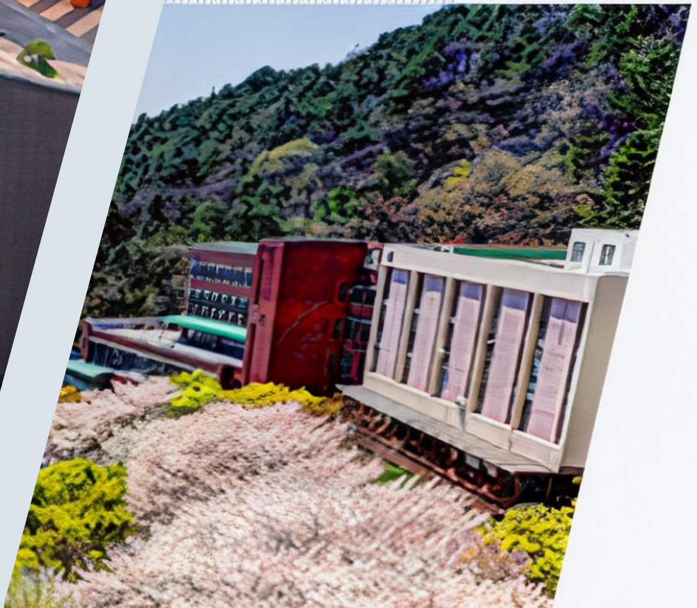
Dong-A Univ. (ISPL)

동아대학교
DONG-A UNIVERSITY

Main Modules for CNN Design

2024년 2학기 머신러닝



인쇄

2024학년도 2학기 강의평가 주관식 입력 결과 CSE320-02 머신러닝

주관식 번호	주관식문항
1	이 수업의 좋은 점 및 개선할 사항에 대해서 자유롭게 적어주세요. Please write down some good points of this class and any suggestions you have for improvement.

1. 중간고사로 코딩시험을 치기엔 인터넷 연결 문제, 컨닝방지를 위해 제대로 감독이 이루어지지 않는 등 여러 문제가 있었다. 문제가 모호하여 이해하는데 어려움이 있었다.

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1. 올려주시는 자료가 ppt 형식인데 그러다보니 아이패드에서 자료를 열었을 때 파일이 깨져있을때가 많습니다. 번거로우시겠지만 pdf 형식으로 올려주시면 감사하겠습니다.

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1. 이전에 학습했던 개념이나 내용을 복습하는 것보다는 새롭고 심화적인 내용을 배우는 것이 더 좋을 것 같습니다.

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1. 이론과 실습이 적절해서 좋았습니다

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1. 좋아요

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1. .

인쇄

2024학년도 2학기 강의평가 주관식 입력 결과 CSE320-01 머신러닝

주관식 번호	주관식문항
1	이 수업의 좋은 점 및 개선할 사항에 대해서 자유롭게 적어주세요. Please write down some good points of this class and any suggestions you have for improvement.

1. 이번 중간고사 시험 문제에 대해서 불만이 조금 있습니다. 파이썬에 대해 깊게 알지 못하는 학생은 작성이 매우 어려웠습니다. 저희가 배우는 내용은 머신러닝이지만 파이썬 코드 문법 문제 같았습니다. 물론 파이썬이 중요하긴 하지만 원래 저희가 코드를 작성할 때는 검색을 통해 모르는 문법을 알아갔습니다. 그러나 이를 통제할 뿐만 아니라 수업 때도 언급이 없던 내용이었기에 아쉬웠습니다.

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1. 교수님께서 학생들 이름 부르면서 장난치실 때 마다 너무 재밌습니다.

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1. 중간에 쉬는시간이 있어 좋습니다.

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1. 그냥 다 좋음

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1. 재미가 없음

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1. 없습니다

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1. 없습니다

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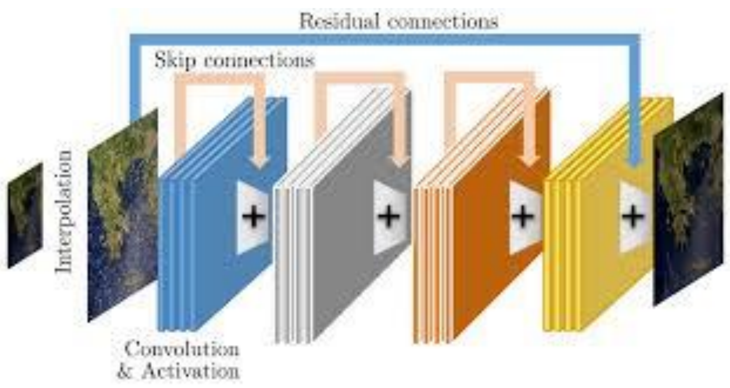
1. ...

딥러닝 주요모델 구성요소

- Skip connection (ResNet, 2015)
- Dense connection (DenseNet, 2017)
- Channel attention (SENet, 2018)

❖ Skip connection



❖ Dense connection

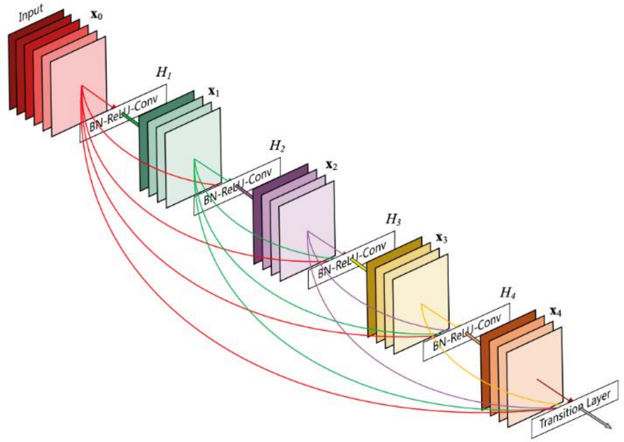
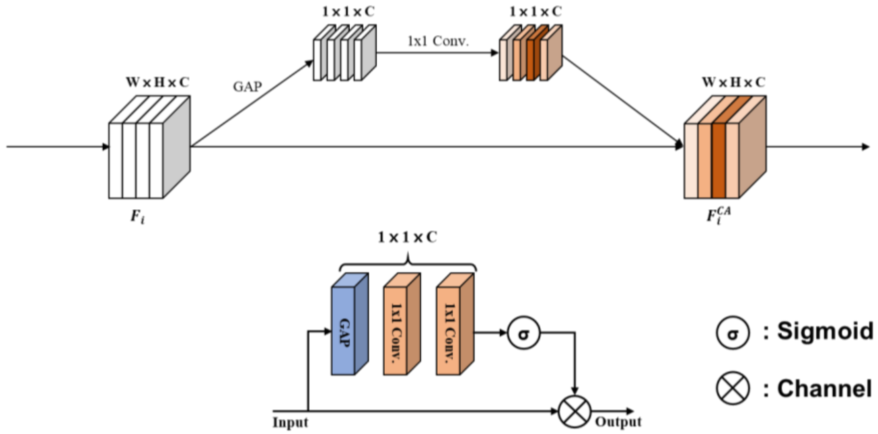


Figure 1: A 5-layer dense block with a growth rate of $k = 4$. Each layer takes all preceding feature-maps as input.

❖ Channel attention

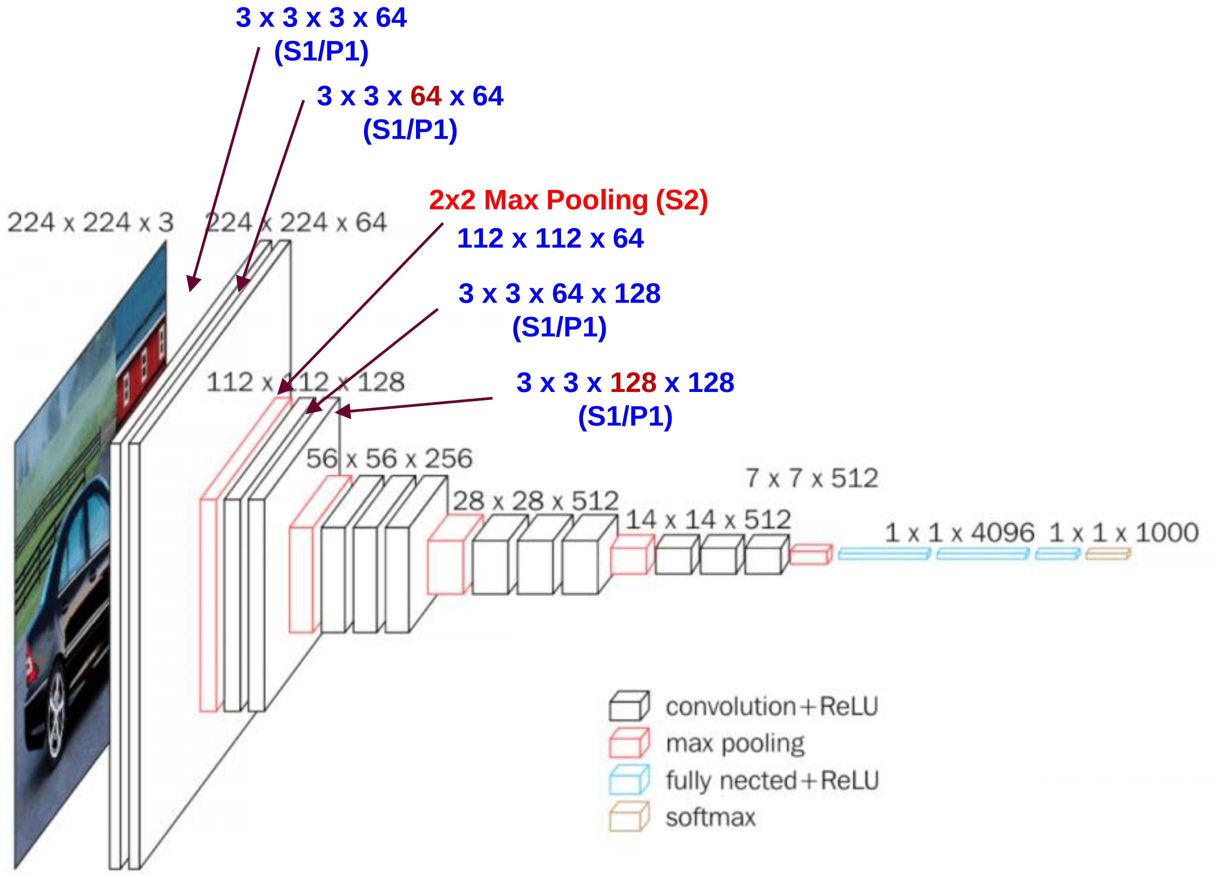


σ : Sigmoid 함수

⊗ : Channel 간 곱

Orig. Network - VGGNet(VGG-16)

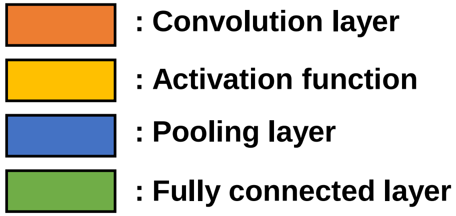
- 기존 VGGNet을 사용하여 실습 시 많은 시간 소요 ➔ 금일 실습 시 간소화된 모델 사용

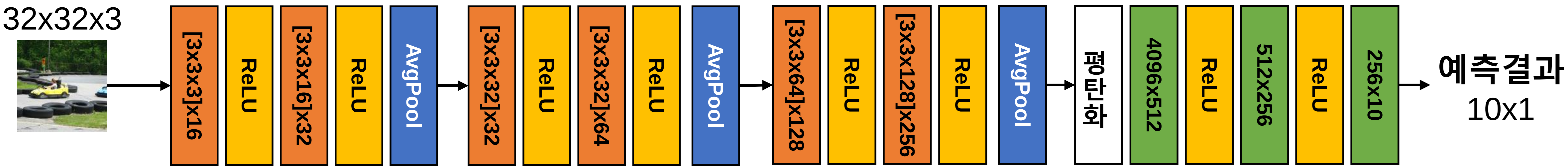


<VGG-16 구조>

Modified Network - VGGNet(VGG-16)

- 기존 VGG16을 CNN layer를 6개로 간소화
- CIFAR-10 데이터셋 분류를 위해 네트워크 구조 변경 (32x32x3, 10 classes)
- 실제 VGG 네트워크는 Max Pooling을 사용





CIFAR10 분류 실습 - CNN을 이용한 분류(VGGNet)

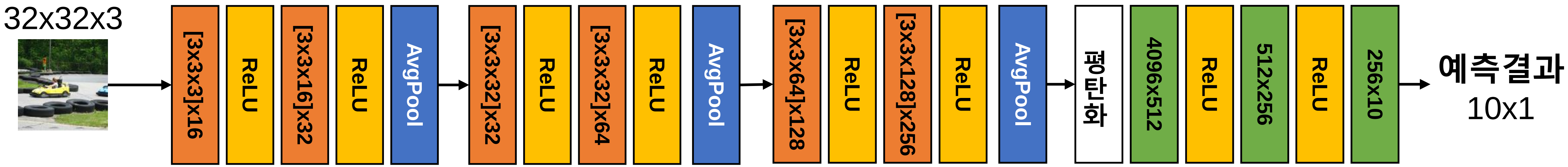
- **VGG 간소화 모델 코드 공유**
  - LMS 12주차 VGG base code 다운로드
  - 실습 시 **[3] Model 구조 선언** 부분만 수정

```python
class Model(nn.Module):
    def __init__(self):
        super(Model, self).__init__()

        self.conv1_1 = nn.Conv2d(in_channels=3, out_channels=16, kernel_size=3, padding=1)      # Convolution: [3x3x3]x16, s1, p1
        self.conv1_2 = nn.Conv2d(in_channels=16, out_channels=32, kernel_size=3, padding=1)     # Convolution: [3x3x16]x32, s1, p1

        self.conv2_1 = nn.Conv2d(in_channels=32, out_channels=32, kernel_size=3, padding=1)     # Convolution: [3x3x32]x32, s1, p1
        self.conv2_2 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1)     # Convolution: [3x3x32]x64, s1, p1

        self.conv3_1 = nn.Conv2d(in_channels=64, out_channels=128, kernel_size=3, padding=1)    # Convolution: [3x3x64]x128, s1, p1
        self.conv3_2 = nn.Conv2d(in_channels=128, out_channels=256, kernel_size=3, padding=1)   # Convolution: [3x3x128]x256, s1, p1

        self.fc1 = nn.Linear(in_features=4096, out_features=512)    # Fully connected: 4096x512
        self.fc2 = nn.Linear(in_features=512, out_features=256)     # Fully connected: 512x256
        self.fc3 = nn.Linear(in_features=256, out_features=10)      # Fully connected: 256x10

        # 파라미터를 가지지 않은 layer는 한번만 선언해도 문제 없음
        self.relu = nn.ReLU()
        self.avgPool2d = nn.AvgPool2d(kernel_size=2, stride=2)

    def forward(self, x):

        # convolutional layers
        out = self.relu(self.conv1_1(x))
        out = self.relu(self.conv1_2(out))
        out = self.avgPool2d(out)

        out = self.relu(self.conv2_1(out))
        out = self.relu(self.conv2_2(out))
        out = self.avgPool2d(out)

        out = self.relu(self.conv3_1(out))
        out = self.relu(self.conv3_2(out))
        out = self.avgPool2d(out)

        out = torch.reshape(out, (-1, 4096)) # feature map 평탄화

        # fully connected layers
        out = self.relu(self.fc1(out))
        out = self.relu(self.fc2(out))
        out = self.fc3(out)

        return out
```

CIFAR10 분류 실습 - CNN을 이용한 분류(VGGNet)

- **CIFAR-10 데이터셋 분류를 위해 네트워크 구조 변경 (32x32x3, 10 classes)**

: Convolution layer
: Activation function
: Pooling layer
: Fully connected layer



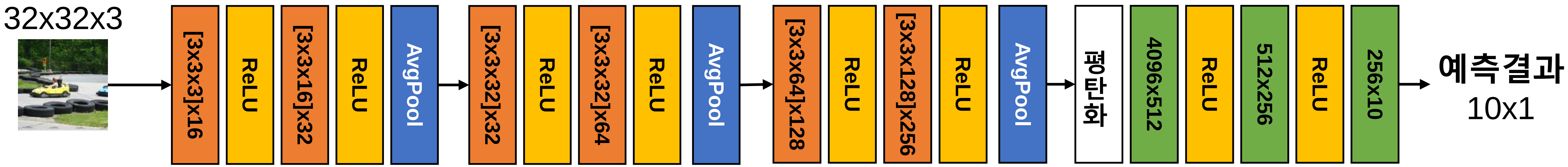
실습 Network base 구조 (Stride와 Padding size는 1로 고정)

```
class Model(nn.Module):
    def __init__(self):
        super(Model, self).__init__()

        self.conv1_1 = nn.Conv2d(in_channels=3, out_channels=16, kernel_size=3, padding=1)      # Convolution: [3x3x3]x16, s1, p1
        self.conv1_2 = nn.Conv2d(in_channels=16, out_channels=32, kernel_size=3, padding=1)     # Convolution: [3x3x16]x32, s1, p1

        self.conv2_1 = nn.Conv2d(in_channels=32, out_channels=32, kernel_size=3, padding=1)     # Convolution: [3x3x32]x32, s1, p1
        self.conv2_2 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1)     # Convolution: [3x3x32]x64, s1, p1

        self.conv3_1 = nn.Conv2d(in_channels=64, out_channels=128, kernel_size=3, padding=1)    # Convolution: [3x3x64]x128, s1, p1
        self.conv3_2 = nn.Conv2d(in_channels=128, out_channels=256, kernel_size=3, padding=1)   # Convolution: [3x3x128]x256, s1, p1

        self.fc1 = nn.Linear(in_features=4096, out_features=512)    # Fully connected: 4096x512
        self.fc2 = nn.Linear(in_features=512, out_features=256)     # Fully connected: 512x256
        self.fc3 = nn.Linear(in_features=256, out_features=10)      # Fully connected: 256x10

        # 파라미터를 가지지 않은 layer는 한번만 선언해도 문제 없음
        self.relu = nn.ReLU()
        self.avgPool2d = nn.AvgPool2d(kernel_size=2, stride=2)
```

CIFAR10 분류 실습 - CNN을 이용한 분류(VGGNet)

- CIFAR-10 데이터셋 분류를 위해 네트워크 구조 변경 (32x32x3, 10 classes)

: Convolution layer
: Activation function
: Pooling layer
: Fully connected layer



실습 Network base 구조 (Stride와 Padding size는 1로 고정)

```
    def forward(self, x):

        # convolutional layers
        out = self.relu(self.conv1_1(x))
        out = self.relu(self.conv1_2(out))
        out = self.avgPool2d(out)

        out = self.relu(self.conv2_1(out))
        out = self.relu(self.conv2_2(out))
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        out = self.relu(self.conv3_1(out))
        out = self.relu(self.conv3_2(out))
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        out = torch.reshape(out, (-1, 4096)) # feature map 평탄화

        # fully connected layers
        out = self.relu(self.fc1(out))
        out = self.relu(self.fc2(out))
        out = self.fc3(out)

        return out
```

CIFAR10 분류 실습 - CNN을 이용한 분류(VGGNet)

- **CIFAR-10 데이터셋 분류를 위해 네트워크 구조 변경 (32x32x3, 10 classes)**

: Convolution layer
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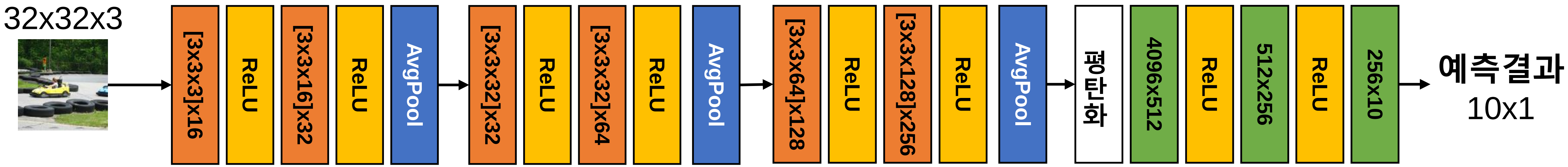
: Pooling layer
: Fully connected layer



실습 Network base 구조 (Stride와 Padding size는 1로 고정)

- **하이퍼 파라미터**
  - Training epoch: 20
  - Batch size: 100
  - Learning rate: 0.1
  - Loss function: Cross Entropy Loss
  - Optimizer: SGD

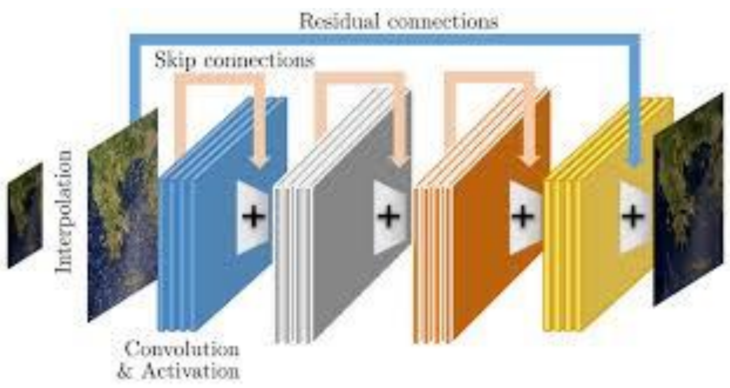
```
network.eval()
network = network.to('cpu')
img_test = torch.tensor(np.transpose(cifar10_test.data , (0, 3, 1, 2))) /255.
label_test = torch.tensor(cifar10_test.targets)

with torch.no_grad(): # test에서는 기울기 계산 제외
    prediction = network(img_test) # 전체 test data를 한번에 계산

correct_prediction = torch.argmax(prediction, 1) == label_test
accuracy = correct_prediction.float().mean()
print('Accuracy:', accuracy.item())
```

```
Accuracy: 0.6011000275611877
```

딥러닝 주요모델 구성요소

- **Skip connection (ResNet, 2015)**
- Dense connection (DenseNet, 2017)
- Channel attention (SENet, 2018)

❖ Skip connection



❖ Dense connection

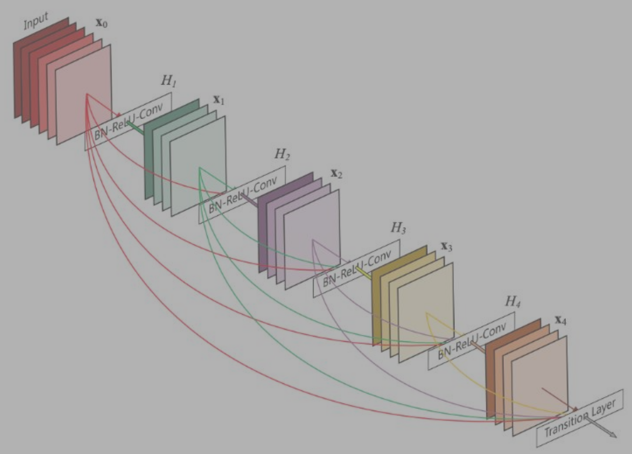
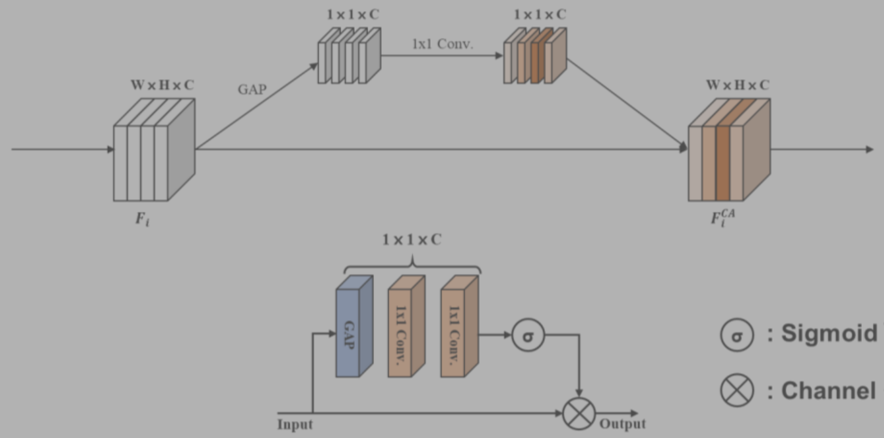


Figure 1: A 5-layer dense block with a growth rate of $k = 4$. Each layer takes all preceding feature-maps as input.

❖ Channel attention



σ : Sigmoid 함수

⊗ : Channel 간 곱

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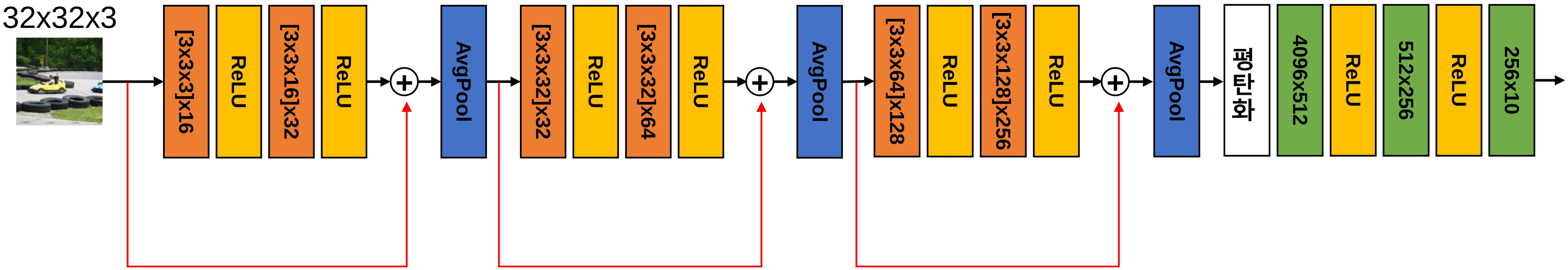
CIFAR10 분류 실습 - CNN을 이용한 분류(VGGNet)

- **Skip connection 추가 실험**

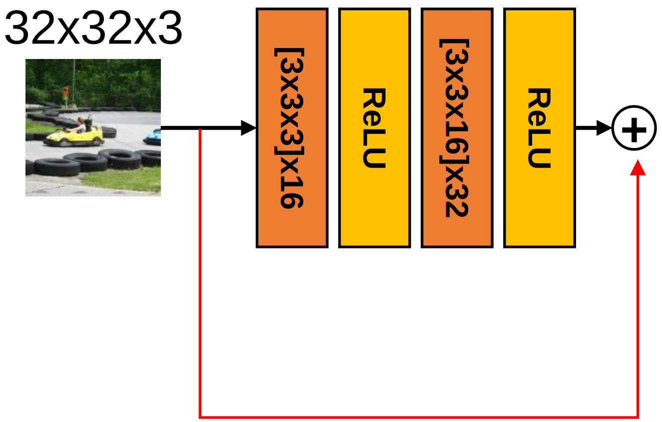
: Convolution layer
: Activation function
: Pooling layer
: Fully connected layer

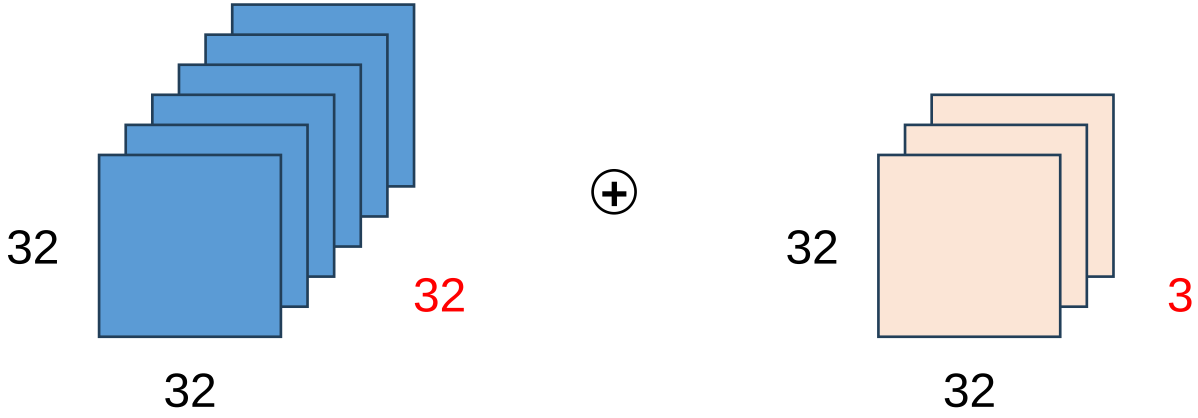


❖ 주의사항: Skip connection은 Width, Height, Channel이 모두 같아야 사용 가능

CIFAR10 분류 실습 - CNN을 이용한 분류(VGGNet)

- **Skip connection 추가 실험**





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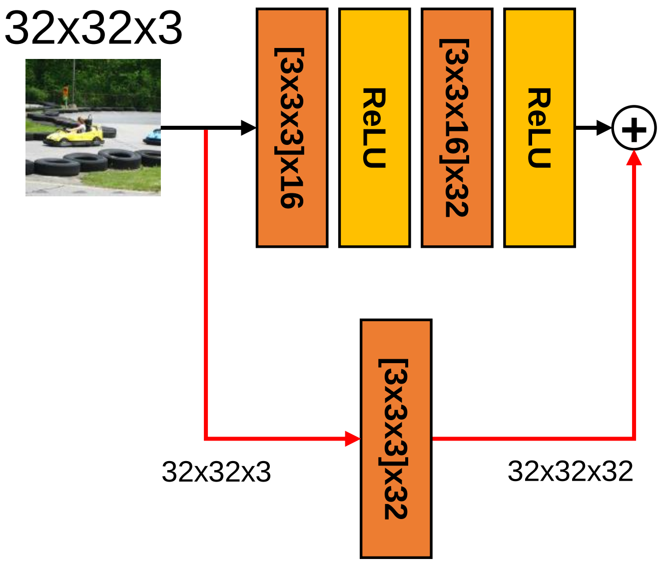
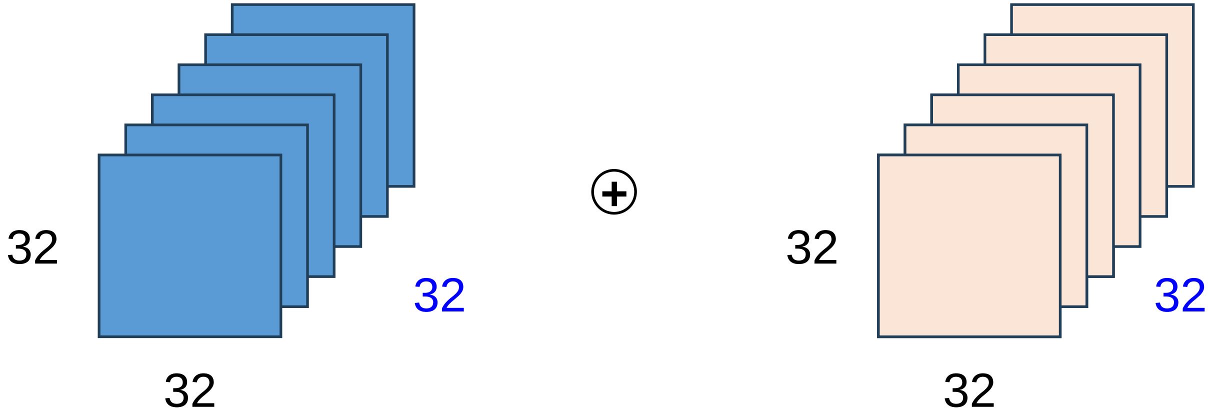
CIFAR10 분류 실습 - CNN을 이용한 분류(VGGNet)

- **Skip connection 추가 실험**

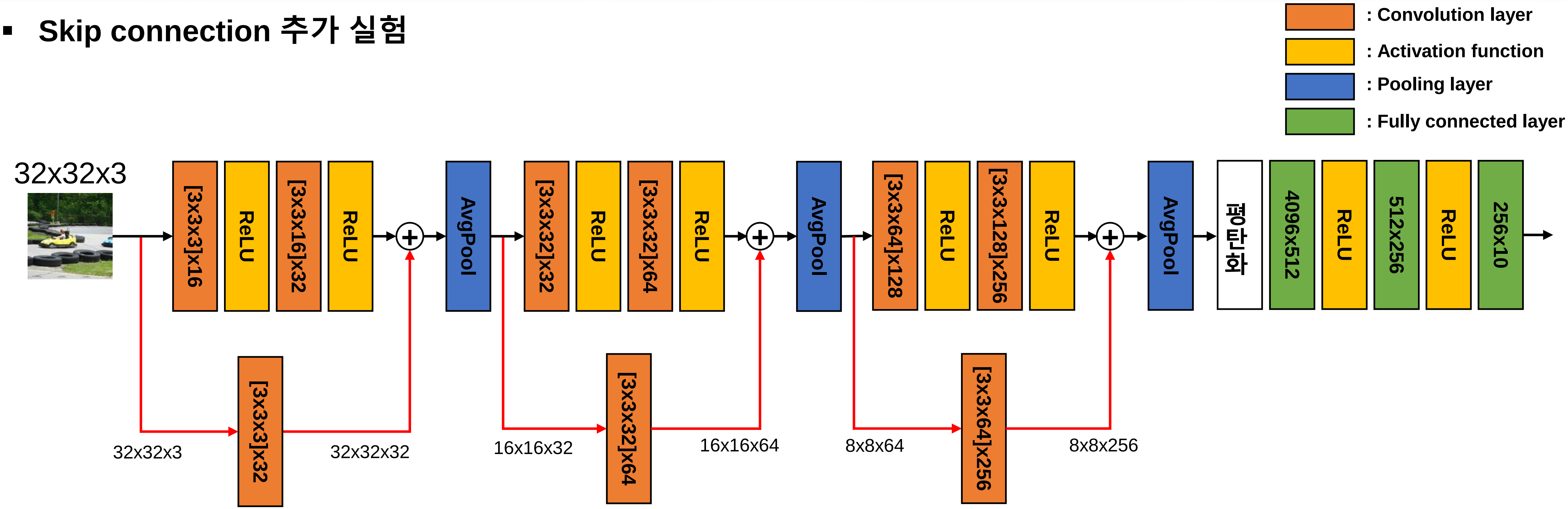




❖ **주의사항: Skip connection은 Width, Height, Channel이 모두 같아야 사용 가능**

CIFAR10 분류 실습 - CNN을 이용한 분류(VGGNet)

- Skip connection 추가 실험

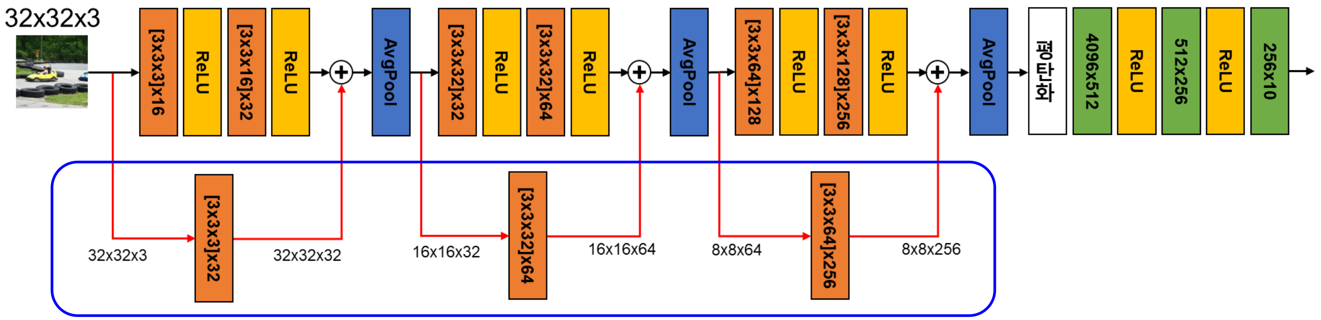


❖ 주의사항: Skip connection은 Width, Height, Channel이 모두 같아야 사용 가능

CIFAR10 분류 실습 - CNN을 이용한 분류(VGGNet)

- **Skip connection 추가 실험**
  - Skip connection을 위한 convolution layer 선언

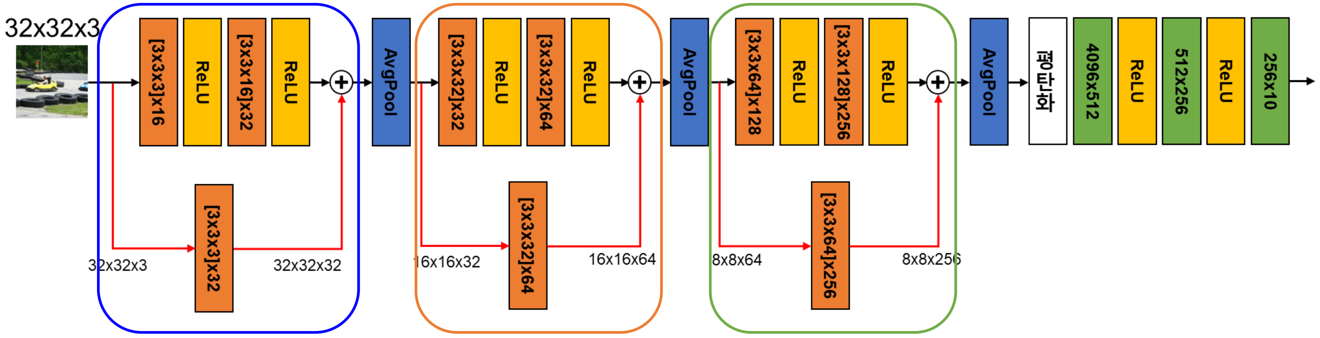
```
class VGG_SKIP (nn.Module):
    def __init__(self): # 신경망 구성요소 정의
        super(VGG_SKIP, self).__init__()
        self.conv1_1 = nn.Conv2d(in_channels=3, out_channels=16, kernel_size=3, padding=1)
        self.conv1_2 = nn.Conv2d(in_channels=16, out_channels=32, kernel_size=3, padding=1)

        self.conv2_1 = nn.Conv2d(in_channels=32, out_channels=32, kernel_size=3, padding=1)
        self.conv2_2 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1)

        self.conv3_1 = nn.Conv2d(in_channels=64, out_channels=128, kernel_size=3, padding=1)
        self.conv3_2 = nn.Conv2d(in_channels=128, out_channels=256, kernel_size=3, padding=1)

        # Skip Connection을 위한 Conv. layer
        self.conv_skip1 = nn.Conv2d(in_channels=3, out_channels=32, kernel_size=3, padding=1)
        self.conv_skip2 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1)
        self.conv_skip3 = nn.Conv2d(in_channels=64, out_channels=256, kernel_size=3, padding=1)

        self.fc1 = nn.Linear(in_features=4096, out_features=512)
        self.fc2 = nn.Linear(in_features=512, out_features=256)
        self.fc3 = nn.Linear(in_features=256, out_features=10)

        self.relu = nn.ReLU()
        self.avgPool2d = nn.AvgPool2d(kernel_size=2, stride=2)
```



CIFAR10 분류 실습 - CNN을 이용한 분류(VGGNet)

- **Skip connection 추가 실험**
  - Skip connection 적용

```python
def forward(self,x):

    input_feature1 = x #Skip 입력을 위한 Input 저장
    out = self.relu(self.conv1_1(x))
    out = self.relu(self.conv1_2(out))
    input_skip1 = self.relu(self.conv_skip1(input_feature1)) #Skip 입력을 위한 Conv layer 적용
    out = torch.add(out, input_skip1) #Skip connection 적용
    out = self.avgPool2d(out)

    input_feature2 = out #Skip 입력을 위한 Input 저장
    out = self.relu(self.conv2_1(out))
    out = self.relu(self.conv2_2(out))
    input_skip2 = self.relu(self.conv_skip2(input_feature2)) #Skip 입력을 위한 Conv layer 적용
    out = torch.add(out, input_skip2) #Skip connection 적용
    out = self.avgPool2d(out)

    input_feature3 = out #Skip 입력을 위한 Input 저장
    out = self.relu(self.conv3_1(out))
    out = self.relu(self.conv3_2(out))
    input_skip3 = self.relu(self.conv_skip3(input_feature3)) #Skip 입력을 위한 Conv layer 적용
    out = torch.add(out, input_skip3) #Skip connection 적용
    out = self.avgPool2d(out)

    out = out.view(-1, 4096) # feature map 평탄화

    out = self.relu(self.fc1(out))
    out = self.relu(self.fc2(out))
    out = self.fc3(out)
    return out
```

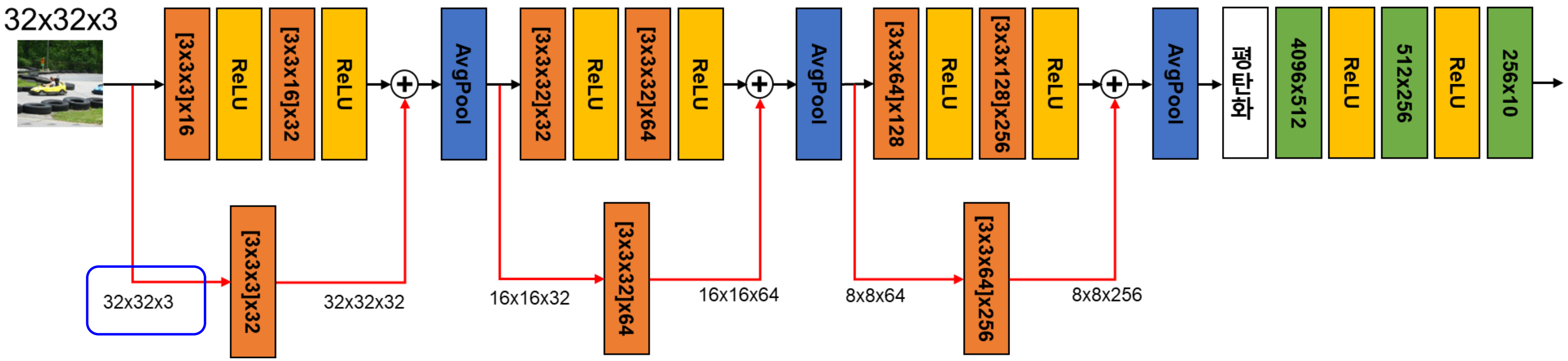


CIFAR10 분류 실습 - CNN을 이용한 분류(VGGNet)

- **Skip connection 추가 실험**

```python
def forward(self,x):

    input_feature1 = x #Skip 입력을 위한 Input 저장
    out = self.relu(self.conv1_1(x))
    out = self.relu(self.conv1_2(out))
    input_skip1 = self.relu(self.conv_skip1(input_feature1)) #Skip 입력을 위한 Conv layer 적용
    out = torch.add(out, input_skip1) #Skip connection 적용
    out = self.avgPool2d(out)
```

Skip connection적용을 위해 Conv. 입력 저장

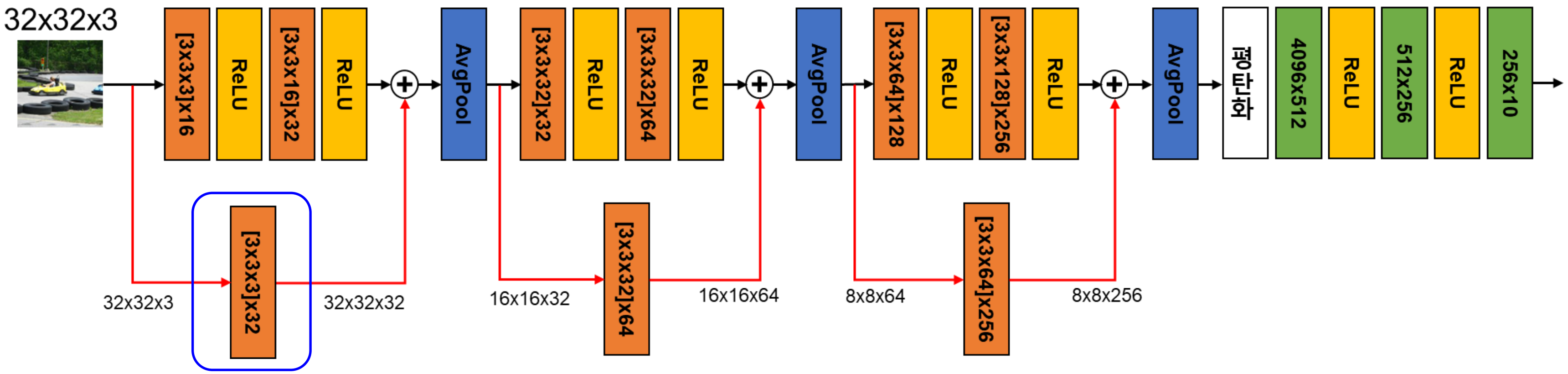


CIFAR10 분류 실습 - CNN을 이용한 분류(VGGNet)

- **Skip connection 추가 실험**

```
def forward(self,x):

    input_feature1 = x #Skip 입력을 위한 Input 저장
    out = self.relu(self.conv1_1(x))
    out = self.relu(self.conv1_2(out))
    input_skip1 = self.relu(self.conv_skip1(input_feature1)) #Skip 입력을 위한 Conv layer 적용
    out = torch.add(out, input_skip1) #Skip connection 적용
    out = self.avgPool2d(out)
```

→ Width, Height, Channel을 맞춰 주기 위한 Conv. 적용



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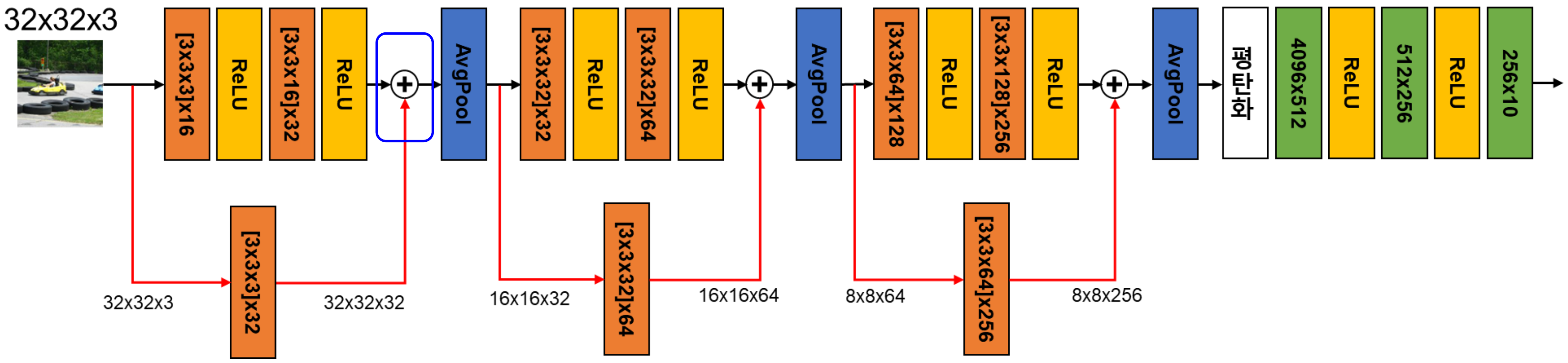
CIFAR10 분류 실습 - CNN을 이용한 분류(VGGNet)

- **Skip connection 추가 실험**

```python
def forward(self,x):

    input_feature1 = x #Skip 입력을 위한 Input 저장
    out = self.relu(self.conv1_1(x))
    out = self.relu(self.conv1_2(out))
    input_skip1 = self.relu(self.conv_skip1(input_feature1)) #Skip 입력을 위한 Conv layer 적용
    out = torch.add(out, input_skip1) #Skip connection 적용
    out = self.avgPool2d(out)
```

→ Skip connection 적용 코드



CIFAR10 분류 실습 - CNN을 이용한 분류(VGGNet)

- **Skip connection 추가 실험 결과 확인**

```
Epoch: 1 Loss = 2.303002
Epoch: 2 Loss = 2.302858
Epoch: 3 Loss = 2.302659
Epoch: 4 Loss = 2.246866
Epoch: 5 Loss = 1.997299
Epoch: 6 Loss = 1.824729
Epoch: 7 Loss = 1.672605
Epoch: 8 Loss = 1.496609
Epoch: 9 Loss = 1.346635
Epoch: 10 Loss = 1.229228
Epoch: 11 Loss = 1.127741
Epoch: 12 Loss = 1.025967
Epoch: 13 Loss = 0.922246
Epoch: 14 Loss = 0.813664
Epoch: 15 Loss = 0.702598
Epoch: 16 Loss = 0.583456
Epoch: 17 Loss = 0.467354
Epoch: 18 Loss = 0.360702
Epoch: 19 Loss = 0.284199
Epoch: 20 Loss = 0.228450
Learning finished
```

```
Epoch: 1 Loss = 2.133430
Epoch: 2 Loss = 1.784824
Epoch: 3 Loss = 1.573649
Epoch: 4 Loss = 1.431847
Epoch: 5 Loss = 1.312706
Epoch: 6 Loss = 1.211934
Epoch: 7 Loss = 1.106290
Epoch: 8 Loss = 1.014058
Epoch: 9 Loss = 0.923362
Epoch: 10 Loss = 0.828185
Epoch: 11 Loss = 0.733846
Epoch: 12 Loss = 0.639242
Epoch: 13 Loss = 0.537734
Epoch: 14 Loss = 0.442022
Epoch: 15 Loss = 0.353637
Epoch: 16 Loss = 0.271488
Epoch: 17 Loss = 0.220454
Epoch: 18 Loss = 0.166728
Epoch: 19 Loss = 0.135304
Epoch: 20 Loss = 0.108017
Learning finished
```

Training 결과

```python
network.eval()
network = network.to('cpu')
img_test = torch.tensor(np.transpose(cifar10_test.data , (0, 3, 1, 2))) /255.
label_test = torch.tensor(cifar10_test.targets)

with torch.no_grad(): # test에서는 기울기 계산 제외
    prediction = network(img_test) # 전체 test data를 한번에 계산

correct_prediction = torch.argmax(prediction, 1) == label_test
accuracy = correct_prediction.float().mean()
print('Accuracy:', accuracy.item())
```

```
Accuracy: 0.6011000275611877
```

```python
network.eval()
network = network.to('cpu')
img_test = torch.tensor(np.transpose(cifar10_test.data , (0, 3, 1, 2))) /255.
label_test = torch.tensor(cifar10_test.targets)

with torch.no_grad(): # test에서는 기울기 계산 제외
    prediction = network(img_test) # 전체 test data를 한번에 계산

correct_prediction = torch.argmax(prediction, 1) == label_test
accuracy = correct_prediction.float().mean()
print('Accuracy:', accuracy.item())
```

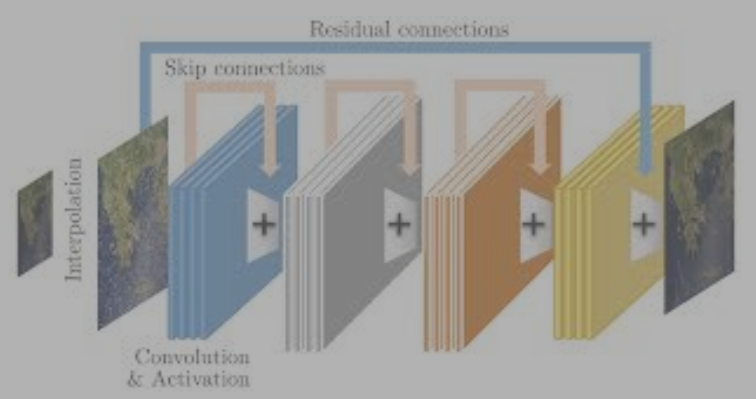
```
Accuracy: 0.6686999797821045
```

Test 결과

딥러닝 주요모델 구성요소

- Skip connection (ResNet, 2015)
- **Dense connection (DenseNet, 2017)**
- Channel attention (SENet, 2018)

❖ Skip connection



❖ **Dense connection**

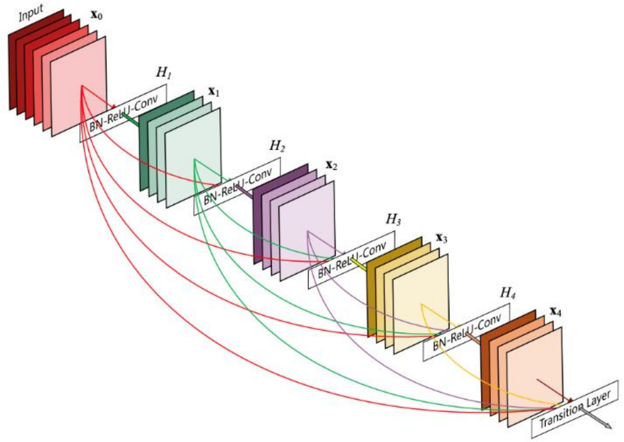
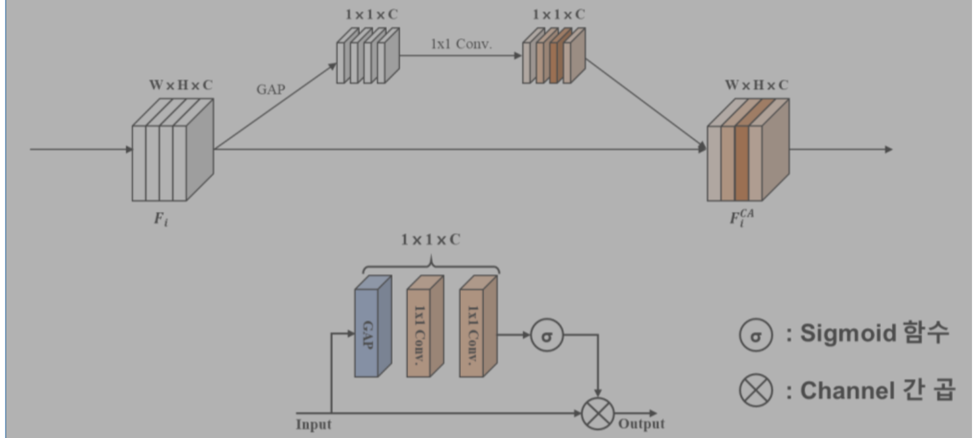


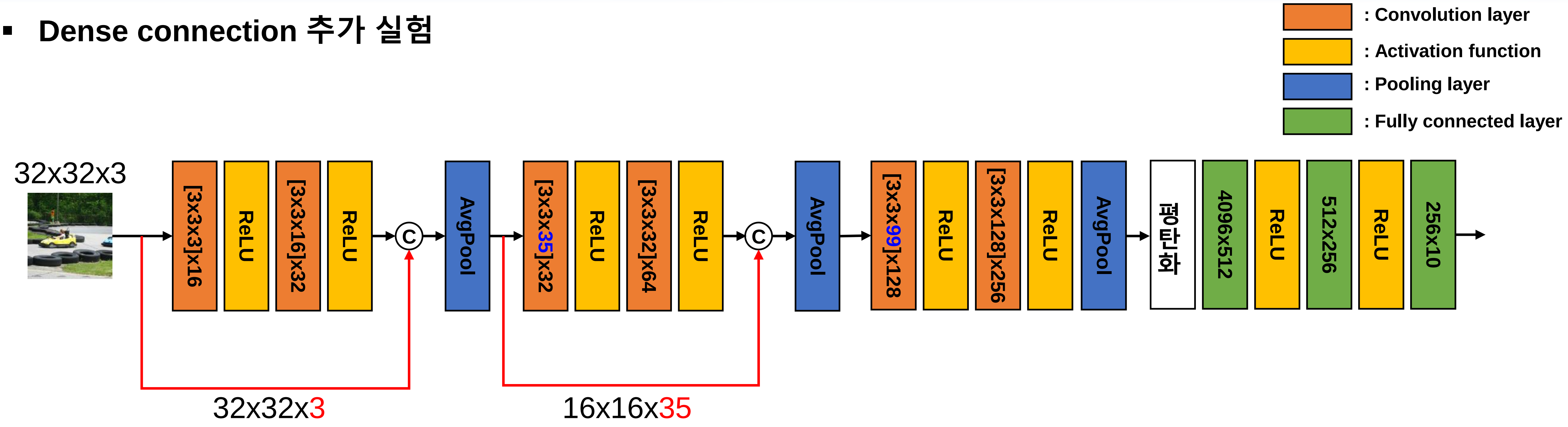
Figure 1: A 5-layer dense block with a growth rate of $k = 4$. Each layer takes all preceding feature-maps as input.

❖ Channel attention



CIFAR10 분류 실습 - CNN을 이용한 분류(VGGNet)

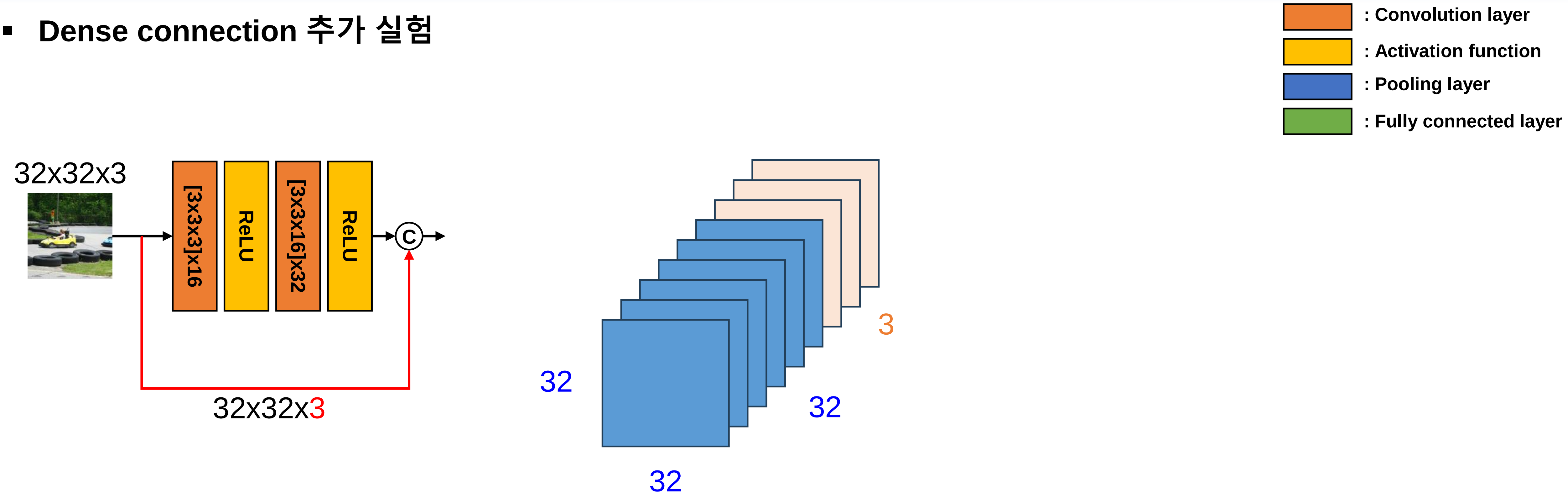
- **Dense connection 추가 실험**



❖ **주의사항: Dense connection (torch.cat)은 width, height이 동일해야 적용 가능**

CIFAR10 분류 실습 - CNN을 이용한 분류(VGGNet)

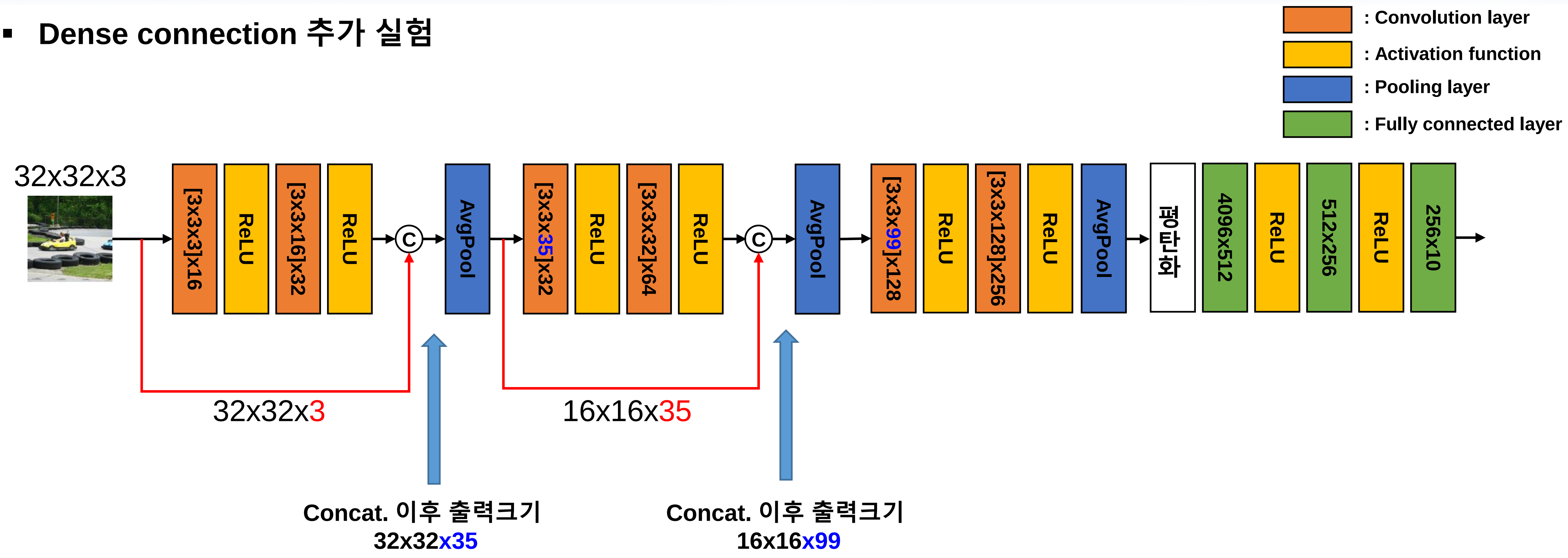
- **Dense connection 추가 실험**



❖ **주의사항: Dense connection (torch.cat)은 width, height이 동일해야 적용 가능**

CIFAR10 분류 실습 - CNN을 이용한 분류(VGGNet)

- **Dense connection 추가 실험**



❖ **주의사항: Dense connection (torch.cat)은 width, height이 동일해야 적용 가능**

CIFAR10 분류 실습 - CNN을 이용한 분류(VGGNet)

- **Dense connection 추가 실험**
  - Dense 추가로 인한 Input channels 변경

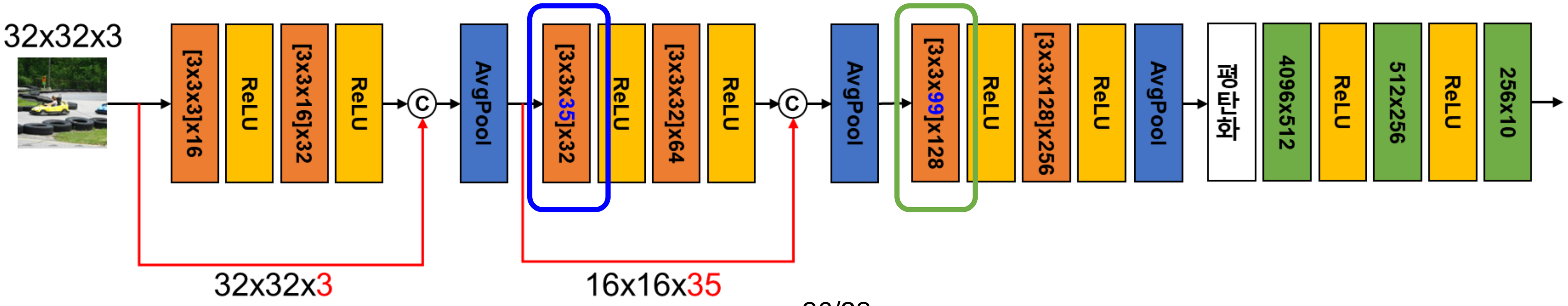
```python
class VGG_DENSE (nn.Module):
    def __init__(self): # 신경망 구성요소 정의
        super(VGG_DENSE, self).__init__()
        self.conv1_1 = nn.Conv2d(in_channels=3, out_channels=16, kernel_size=3, padding=1)
        self.conv1_2 = nn.Conv2d(in_channels=16, out_channels=32, kernel_size=3, padding=1)

        self.conv2_1 = nn.Conv2d(in_channels=35, out_channels=32, kernel_size=3, padding=1)
        self.conv2_2 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1)

        self.conv3_1 = nn.Conv2d(in_channels=99, out_channels=128, kernel_size=3, padding=1)
        self.conv3_2 = nn.Conv2d(in_channels=128, out_channels=256, kernel_size=3, padding=1)

        self.fc1 = nn.Linear(in_features=4096, out_features=512)
        self.fc2 = nn.Linear(in_features=512, out_features=256)
        self.fc3 = nn.Linear(in_features=256, out_features=10)

        self.relu = nn.ReLU()
        self.avgPool2d = nn.AvgPool2d(kernel_size=2, stride=2)
```



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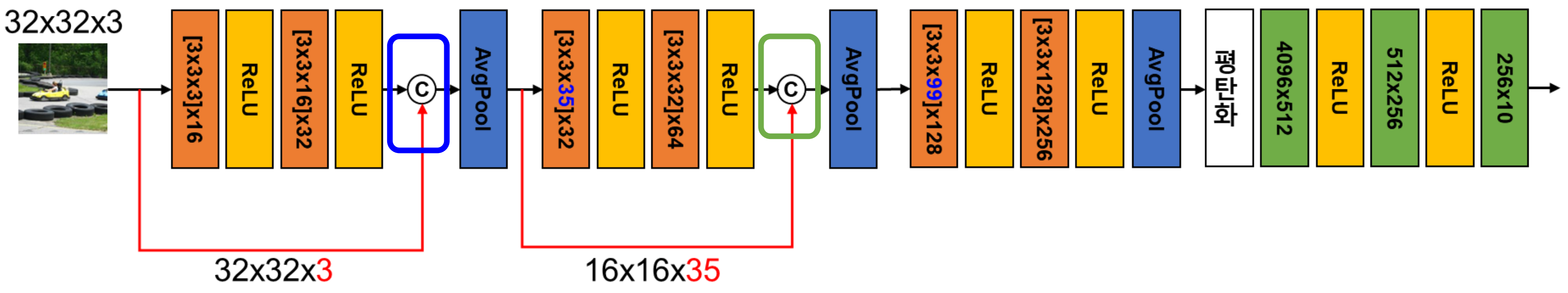
CIFAR10 분류 실습 - CNN을 이용한 분류(VGGNet)

- **Dense connection 추가 실험**
  - Dense를 위한 Concat. 코드 추가

```
def forward(self,x):

    out1 = self.relu(self.conv1_1(x))
    out1 = self.relu(self.conv1_2(out1))
    out1 = torch.cat([x, out1], dim=1)
    out1 = self.avgPool2d(out1)

    out2 = self.relu(self.conv2_1(out1))
    out2 = self.relu(self.conv2_2(out2))
    out2 = torch.cat([out1, out2], dim=1)
    out2 = self.avgPool2d(out2)

    out3 = self.relu(self.conv3_1(out2))
    out3 = self.relu(self.conv3_2(out3))
    #out3 = torch.cat([out2, out3], dim=1)
    out = self.avgPool2d(out3)

    out = out.view(-1, 4096) # feature map 평탄화

    out = self.relu(self.fc1(out))
    out = self.relu(self.fc2(out))
    out = self.fc3(out)
    return out
```



out1 = torch.cat([x, out1], dim=1)

Feature map 형상: (Batch_size, Channel, Width, Height)

dim: 0 1 2 3

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CIFAR10 분류 실습 - CNN을 이용한 분류(VGGNet)

- **Dense connection 추가 실험 결과 확인**

```
Epoch: 1 Loss = 2.303002
Epoch: 2 Loss = 2.302858
Epoch: 3 Loss = 2.302659
Epoch: 4 Loss = 2.246866
Epoch: 5 Loss = 1.997299
Epoch: 6 Loss = 1.824729
Epoch: 7 Loss = 1.672605
Epoch: 8 Loss = 1.496609
Epoch: 9 Loss = 1.346635
Epoch: 10 Loss = 1.229228
Epoch: 11 Loss = 1.127741
Epoch: 12 Loss = 1.025967
Epoch: 13 Loss = 0.922246
Epoch: 14 Loss = 0.813664
Epoch: 15 Loss = 0.702598
Epoch: 16 Loss = 0.583456
Epoch: 17 Loss = 0.467354
Epoch: 18 Loss = 0.360702
Epoch: 19 Loss = 0.284199
Epoch: 20 Loss = 0.228450
Learning finished
```

```
Epoch: 1 Loss = 2.254756
Epoch: 2 Loss = 1.989823
Epoch: 3 Loss = 1.779417
Epoch: 4 Loss = 1.609736
Epoch: 5 Loss = 1.490473
Epoch: 6 Loss = 1.384320
Epoch: 7 Loss = 1.268125
Epoch: 8 Loss = 1.179736
Epoch: 9 Loss = 1.089010
Epoch: 10 Loss = 0.999267
Epoch: 11 Loss = 0.914411
Epoch: 12 Loss = 0.825907
Epoch: 13 Loss = 0.740529
Epoch: 14 Loss = 0.647511
Epoch: 15 Loss = 0.560547
Epoch: 16 Loss = 0.462542
Epoch: 17 Loss = 0.378811
Epoch: 18 Loss = 0.292290
Epoch: 19 Loss = 0.225068
Epoch: 20 Loss = 0.166460
Learning finished
```

Training 결과

```
network.eval()
network = network.to('cpu')
img_test = torch.tensor(np.transpose(cifar10_test.data , (0, 3, 1, 2))) /255.
label_test = torch.tensor(cifar10_test.targets)

with torch.no_grad(): # test에서는 기울기 계산 제외
    prediction = network(img_test) # 전체 test data를 한번에 계산

correct_prediction = torch.argmax(prediction, 1) == label_test
accuracy = correct_prediction.float().mean()
print('Accuracy:', accuracy.item())
```

```
Accuracy: 0.6011000275611877
```

```
network.eval()
network = network.to('cpu')
img_test = torch.tensor(np.transpose(cifar10_test.data , (0, 3, 1, 2))) /255.
label_test = torch.tensor(cifar10_test.targets)

with torch.no_grad(): # test에서는 기울기 계산 제외
    prediction = network(img_test) # 전체 test data를 한번에 계산

correct_prediction = torch.argmax(prediction, 1) == label_test
accuracy = correct_prediction.float().mean()
print('Accuracy:', accuracy.item())
```

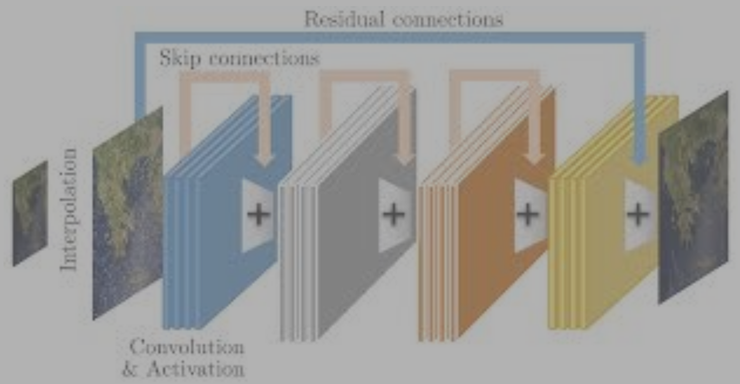
```
Accuracy: 0.6967999935150146
```

Test 결과

딥러닝 주요모델 구성요소

- Skip connection (ResNet, 2015)
- Dense connection (DenseNet, 2017)
- **Channel attention (SENet, 2018)**

❖ Skip connection



❖ Dense connection

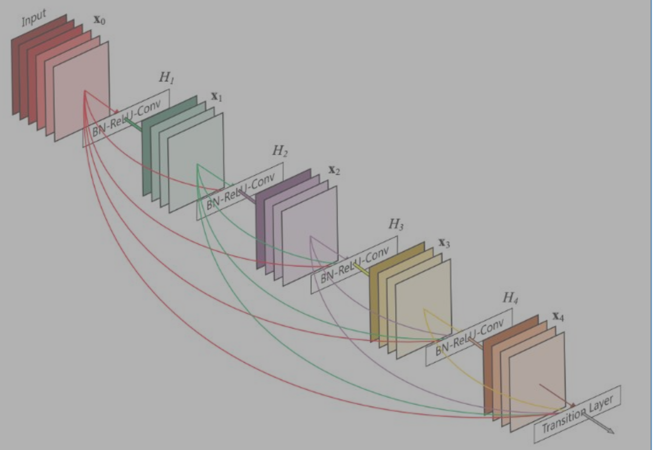
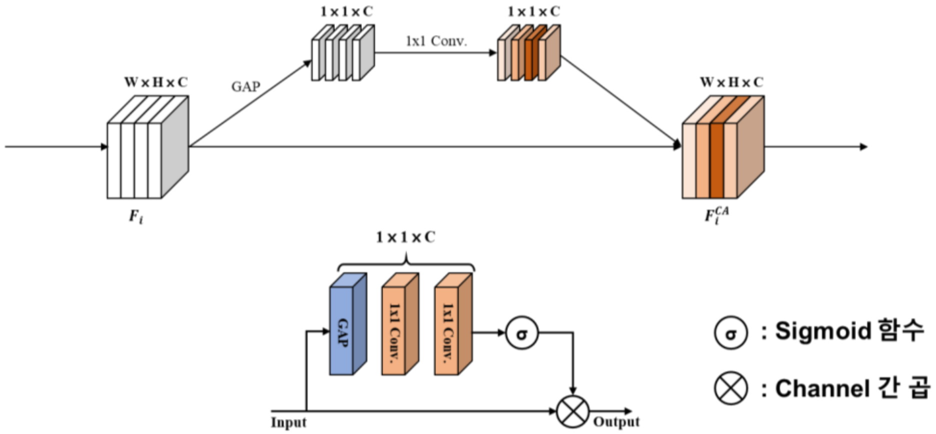


Figure 1: A 5-layer dense block with a growth rate of $k = 4$. Each layer takes all preceding feature-maps as input.

❖ Channel attention



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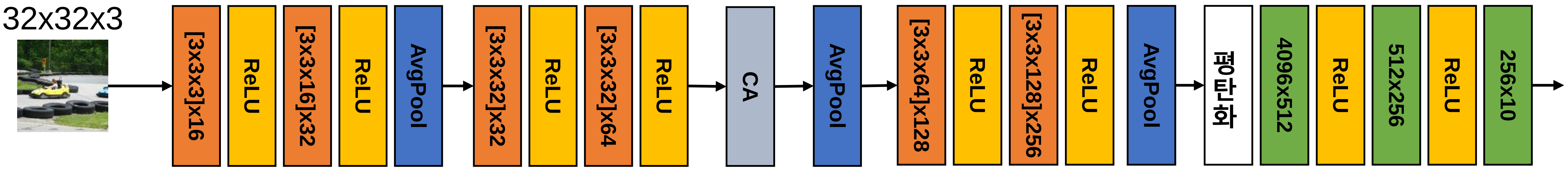
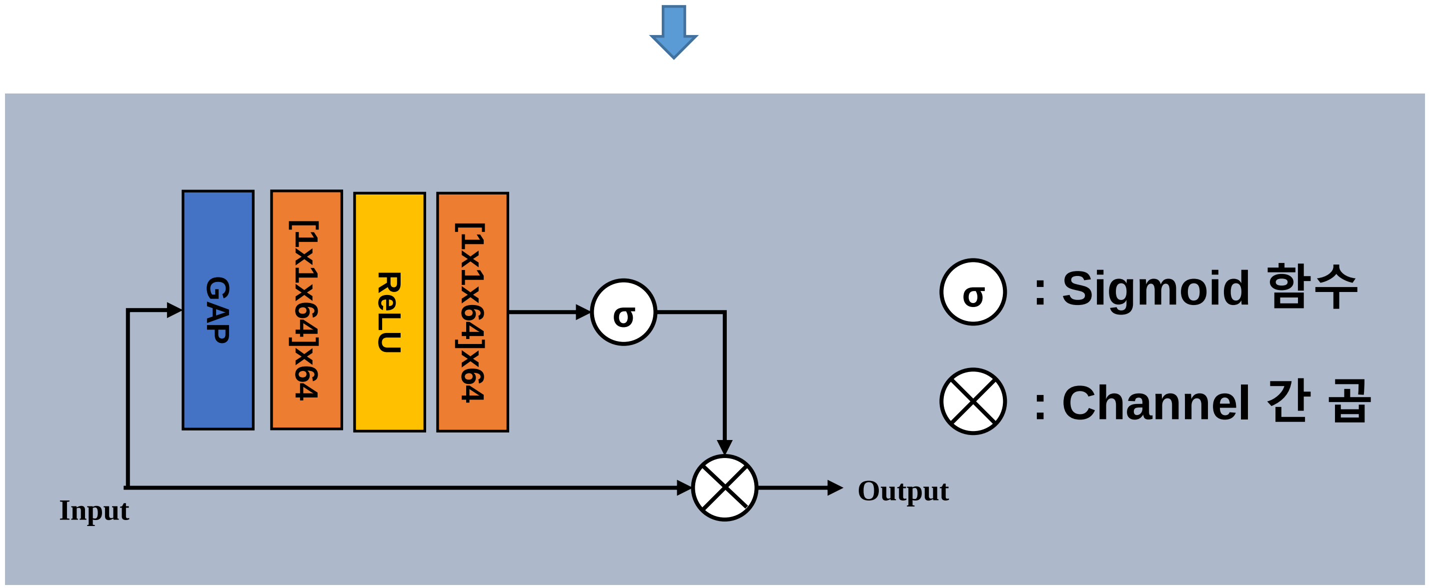
CIFAR10 분류 실습 - CNN을 이용한 분류(VGGNet)

- **Channel attention (CA) 추가 실험**

: Convolution layer
: Activation function
: Pooling layer
: Fully connected layer





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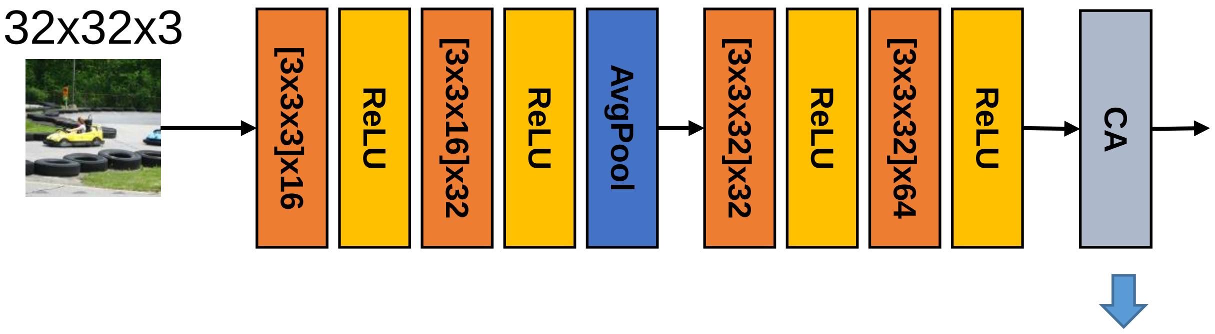
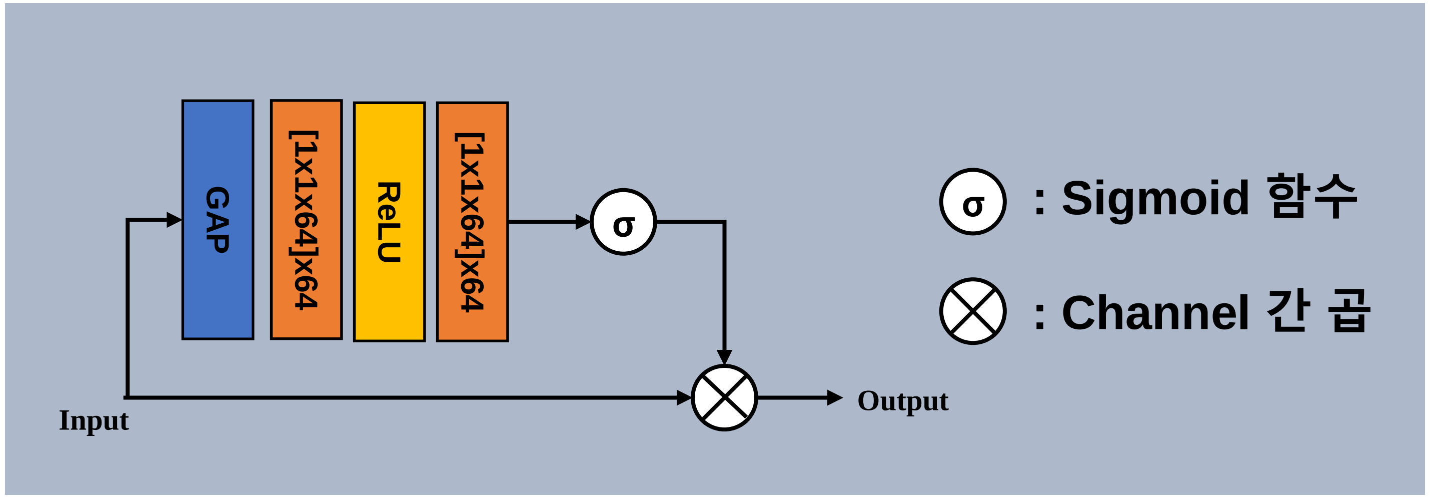
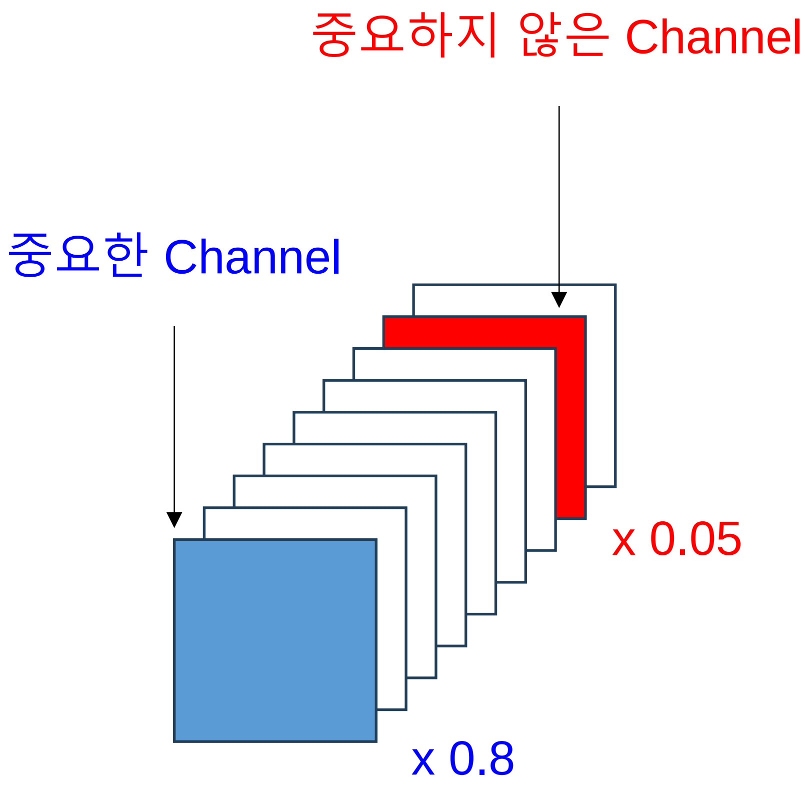
CIFAR10 분류 실습 - CNN을 이용한 분류(VGGNet)

- **Channel attention (CA) 추가 실험**

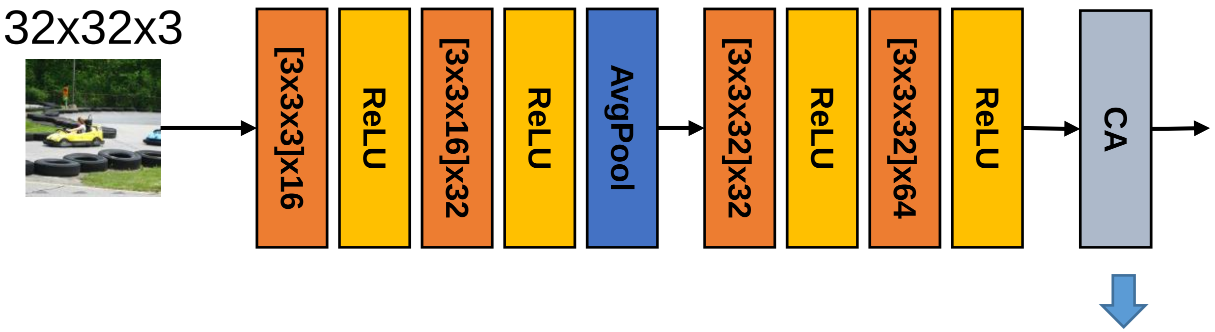


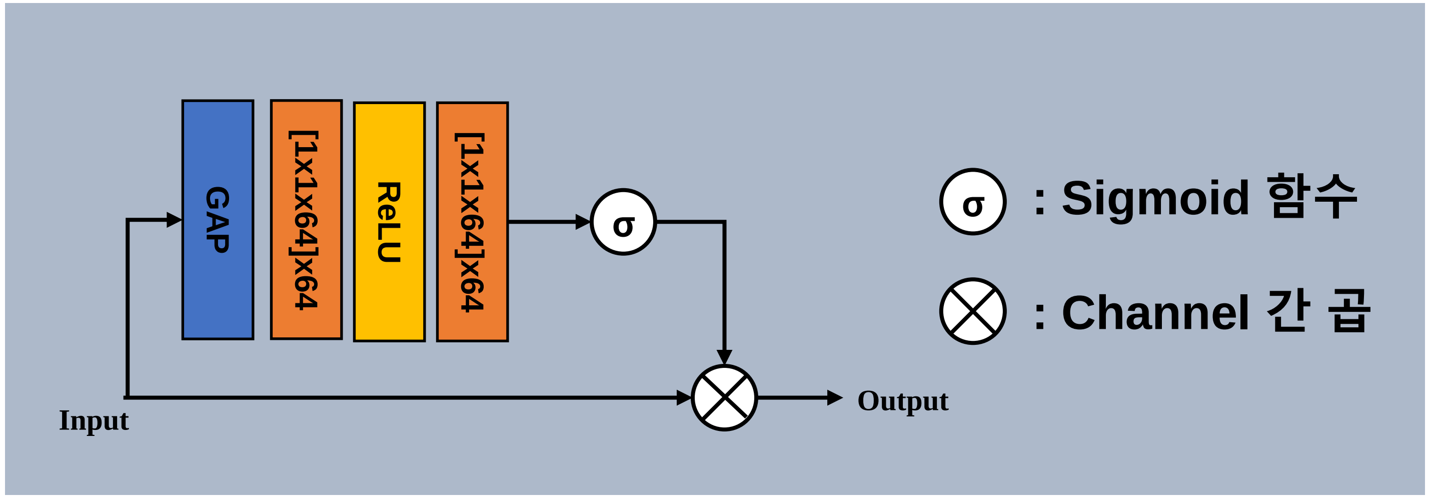


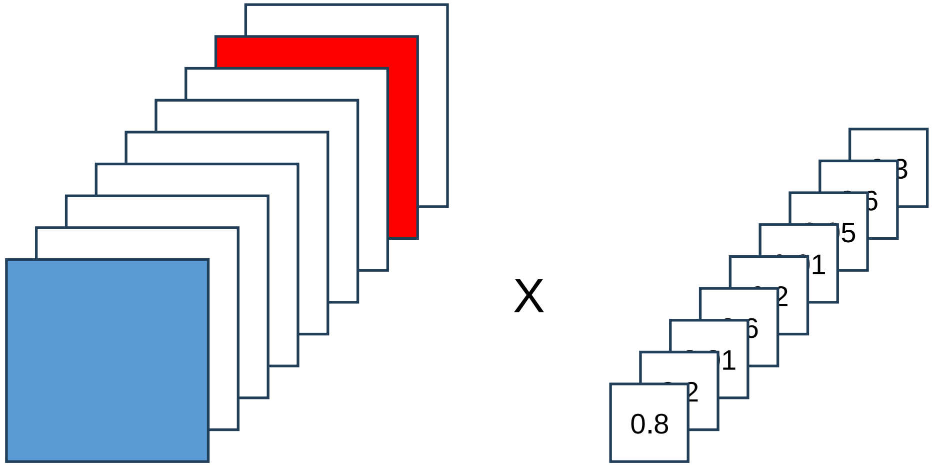


CIFAR10 분류 실습 - CNN을 이용한 분류(VGGNet)

- **Channel attention (CA) 추가 실험**







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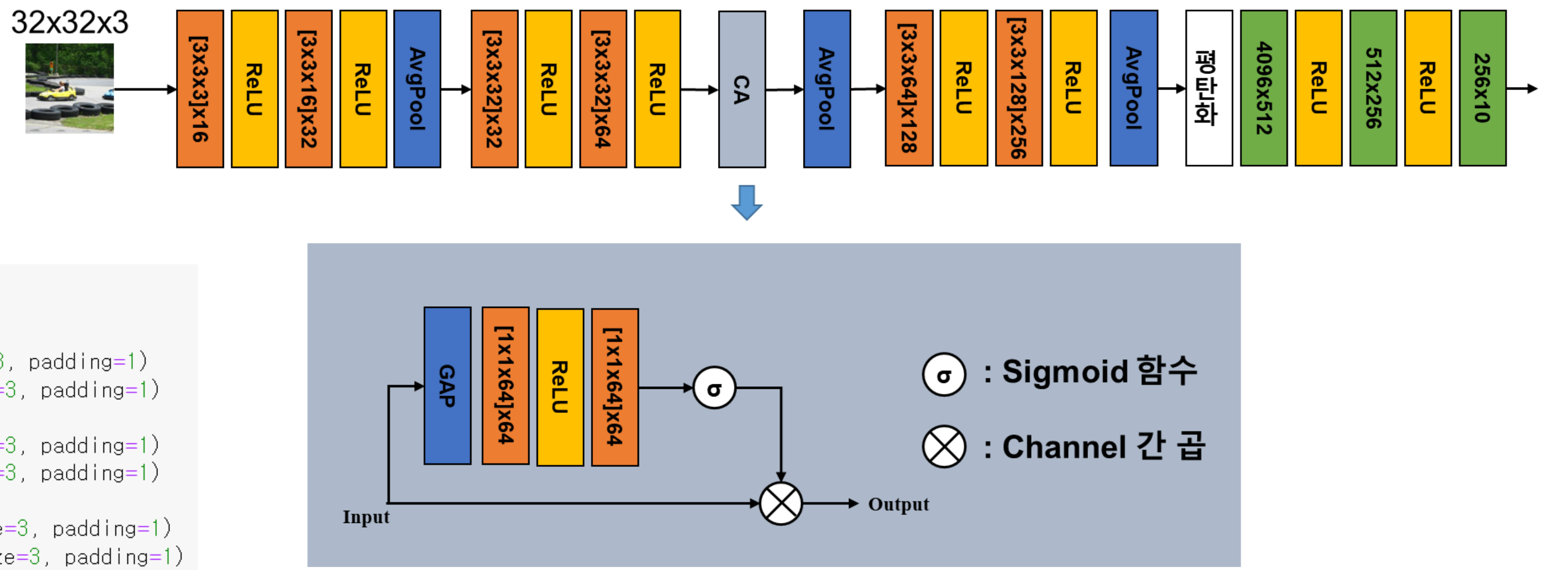
CIFAR10 분류 실습 - CNN을 이용한 분류(VGGNet)

- **Channel attention (CA) 추가 실험**
  - CA 구성요소 정의

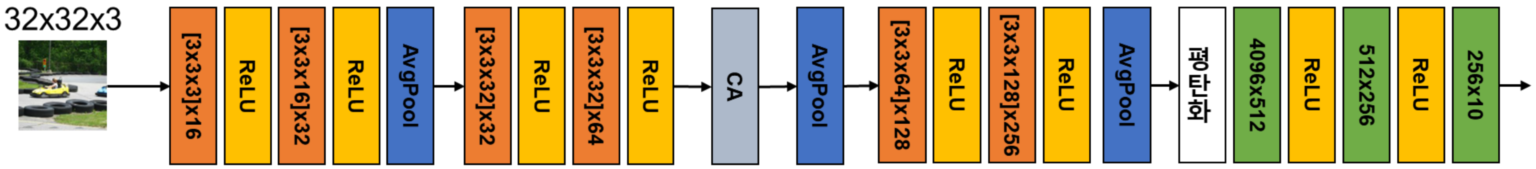


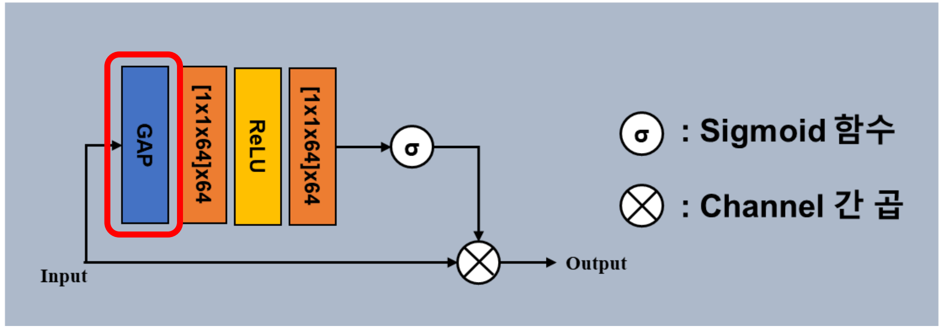

```python
class VGG_CA (nn.Module):
    def __init__(self): # 신경망 구성요소 정의
        super(VGG_CA, self).__init__()
        self.conv1_1 = nn.Conv2d(in_channels=3, out_channels=16, kernel_size=3, padding=1)
        self.conv1_2 = nn.Conv2d(in_channels=16, out_channels=32, kernel_size=3, padding=1)

        self.conv2_1 = nn.Conv2d(in_channels=32, out_channels=32, kernel_size=3, padding=1)
        self.conv2_2 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1)

        self.conv3_1 = nn.Conv2d(in_channels=64, out_channels=128, kernel_size=3, padding=1)
        self.conv3_2 = nn.Conv2d(in_channels=128, out_channels=256, kernel_size=3, padding=1)

        self.fc1 = nn.Linear(in_features=4096, out_features=512)
        self.fc2 = nn.Linear(in_features=512, out_features=256)
        self.fc3 = nn.Linear(in_features=256, out_features=10)

        # Channel Attention
        self.adaptiveAvgPool2d = nn.AdaptiveAvgPool2d((1, 1)) # Global average pooling
        self.caconv1 = nn.Conv2d(in_channels=64, out_channels=64, kernel_size=1)
        self.caconv2 = nn.Conv2d(in_channels=64, out_channels=64, kernel_size=1)
        self.sigmoid = nn.Sigmoid()

        self.relu = nn.ReLU()
        self.avgPool2d = nn.AvgPool2d(kernel_size=2, stride=2)
```

CIFAR10 분류 실습 - CNN을 이용한 분류(VGGNet)

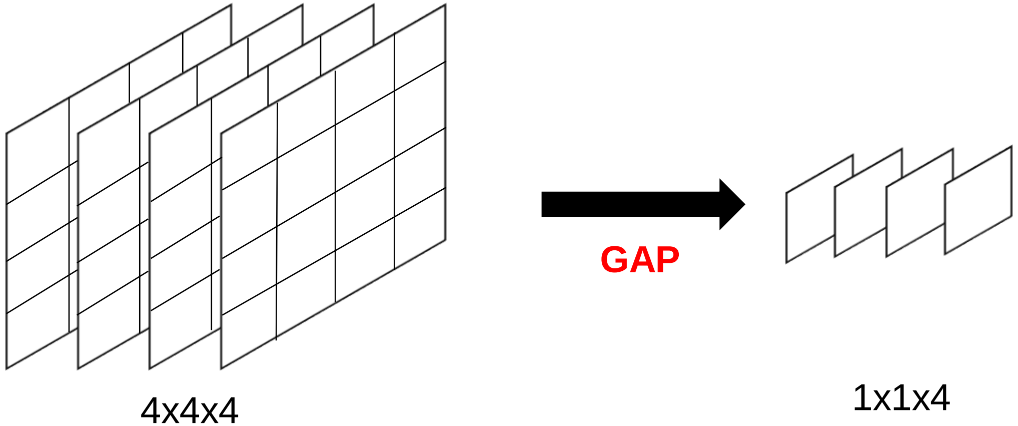
- **Channel attention (CA) 추가 실험**
  - CA 동작 코드 작성

```
def forward(self,x):

    out = self.relu(self.conv1_1(x))
    out = self.relu(self.conv1_2(out))
    out = self.avgPool2d(out)

    out = self.relu(self.conv2_1(out))
    out = self.relu(self.conv2_2(out))

    ## Channel attention 적용
    caout = self.adaptiveAvgPool2d(out)
    caout = self.relu(self.caconv1(caout))
    caout = self.sigmoid(self.caconv2(caout))
    CA_map = caout.expand_as(out)
    out = out * CA_map

    out = self.avgPool2d(out)

    out = self.relu(self.conv3_1(out))
    out = self.relu(self.conv3_2(out))
    out = self.avgPool2d(out)

    out = out.view(-1, 4096) # feature map 평탄화

    out = self.relu(self.fc1(out))
    out = self.relu(self.fc2(out))
    out = self.fc3(out)
    return out
```





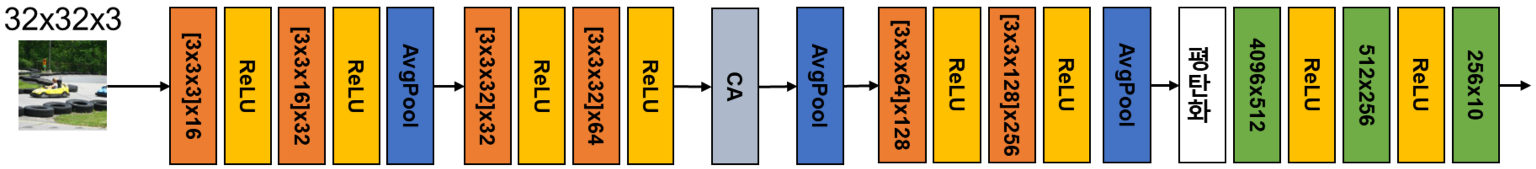
ex)

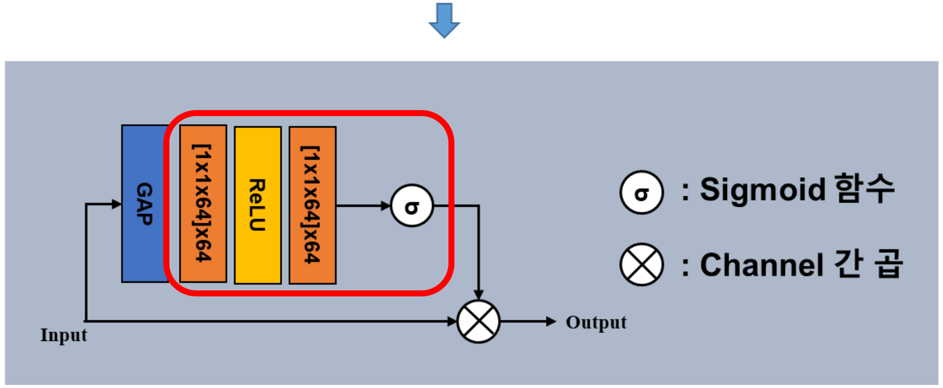


CIFAR10 분류 실습 - CNN을 이용한 분류(VGGNet)

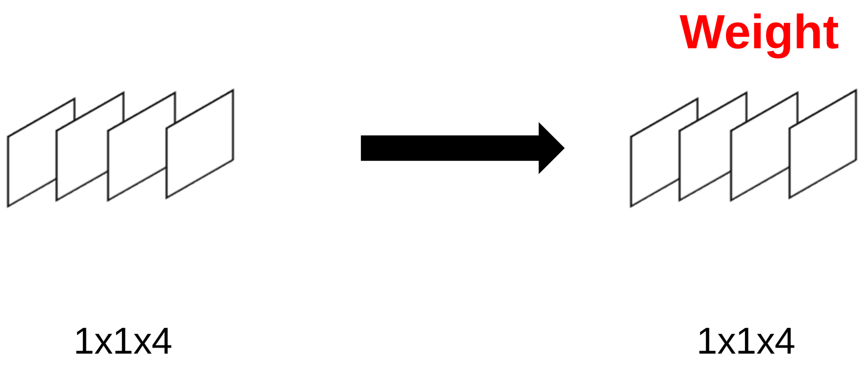
- **Channel attention (CA) 추가 실험**
  - CA 동작 코드 작성

```
def forward(self,x):

    out = self.relu(self.conv1_1(x))
    out = self.relu(self.conv1_2(out))
    out = self.avgPool2d(out)

    out = self.relu(self.conv2_1(out))
    out = self.relu(self.conv2_2(out))

    ## Channel attention 적용
    caout = self.adaptiveAvgPool2d(out)
    caout = self.relu(self.caconv1(caout))
    caout = self.sigmoid(self.caconv2(caout))
    CA_map = caout.expand_as(out)
    out = out * CA_map

    out = self.avgPool2d(out)

    out = self.relu(self.conv3_1(out))
    out = self.relu(self.conv3_2(out))
    out = self.avgPool2d(out)

    out = out.view(-1, 4096) # feature map 평탄화

    out = self.relu(self.fc1(out))
    out = self.relu(self.fc2(out))
    out = self.fc3(out)
    return out
```





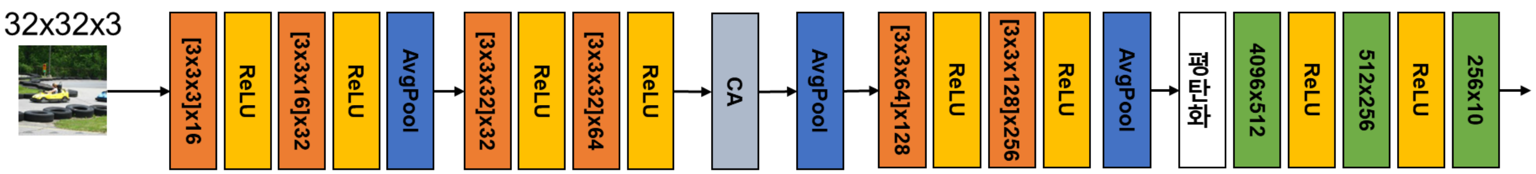
ex)

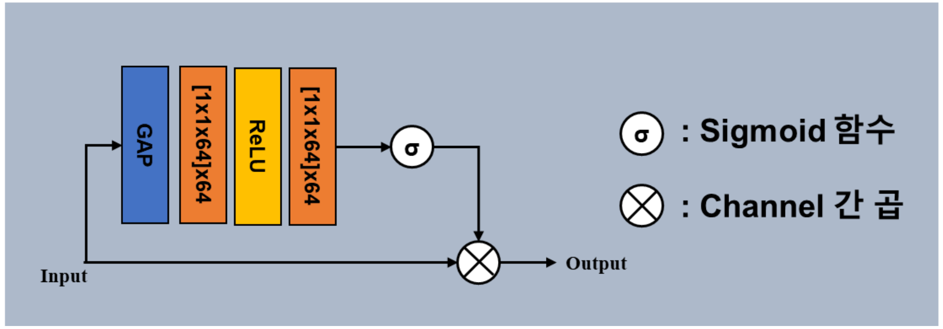


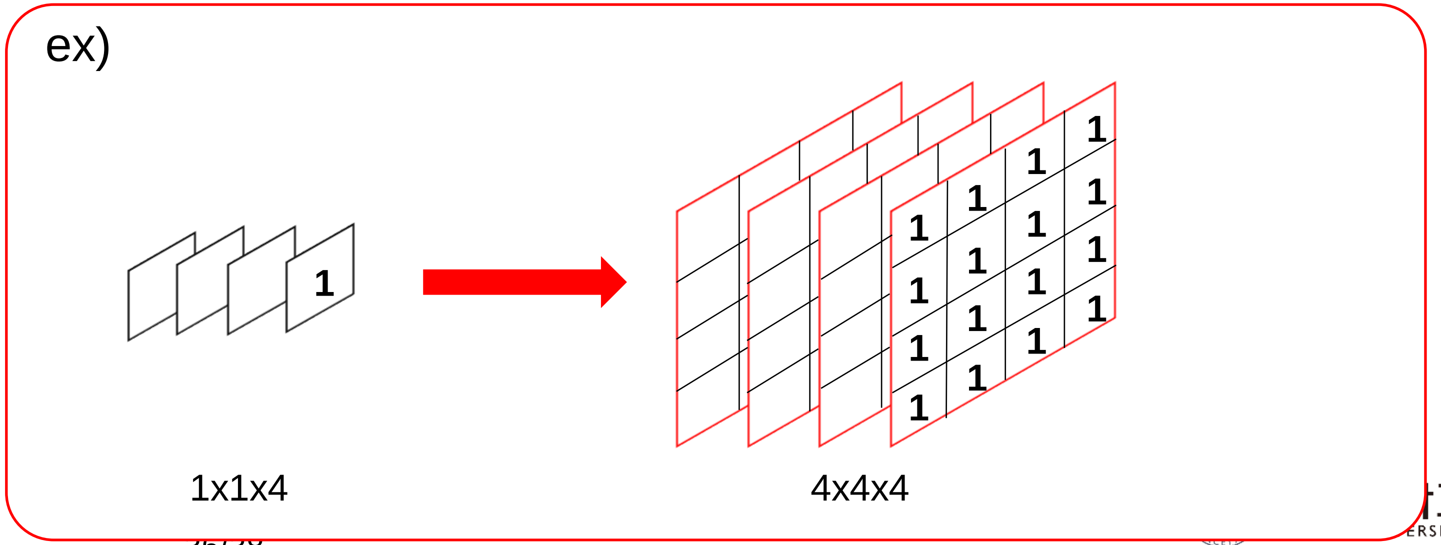
CIFAR10 분류 실습 - CNN을 이용한 분류(VGGNet)

- **Channel attention (CA) 추가 실험**
  - CA 동작 코드 작성

```python
def forward(self,x):

    out = self.relu(self.conv1_1(x))
    out = self.relu(self.conv1_2(out))
    out = self.avgPool2d(out)

    out = self.relu(self.conv2_1(out))
    out = self.relu(self.conv2_2(out))

    ## Channel attention 적용
    caout = self.adaptiveAvgPool2d(out)
    caout = self.relu(self.caconv1(caout))
    caout = self.sigmoid(self.caconv2(caout))
    CA_map = caout.expand_as(out)
    out = out * CA_map

    out = self.avgPool2d(out)

    out = self.relu(self.conv3_1(out))
    out = self.relu(self.conv3_2(out))
    out = self.avgPool2d(out)

    out = out.view(-1, 4096) # feature map 평탄화

    out = self.relu(self.fc1(out))
    out = self.relu(self.fc2(out))
    out = self.fc3(out)
    return out
```



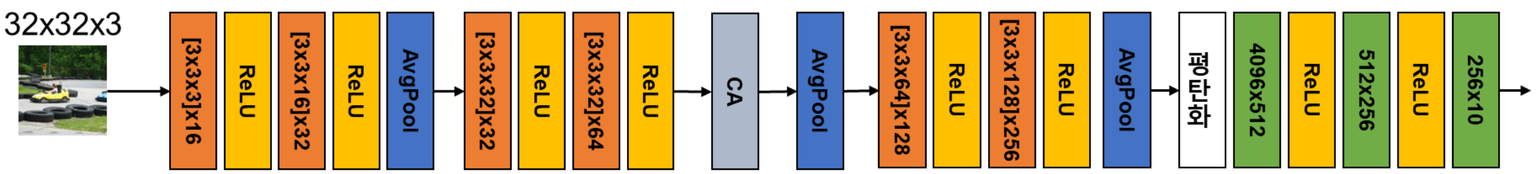


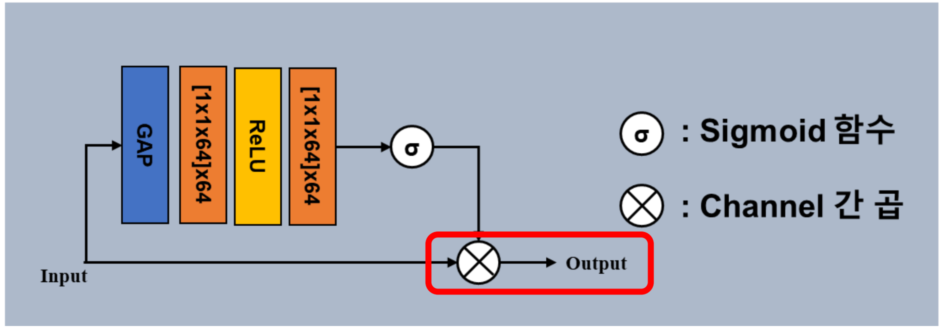


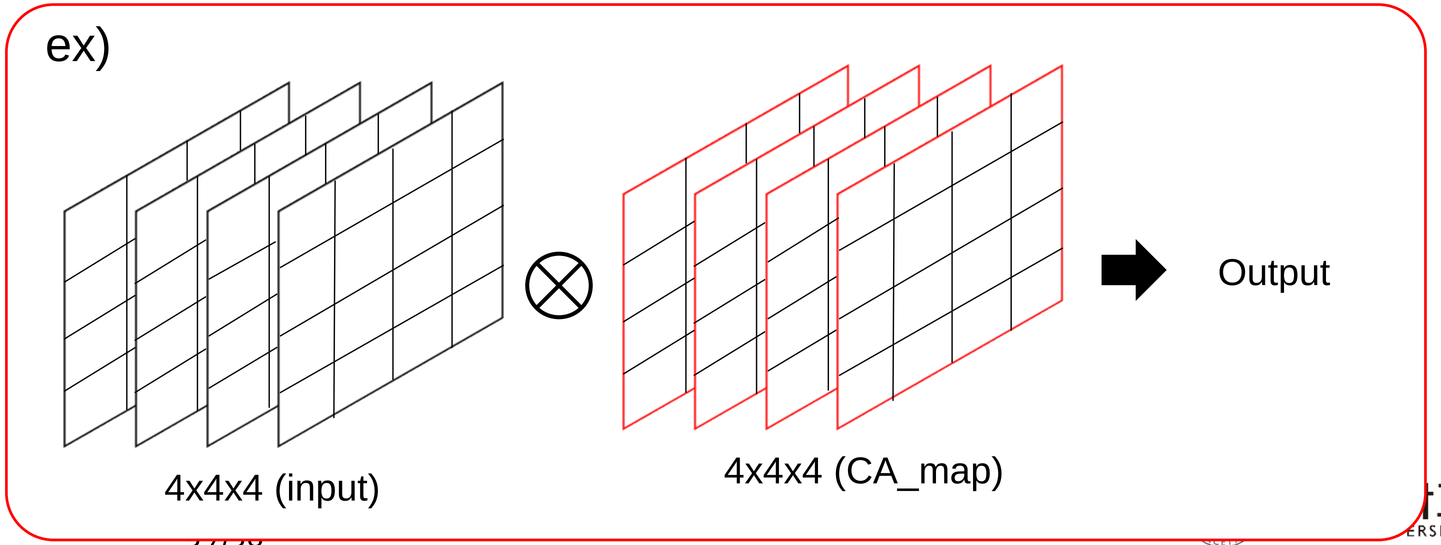
CIFAR10 분류 실습 - CNN을 이용한 분류(VGGNet)

- **Channel attention (CA) 추가 실험**
  - CA 동작 코드 작성

```python
def forward(self,x):

    out = self.relu(self.conv1_1(x))
    out = self.relu(self.conv1_2(out))
    out = self.avgPool2d(out)

    out = self.relu(self.conv2_1(out))
    out = self.relu(self.conv2_2(out))

    ## Channel attention 적용
    caout = self.adaptiveAvgPool2d(out)
    caout = self.relu(self.caconv1(caout))
    caout = self.sigmoid(self.caconv2(caout))
    CA_map = caout.expand_as(out)
    out = out * CA_map

    out = self.avgPool2d(out)

    out = self.relu(self.conv3_1(out))
    out = self.relu(self.conv3_2(out))
    out = self.avgPool2d(out)

    out = out.view(-1, 4096) # feature map 평탄화

    out = self.relu(self.fc1(out))
    out = self.relu(self.fc2(out))
    out = self.fc3(out)
    return out
```







CIFAR10 분류 실습 - CNN을 이용한 분류(VGGNet)

- **Channel attention 추가 실험 결과 확인**

```
Epoch: 1 Loss = 2.303002
Epoch: 2 Loss = 2.302858
Epoch: 3 Loss = 2.302659
Epoch: 4 Loss = 2.246866
Epoch: 5 Loss = 1.997299
Epoch: 6 Loss = 1.824729
Epoch: 7 Loss = 1.672605
Epoch: 8 Loss = 1.496609
Epoch: 9 Loss = 1.346635
Epoch: 10 Loss = 1.229228
Epoch: 11 Loss = 1.127741
Epoch: 12 Loss = 1.025967
Epoch: 13 Loss = 0.922246
Epoch: 14 Loss = 0.813664
Epoch: 15 Loss = 0.702598
Epoch: 16 Loss = 0.583456
Epoch: 17 Loss = 0.467354
Epoch: 18 Loss = 0.360702
Epoch: 19 Loss = 0.284199
Epoch: 20 Loss = 0.228450
Learning finished
```

```
Epoch: 1 Loss = 2.302945
Epoch: 2 Loss = 2.302926
Epoch: 3 Loss = 2.302883
Epoch: 4 Loss = 2.302598
Epoch: 5 Loss = 2.238352
Epoch: 6 Loss = 1.993443
Epoch: 7 Loss = 1.834756
Epoch: 8 Loss = 1.717770
Epoch: 9 Loss = 1.580547
Epoch: 10 Loss = 1.429867
Epoch: 11 Loss = 1.297576
Epoch: 12 Loss = 1.185068
Epoch: 13 Loss = 1.087217
Epoch: 14 Loss = 0.992931
Epoch: 15 Loss = 0.889833
Epoch: 16 Loss = 0.785588
Epoch: 17 Loss = 0.673162
Epoch: 18 Loss = 0.555354
Epoch: 19 Loss = 0.444460
Epoch: 20 Loss = 0.362085
Learning finished
```

Training 결과

```
network.eval()
network = network.to('cpu')
img_test = torch.tensor(np.transpose(cifar10_test.data , (0, 3, 1, 2))) /255.
label_test = torch.tensor(cifar10_test.targets)

with torch.no_grad(): # test에서는 기울기 계산 제외
    prediction = network(img_test) # 전체 test data를 한번에 계산

correct_prediction = torch.argmax(prediction, 1) == label_test
accuracy = correct_prediction.float().mean()
print('Accuracy:', accuracy.item())
```

```
Accuracy: 0.6011000275611877
```

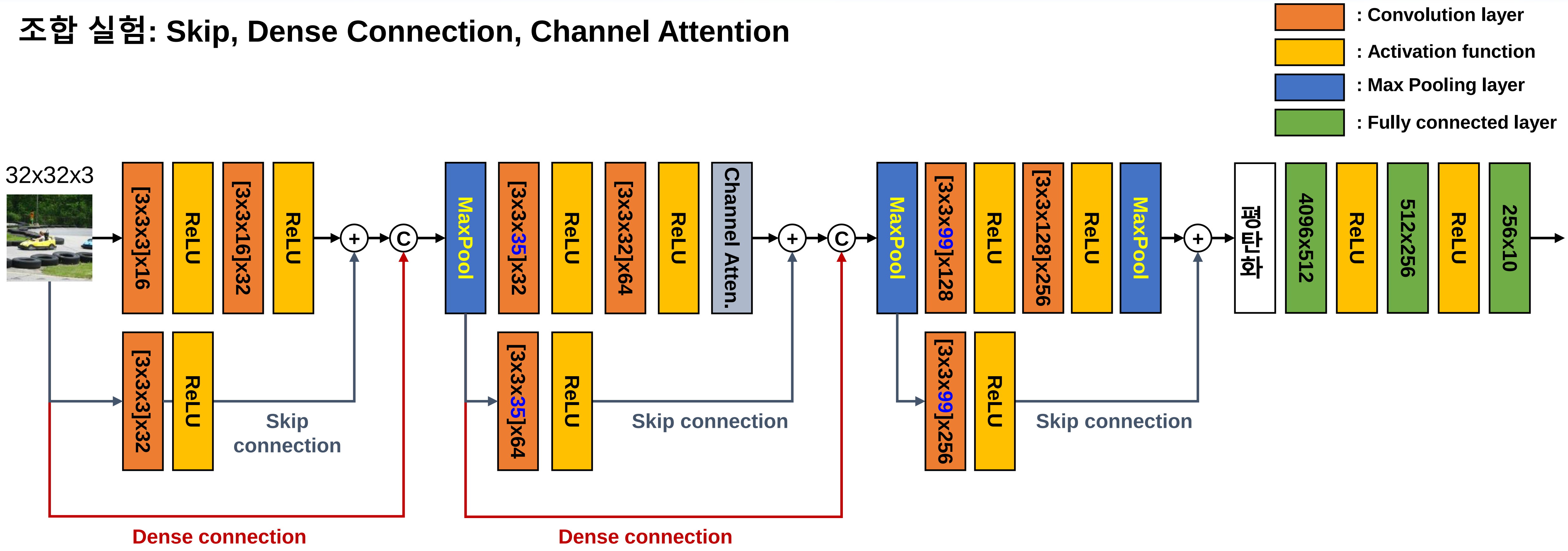
```
network.eval()
network = network.to('cuda:0')
img_test = torch.tensor(np.transpose(cifar10_test.data , (0, 3, 1, 2))) /255.
label_test = torch.tensor(cifar10_test.targets)

img_test = img_test.to('cuda:0')
label_test = label_test.to('cuda:0')

with torch.no_grad(): # test에서는 기울기 계산 제외
    prediction = network(img_test) # 전체 test data를 한번에 계산

correct_prediction = torch.argmax(prediction, 1) == label_test
accuracy = correct_prediction.float().mean()
print('Accuracy:', accuracy.item())
```

```
Accuracy: 0.6122999787330627
```

Test 결과

Appendix – CNN 구성요소 조합 실험

- 조합 실험: Skip, Dense Connection, Channel Attention



❖ 주의사항(1): Skip connection은 Width, Height, Channel이 모두 같아야 사용 가능

❖ 주의사항(2): Dense connection (torch.cat)은 width, height이 동일해야 적용 가능

Questions & Answers

Dongsan Jun (dsjun@dau.ac.kr)
Image Signal Processing Laboratory (www.donga-ispl.kr)
Dept. of Computer Engineering
Dong-A University, Busan, Rep. of Korea