

AI 기반 영상 데이터 분석 실습

- Day 3 -

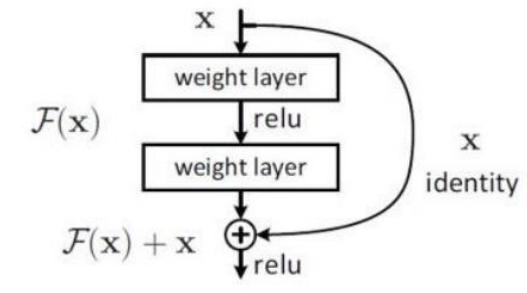
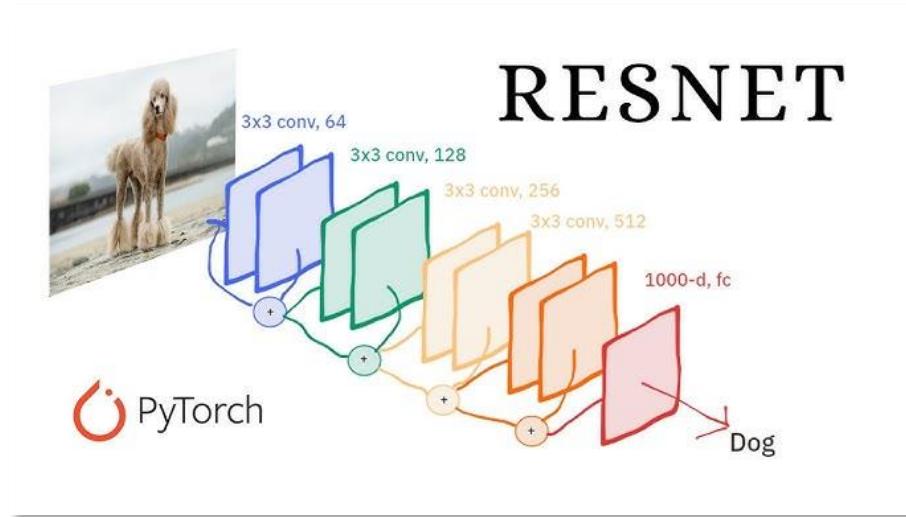
index



Afternoon Lab session (실습)

Day 3 : Course overview

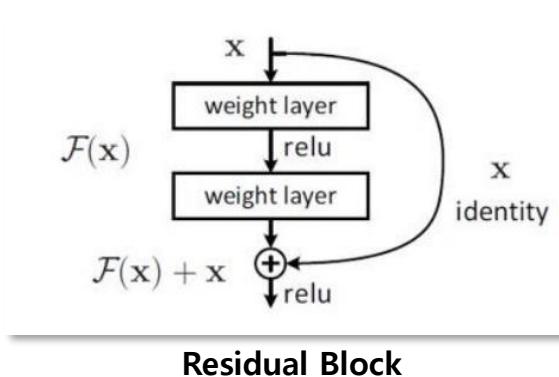
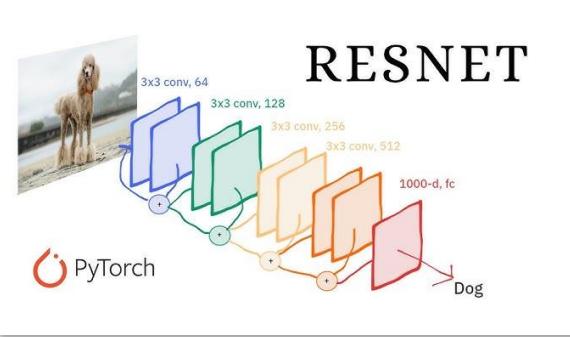
- 학습시킬 모델(ResNet) 아키텍쳐 구현



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ResNet이란?

- CNN 기반의 딥러닝 모델 중 가장 핵심적인 모델.
- Residual Block의 Skip connection 구조로 gradient vanishing 문제를 극복하여 100층 이상의 깊은 신경망을 학습시킬 수 있는 길을 열음.
- 2015년도에 발표된 딥러닝 모델임에도 불구하고 현재까지도 많은 연구들의 Baseline으로 자주 언급됨.



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코드 실습

- **def __init__(self) :**
 - 필요한 layer를 선언하는 공간
- **def forward(self) :**
 - 위에서 선언한 layer를 바탕으로 연산 흐름을 정의

```
class BasicBlock(nn.Module):
    expansion_factor = 1
    def __init__(self, in_channels: int, out_channels: int, stride: int = 1):
        super(BasicBlock, self).__init__()
        self.conv1 = nn.Conv2d(in_channels, out_channels, kernel_size=3, stride=stride, padding=1, bias=False)
        self.bn1 = nn.BatchNorm2d(out_channels)
        self.relu1 = nn.ReLU()

    # ...

    def forward(self, x):
        out = x
        x = self.conv1(x)
        x = self.bn1(x)
        x = self.relu1(x)

    # ...

    return x
```

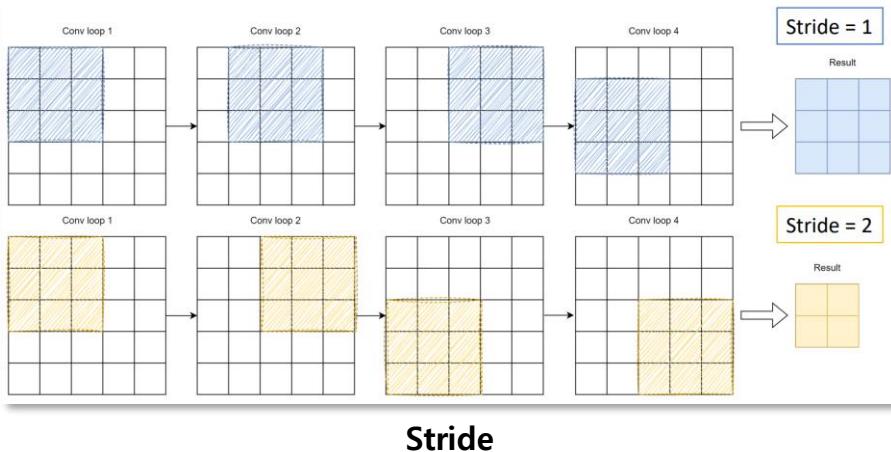
코드 예시

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Layer 구성 모듈

- `nn.Conv2d(in_channels, out_channels, kernel_size, stride, padding)`

- in_channels : input의 channel 수
 - out_channels : output의 channel 수
 - kernel_size : convolution kernel size,
(예시 – 3 or (3, 3))
 - stride : convolution 연산 간격
 - padding : 경계를 몇 칸까지 0으로 채울 지,
(matrix 사이즈 보존의 역할)



```
class BasicBlock(nn.Module):
    expansion_factor = 1
    def __init__(self, in_channels: int, out_channels: int, stride: int = 1):
        super(BasicBlock, self).__init__()
        self.conv1 = nn.Conv2d(in_channels, out_channels, kernel_size=3, stride=stride, padding=1, bias=False)
        self.bn1 = nn.BatchNorm2d(out_channels)
        self.relu1 = nn.ReLU()
        # ...
        def forward(self, x):
            out = x
            x = self.conv1(x)
            x = self.bn1(x)
            x = self.relu1(x)
            # ...
            return x
```

코드 예시

6	3	4	4	5	0	3
4	7	4	0	4	0	4
7	0	2	3	4	5	2
3	7	5	0	3	0	7
5	8	1	2	5	4	2
8	0	1	0	6	0	0
6	4	1	3	0	4	5

Padding

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Layer 구성 모듈

- **nn.Sequential()**
 - Layer를 연속적으로 한 번에 선언할 수 있는 함수
- **nn.BatchNorm2d(channels)**
 - Conv2d 뒤에 붙는 Batch Normalization 함수
- **nn.ReLU()**
 - Activation function

```
class BasicBlock(nn.Module):  
    expansion_factor = 1  
    def __init__(self, in_channels: int, out_channels: int, stride: int = 1):  
        super(BasicBlock, self).__init__()  
        self.conv1 = nn.Conv2d(in_channels, out_channels, kernel_size=3, stride=stride, padding=1, bias=False)  
        self.bn1 = nn.BatchNorm2d(out_channels)  
        self.relu = nn.ReLU()  
  
    # ...  
  
    def forward(self, x):  
        out = x  
        x = self.conv1(x)  
        x = self.bn1(x)  
        x = self.relu(x)  
  
    # ...  
  
    return x
```

코드 예시

```
class BasicBlock(nn.Module):  
    def __init__(self, in_channels: int, out_channels: int, stride: int = 1):  
  
        self.my_block = nn.Sequential(  
            nn.Conv2d(in_channels, out_channels, kernel_size=3, stride=stride, padding=1, bias=False),  
            nn.BatchNorm2d(out_channels),  
            nn.ReLU()  
        )  
  
    # ...  
  
    def forward(self, x):  
        out = x  
        x = self.conv1(x)  
        x = self.bn1(x)  
        x = self.relu(x)  
  
    # ...  
  
    return x
```

- **nn.Sequential() 활용**

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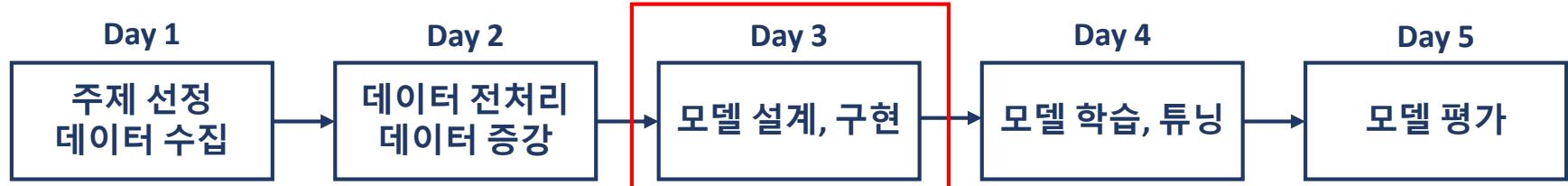
실습

- 목표 : 최종 모델 구현 후, Summary 정상 출력

```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")  
  
# 모델 선언  
model = ResNet().to(device)  
  
# 완성한 모델의 summary를 출력해보세요.  
summary(model, (3, 224, 224))
```

Layer (type)	Output Shape	Param #
Conv2d-1	[1, 64, 112, 112]	9,408
BatchNorm2d-2	[1, 64, 112, 112]	128
ReLU-3	[1, 64, 112, 112]	0
MaxPool2d-4	[1, 64, 56, 56]	0
Conv2d-5	[1, 64, 56, 56]	36,864
BatchNorm2d-6	[1, 64, 56, 56]	128
ReLU-7	[1, 64, 56, 56]	0
Conv2d-8	[1, 64, 56, 56]	36,864
BatchNorm2d-9	[1, 64, 56, 56]	128
ReLU-10	[1, 64, 56, 56]	0
BasicBlock-11	[1, 64, 56, 56]	0
Conv2d-12	[1, 64, 56, 56]	36,864
BatchNorm2d-13	[1, 64, 56, 56]	128
ReLU-14	[1, 64, 56, 56]	0
Conv2d-15	[1, 64, 56, 56]	36,864
BatchNorm2d-16	[1, 64, 56, 56]	128
ReLU-17	[1, 64, 56, 56]	0
BasicBlock-18	[1, 64, 56, 56]	0
Conv2d-19	[1, 128, 28, 28]	73,728
BatchNorm2d-20	[1, 128, 28, 28]	256
ReLU-21	[1, 128, 28, 28]	0
Conv2d-22	[1, 128, 28, 28]	147,456
BatchNorm2d-23	[1, 128, 28, 28]	256
Conv2d-24	[1, 128, 28, 28]	8,192
BatchNorm2d-25	[1, 128, 28, 28]	256
ReLU-26	[1, 128, 28, 28]	0
BasicBlock-27	[1, 128, 28, 28]	0
Conv2d-28	[1, 128, 28, 28]	147,456
BatchNorm2d-29	[1, 128, 28, 28]	256
ReLU-30	[1, 128, 28, 28]	0
Conv2d-31	[1, 128, 28, 28]	147,456
BatchNorm2d-32	[1, 128, 28, 28]	256
ReLU-33	[1, 128, 28, 28]	0
BasicBlock-34	[1, 128, 28, 28]	0
Conv2d-35	[1, 256, 14, 14]	294,912
BatchNorm2d-36	[1, 256, 14, 14]	512
ReLU-37	[1, 256, 14, 14]	0
Conv2d-38	[1, 256, 14, 14]	589,824
BatchNorm2d-39	[1, 256, 14, 14]	512
Conv2d-40	[1, 256, 14, 14]	32,768
BatchNorm2d-41	[1, 256, 14, 14]	512
ReLU-42	[1, 256, 14, 14]	0
BasicBlock-43	[1, 256, 14, 14]	0
Conv2d-44	[1, 256, 14, 14]	589,824
BatchNorm2d-45	[1, 256, 14, 14]	512
ReLU-46	[1, 256, 14, 14]	0
Conv2d-47	[1, 256, 14, 14]	589,824
BatchNorm2d-48	[1, 256, 14, 14]	512
ReLU-49	[1, 256, 14, 14]	0
BasicBlock-50	[1, 256, 14, 14]	0
Conv2d-51	[1, 512, 7, 7]	1,179,648
BatchNorm2d-52	[1, 512, 7, 7]	1,024
ReLU-53	[1, 512, 7, 7]	0
Conv2d-54	[1, 512, 7, 7]	2,359,296
BatchNorm2d-55	[1, 512, 7, 7]	1,024
Conv2d-56	[1, 512, 7, 7]	131,072
BatchNorm2d-57	[1, 512, 7, 7]	1,024
ReLU-58	[1, 512, 7, 7]	0
BasicBlock-59	[1, 512, 7, 7]	0
Conv2d-60	[1, 512, 7, 7]	2,359,296
BatchNorm2d-61	[1, 512, 7, 7]	1,024
ReLU-62	[1, 512, 7, 7]	0
Conv2d-63	[1, 512, 7, 7]	2,359,296
BatchNorm2d-64	[1, 512, 7, 7]	1,024
ReLU-65	[1, 512, 7, 7]	0
BasicBlock-66	[1, 512, 7, 7]	0
AdaptiveAvgPool2d-67	[1, 512, 1, 1]	0
Linear-68	[1, 10]	5,130
Total params: 11,181,642		
Trainable params: 11,181,642		
Non-trainable params: 0		
Input size (MB): 0.57		
Forward/backward pass size (MB): 62.79		
Params size (MB): 42.65		
Estimated Total Size (MB): 106.01		

01/21 To-do



layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112			7×7, 64, stride 2		
		Basic_Block		3×3 max pool, stride 2		
conv2_x	56×56	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix} \times 2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix} \times 3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix} \times 2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix} \times 4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix} \times 8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix} \times 2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix} \times 6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix} \times 6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix} \times 23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix} \times 36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix} \times 2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix} \times 3$
	1×1			average pool, 1000-d fc, softmax		
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9
Kernel size		out_planes				

Kernel size

Basic_Block

out_planes

- 유의사항
 - Convolution 이후, Batch Normalization 적용
 - convolution 연산으로 인해 size가 증가하여 shortcut 연산이 불가능할 경우,
 1×1 conv, BatchNorm으로 차원 맞추기

Thank you