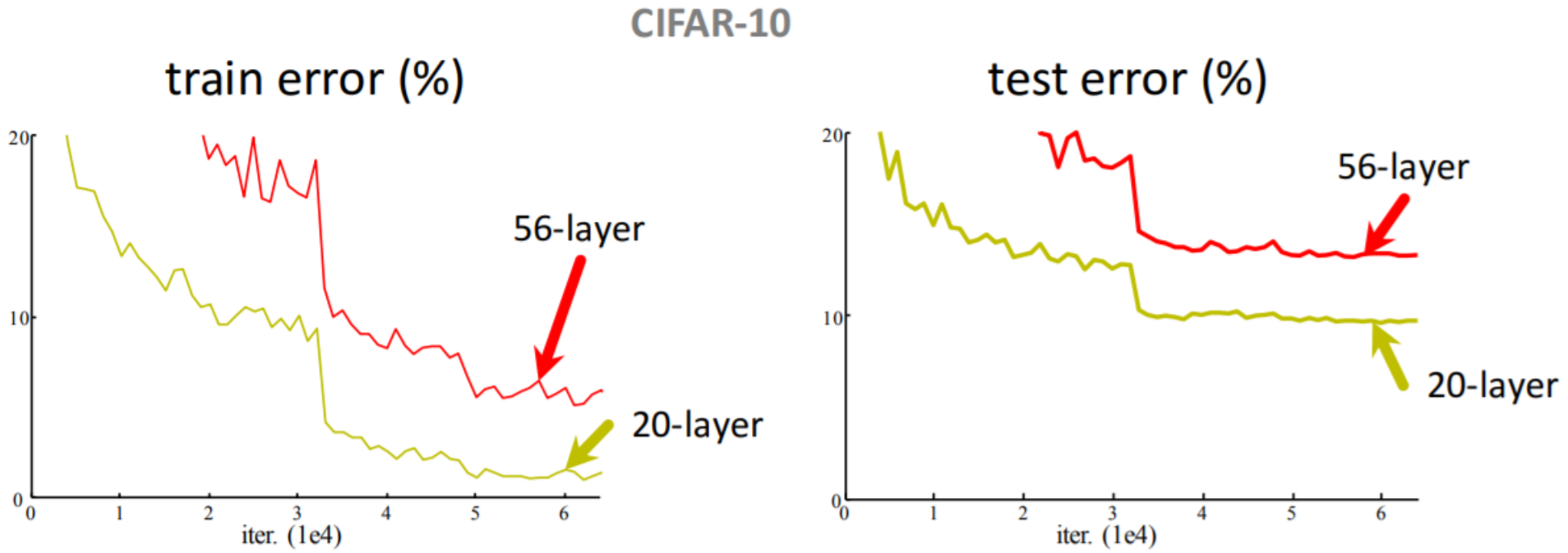
Results of using Inception Module

```
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?

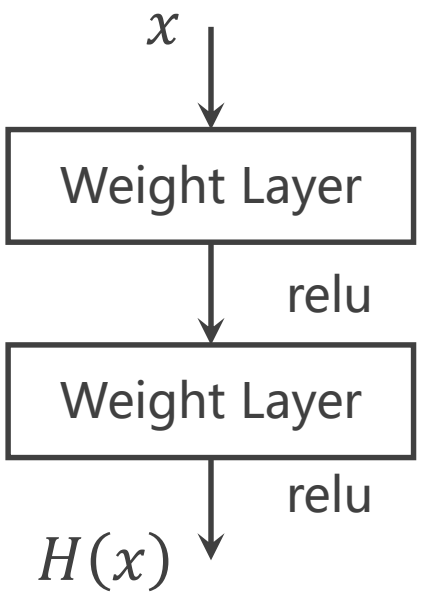


Plain nets: stacking 3x3 conv layers

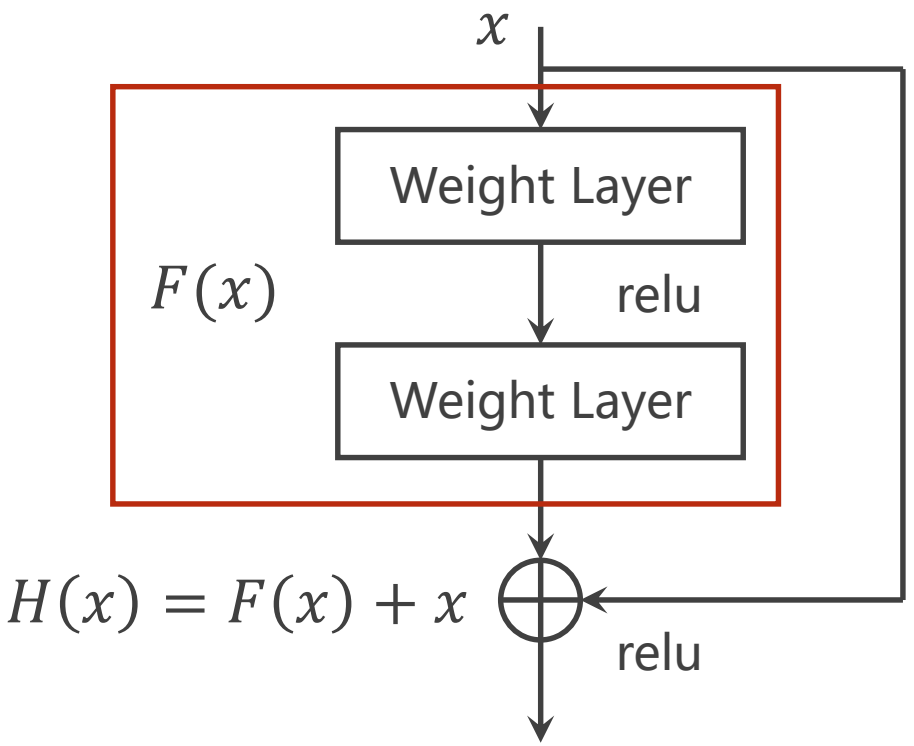
He K, Zhang X, Ren S, et al. Deep Residual Learning for Image Recognition[C]// IEEE Conference on Computer Vision and Pattern Recognition. IEEE Computer Society, 2016:770-778.

Deep Residual Learning

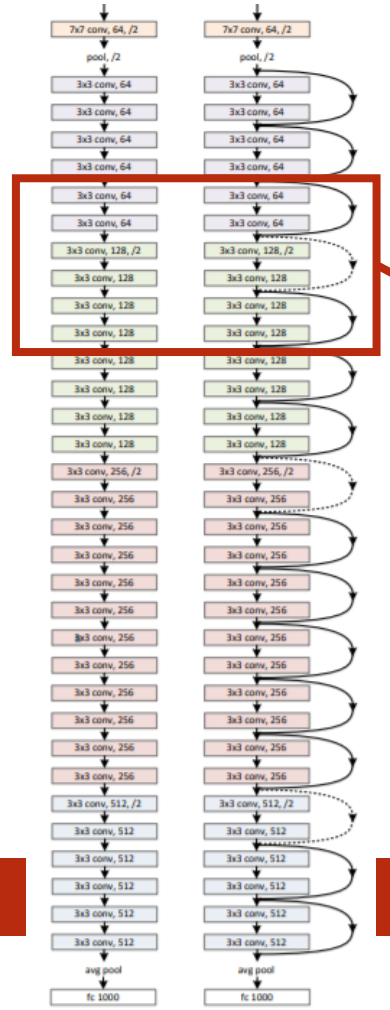
Plain net



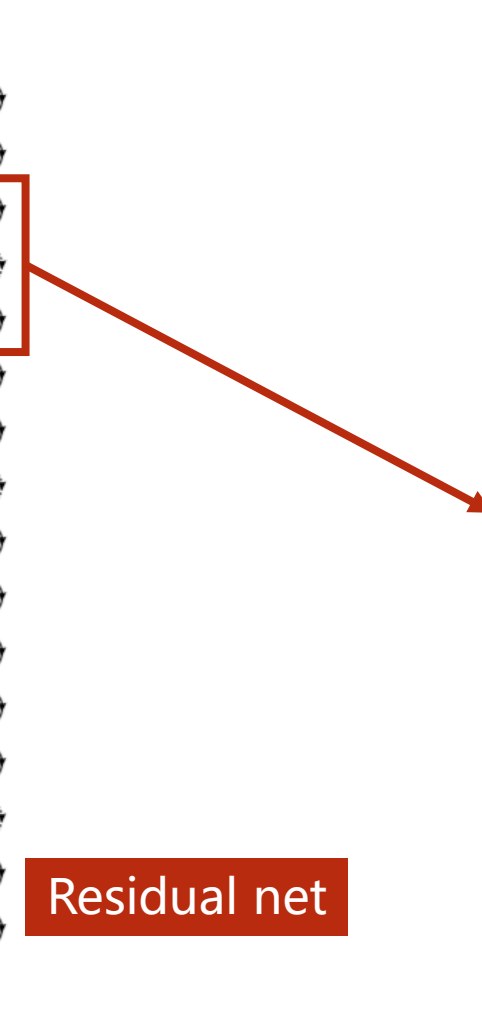
Residual net



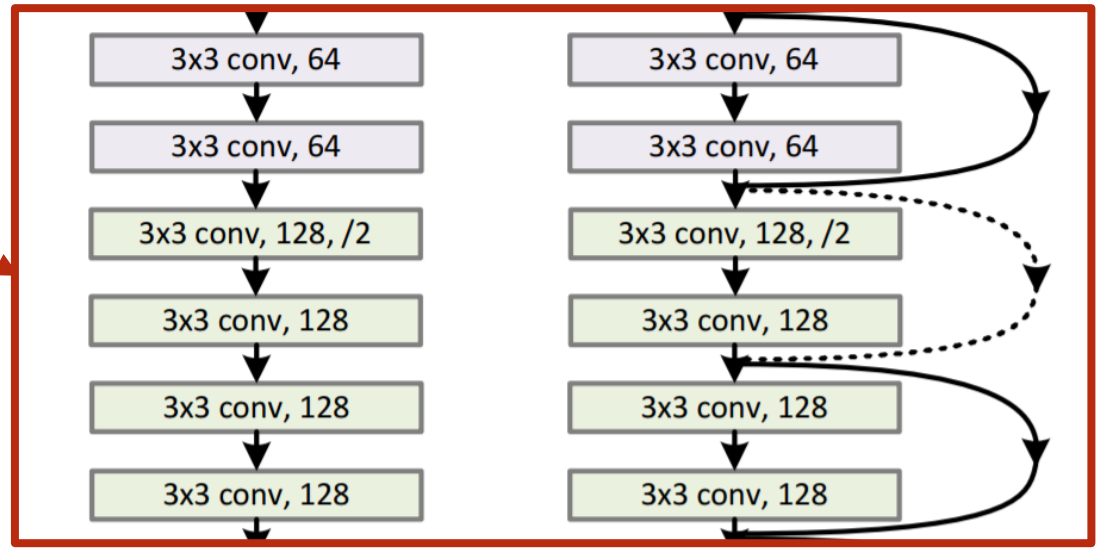
Residual Network



Plain net



Residual net



Implementation of Simple Residual Network

(*batch*, 1,28,28)

(*batch*, 1,28,28)

(*batch*, 16,24,24)

(*batch*, 16,24,24)

(*batch*, 16,12,12)

(*batch*, 16,12,12)

(*batch*, 32,8,8)

(*batch*, 32,8,8)

(*batch*, 32,4,4)

(*batch*, 32,4,4) → (*batch*, 512)

(*batch*, 10)

Input Layer

Conv2d Layer

ReLU Layer

Pooling Layer

Linear Layer

Residual Block

Output Layer

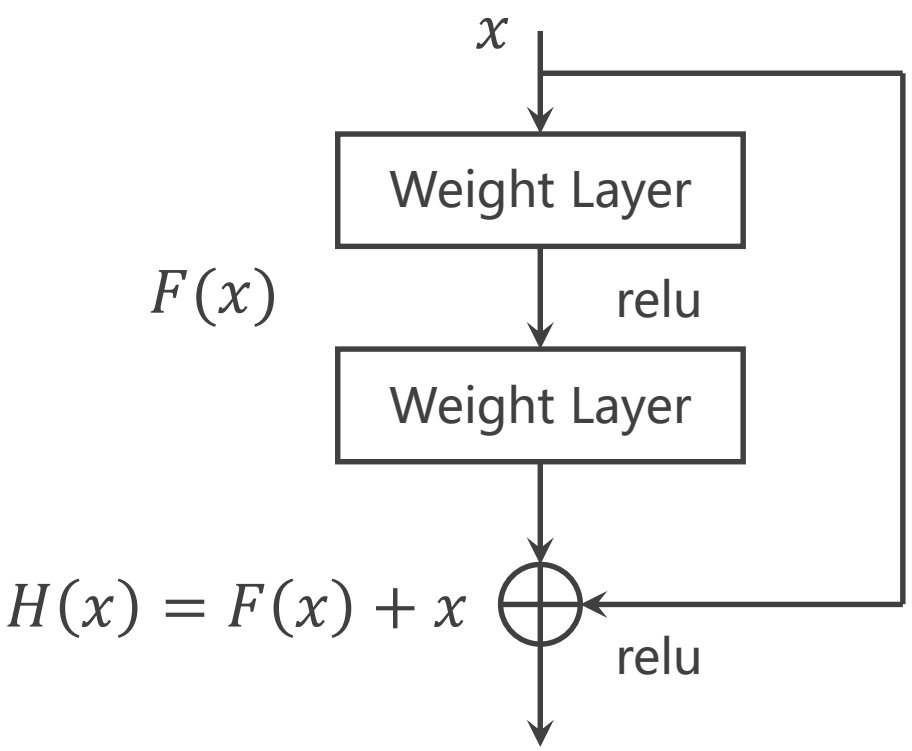
```
self.conv1 = nn.Conv2d(1, 16, kernel_size=5)
```

?

```
self.conv2 = nn.Conv2d(16, 32, kernel_size=5)
```

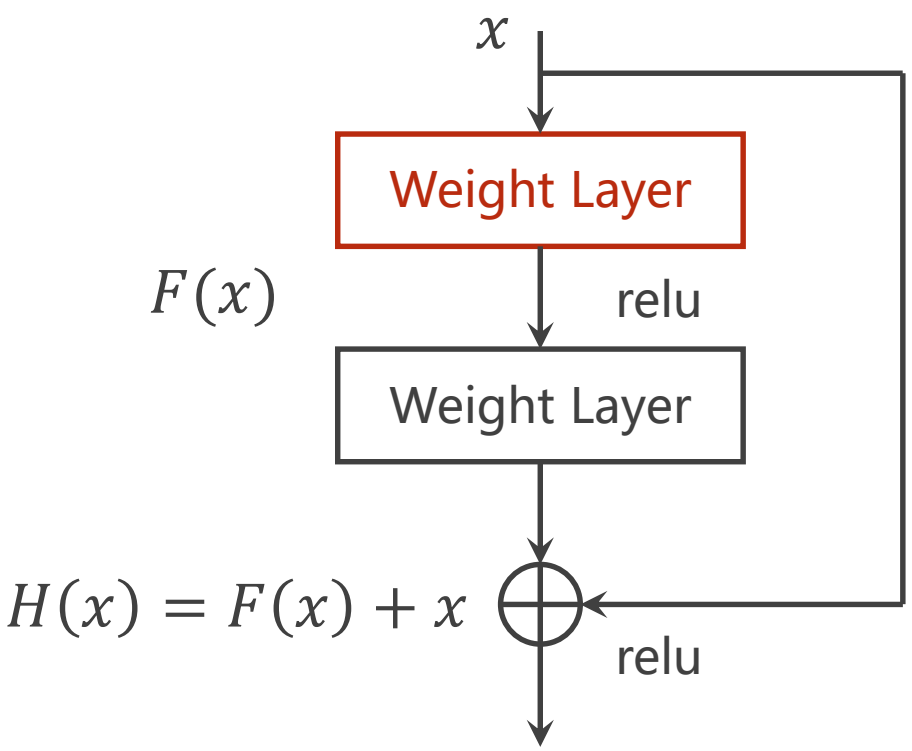
?

Implementation of Residual Block



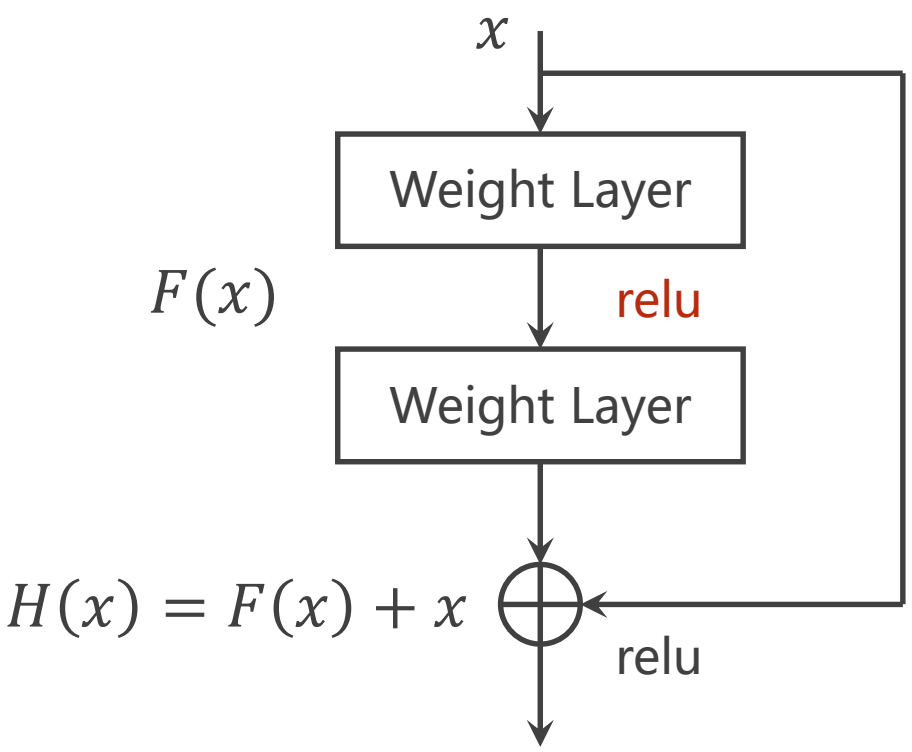

```
class ResidualBlock(nn.Module):
    def __init__(self, channels):
        super(ResidualBlock, self).__init__()
        self.channels = channels
        self.conv1 = nn.Conv2d(channels, channels,
                               kernel_size=3, padding=1)
        self.conv2 = nn.Conv2d(channels, channels,
                               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



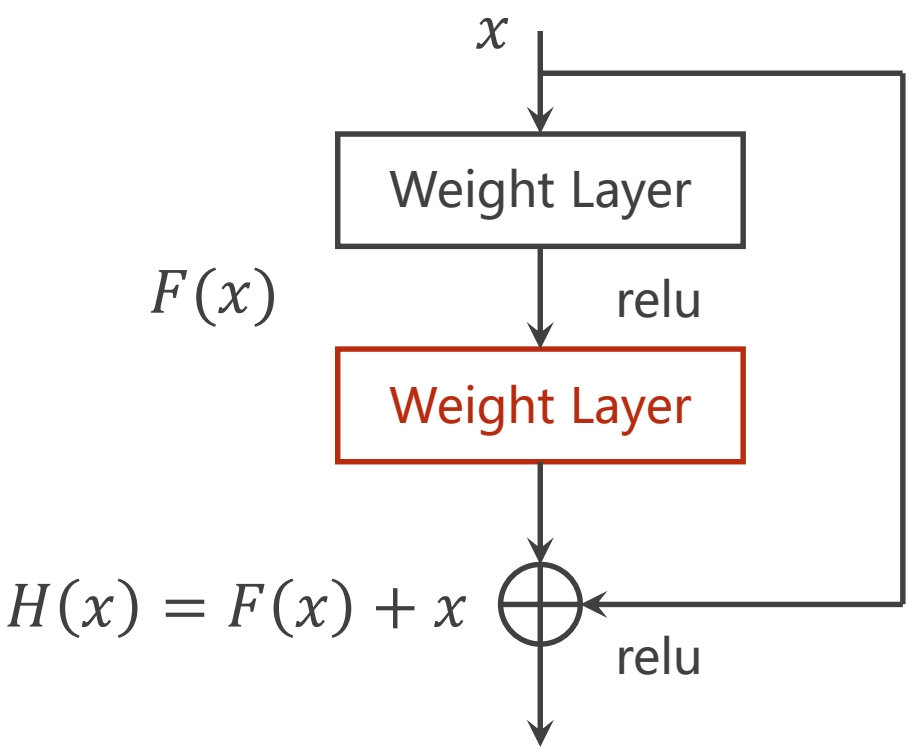

```
class ResidualBlock(nn.Module):
    def __init__(self, channels):
        super(ResidualBlock, self).__init__()
        self.channels = channels
        self.conv1 = nn.Conv2d(channels, channels,
                               kernel_size=3, padding=1)
        self.conv2 = nn.Conv2d(channels, channels,
                               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



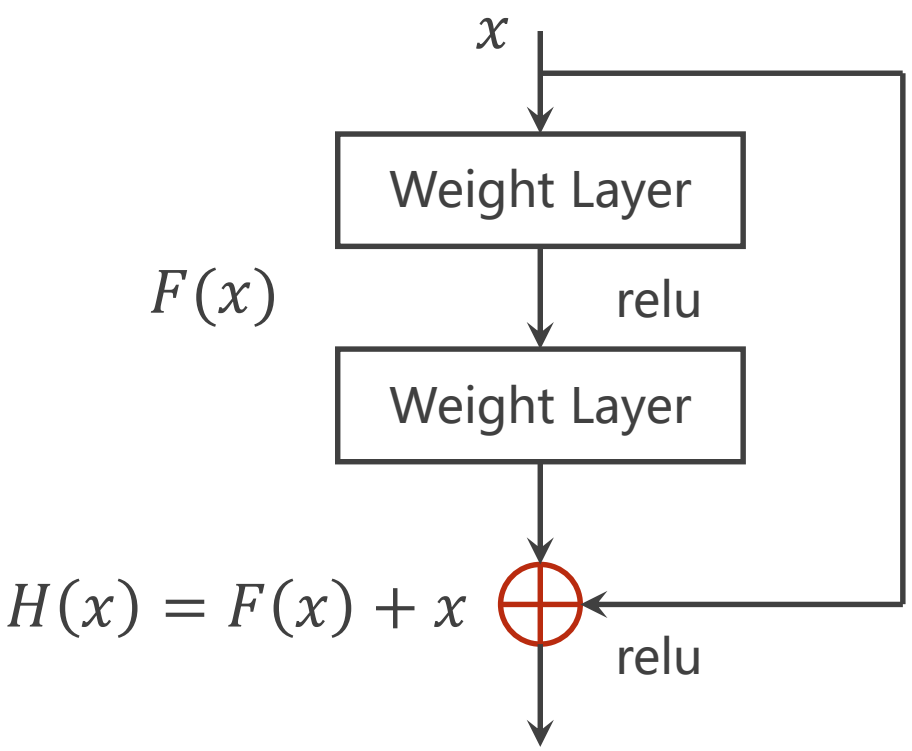

```
class ResidualBlock(nn.Module):
    def __init__(self, channels):
        super(ResidualBlock, self).__init__()
        self.channels = channels
        self.conv1 = nn.Conv2d(channels, channels,
                               kernel_size=3, padding=1)
        self.conv2 = nn.Conv2d(channels, channels,
                               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



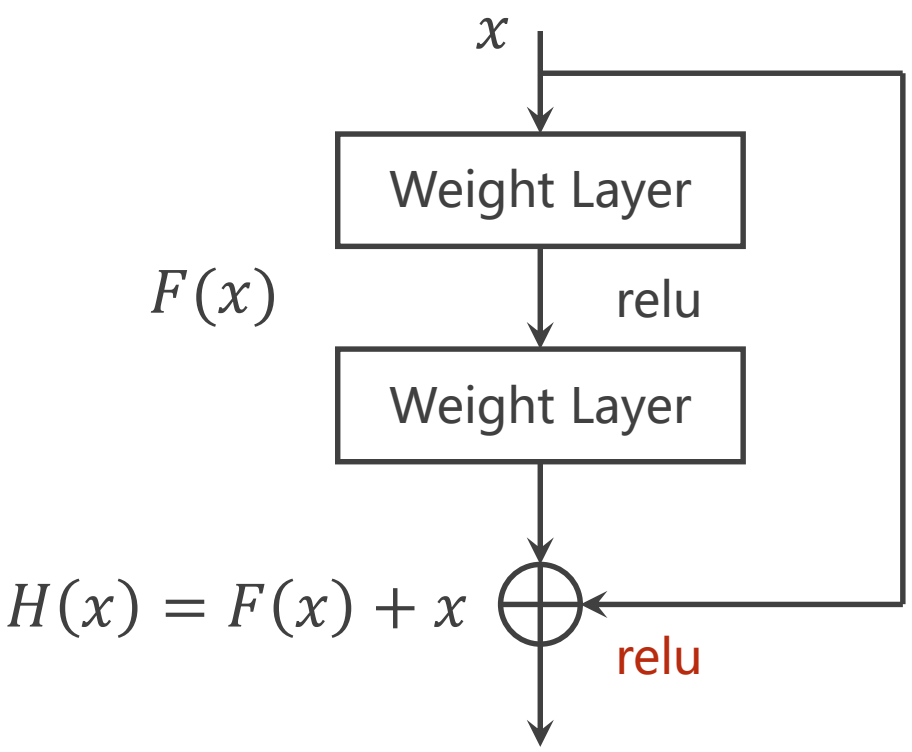

```
class ResidualBlock(nn.Module):
    def __init__(self, channels):
        super(ResidualBlock, self).__init__()
        self.channels = channels
        self.conv1 = nn.Conv2d(channels, channels,
                               kernel_size=3, padding=1)
        self.conv2 = nn.Conv2d(channels, channels,
                               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



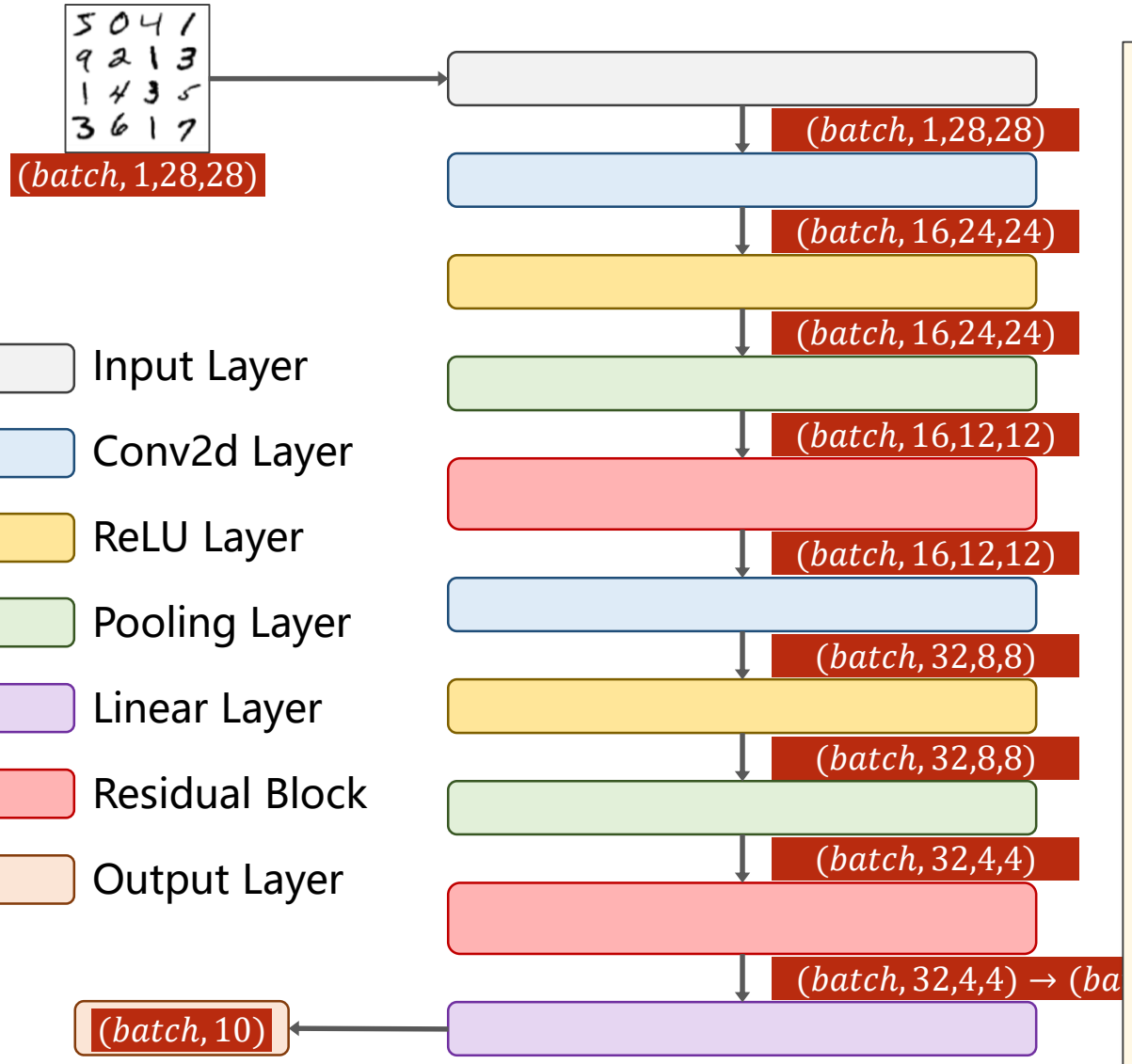

```
class ResidualBlock(nn.Module):
    def __init__(self, channels):
        super(ResidualBlock, self).__init__()
        self.channels = channels
        self.conv1 = nn.Conv2d(channels, channels,
                               kernel_size=3, padding=1)
        self.conv2 = nn.Conv2d(channels, channels,
                               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



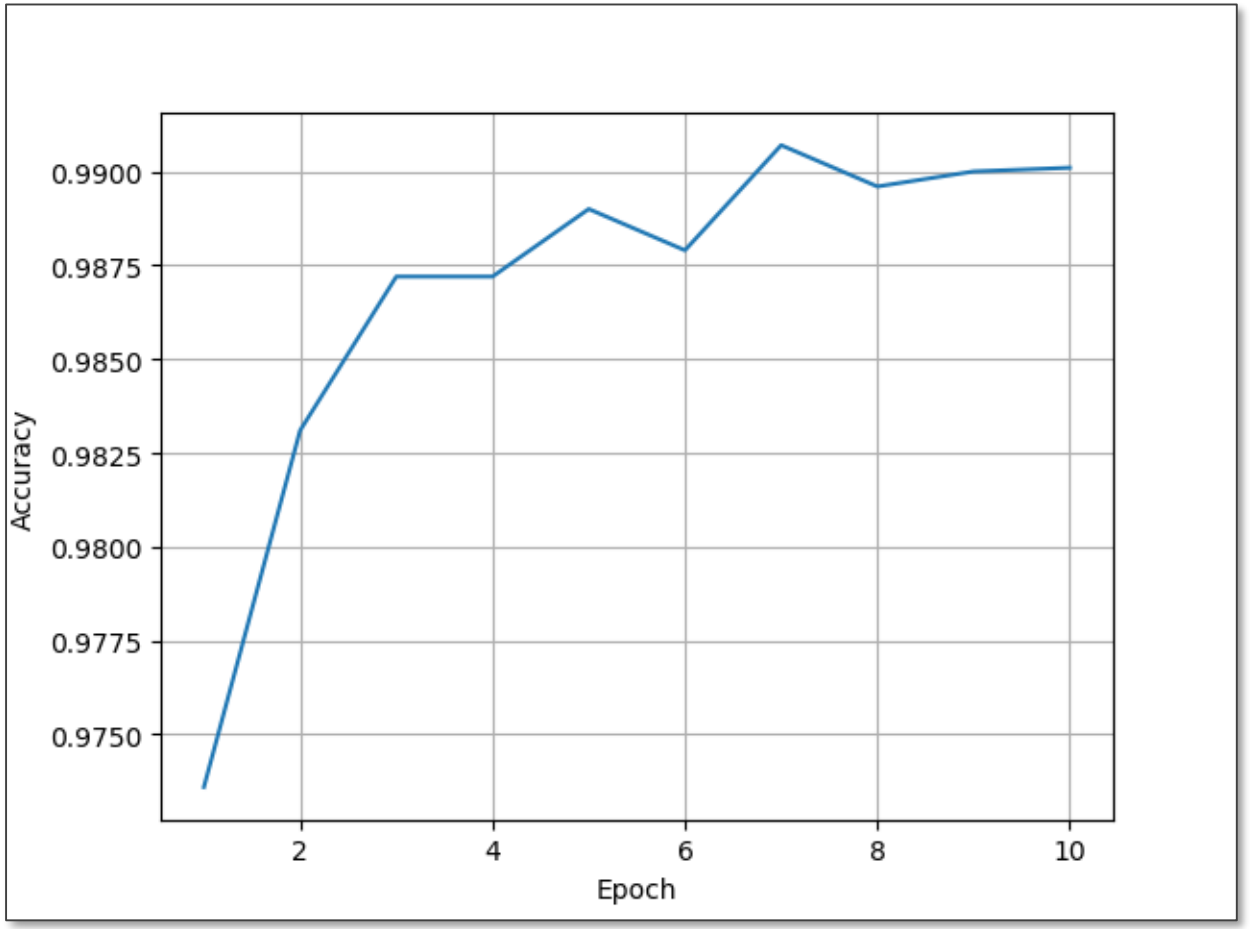

```
class ResidualBlock(nn.Module):
    def __init__(self, channels):
        super(ResidualBlock, self).__init__()
        self.channels = channels
        self.conv1 = nn.Conv2d(channels, channels,
                               kernel_size=3, padding=1)
        self.conv2 = nn.Conv2d(channels, channels,
                               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

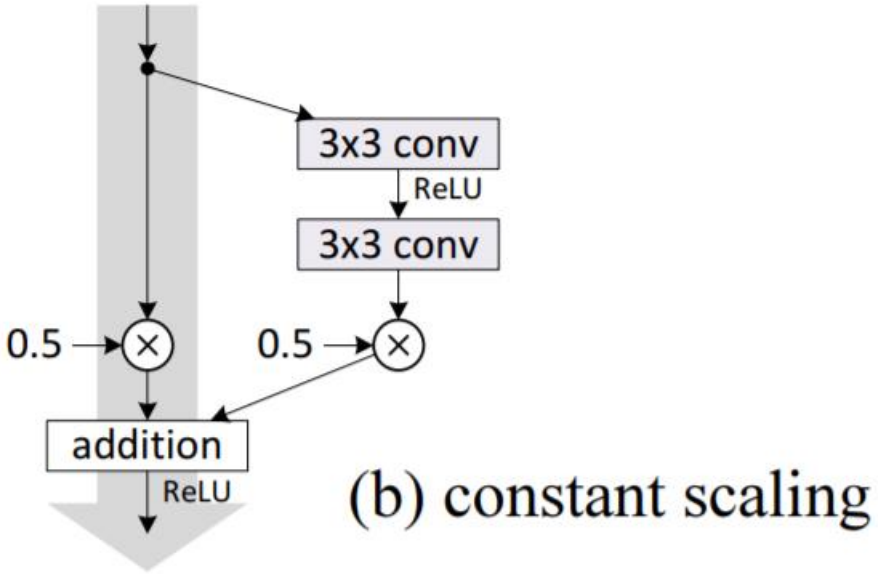



```python
class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(1, 16, kernel_size=5)
        self.conv2 = nn.Conv2d(16, 32, kernel_size=5)
        self.mp = nn.MaxPool2d(2)

        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
```

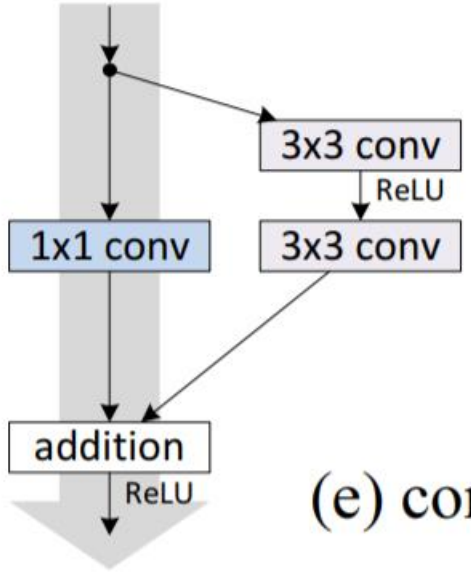
```
Accuracy on test set: 9 % [916/10000]
[1,   300] loss: 0.074
[1,   600] loss: 0.021
[1,   900] loss: 0.017
Accuracy on test set: 97 % [9736/10000]
[2,   300] loss: 0.013
[2,   600] loss: 0.011
[2,   900] loss: 0.011
Accuracy on test set: 98 % [9831/10000]
......
[9,   300] loss: 0.003
[9,   600] 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



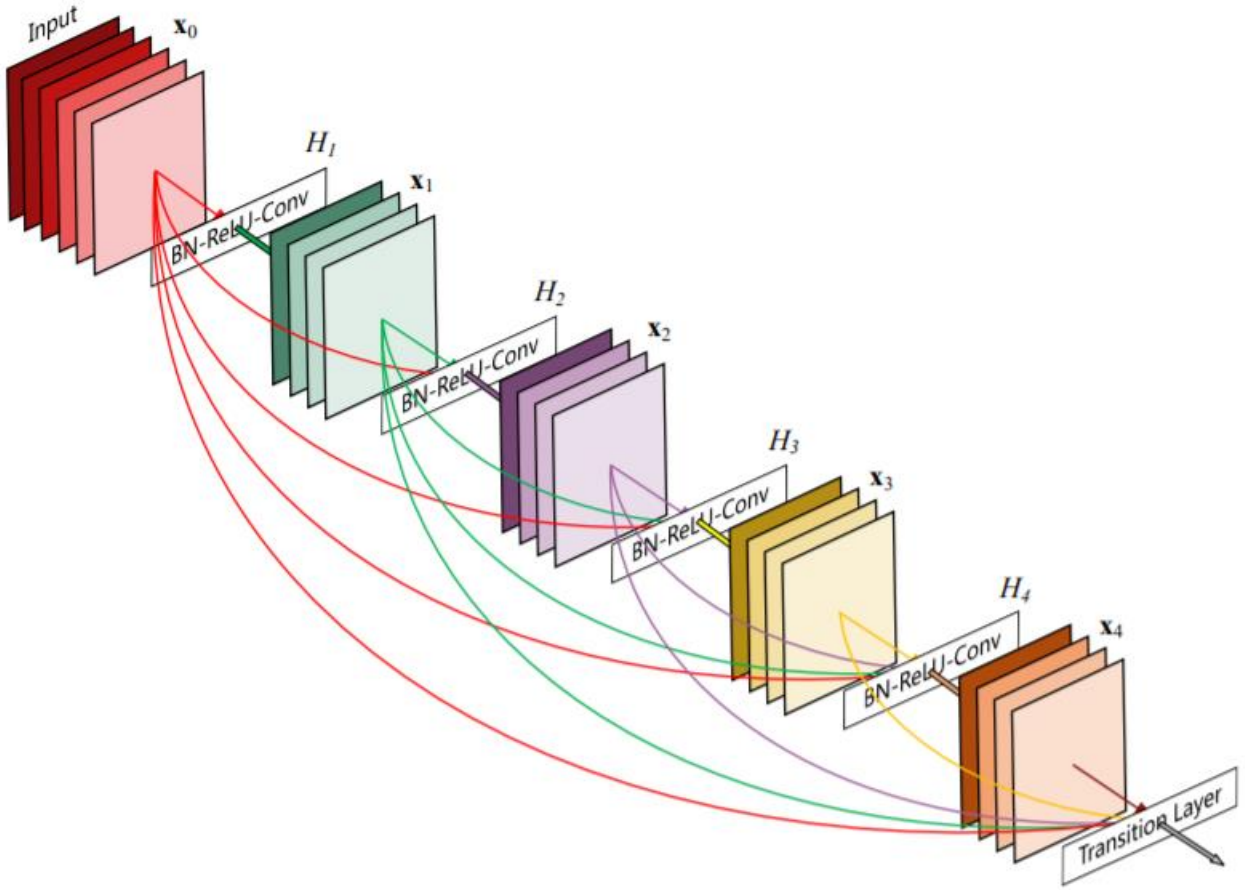
(b) constant scaling



(e) conv shortcut

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