07. Batch Normalization

AILab
Hanyang Univ.

오늘 실습 내용

1. Batch Normalization

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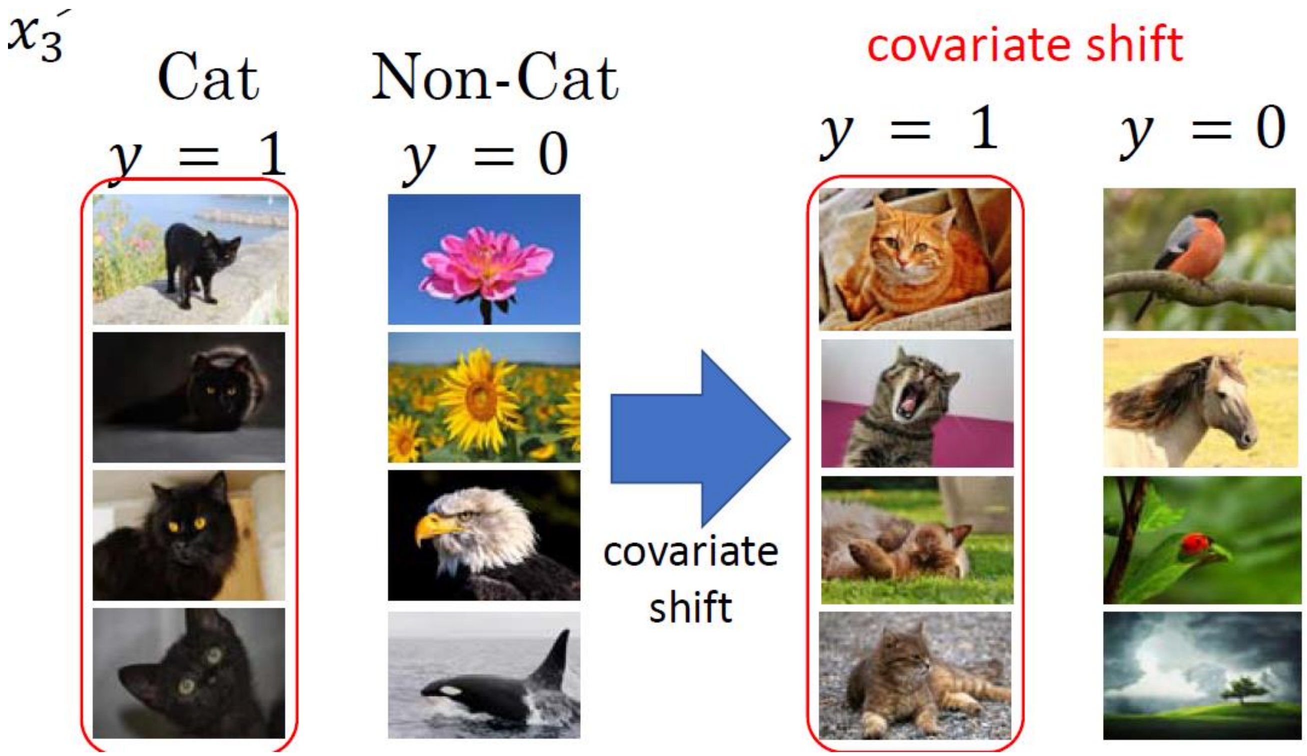
Batch Normalization

- Covariate Shift
  - When the **input distribution** to a learning system changes, it is said to experience covariate shift



Batch Normalization

- (Internal) Covariate Shift
  - Change in the **distribution of network activations** due to the change in **network parameters** during training.
  - 각 Layer의 input은 이전 Layer 들의 output에 영향을 받음
  - Layer가 깊어질 수록 covariate shift가 심해짐

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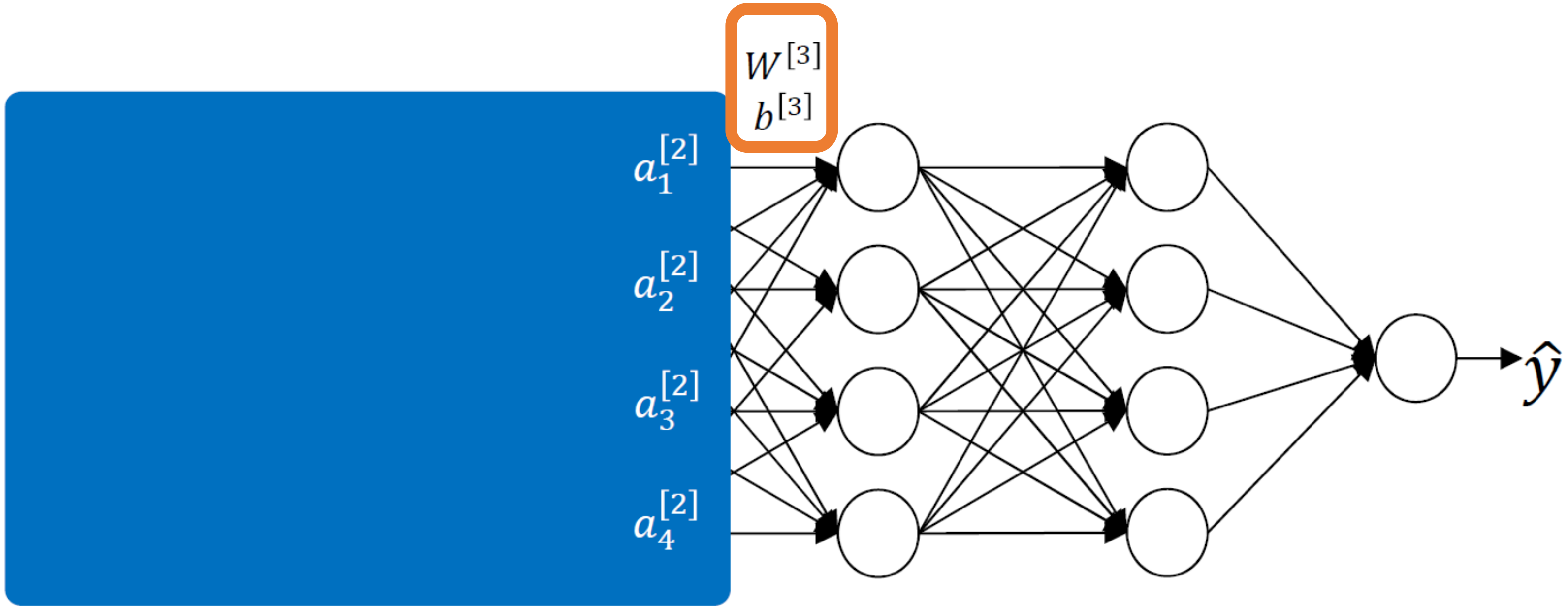

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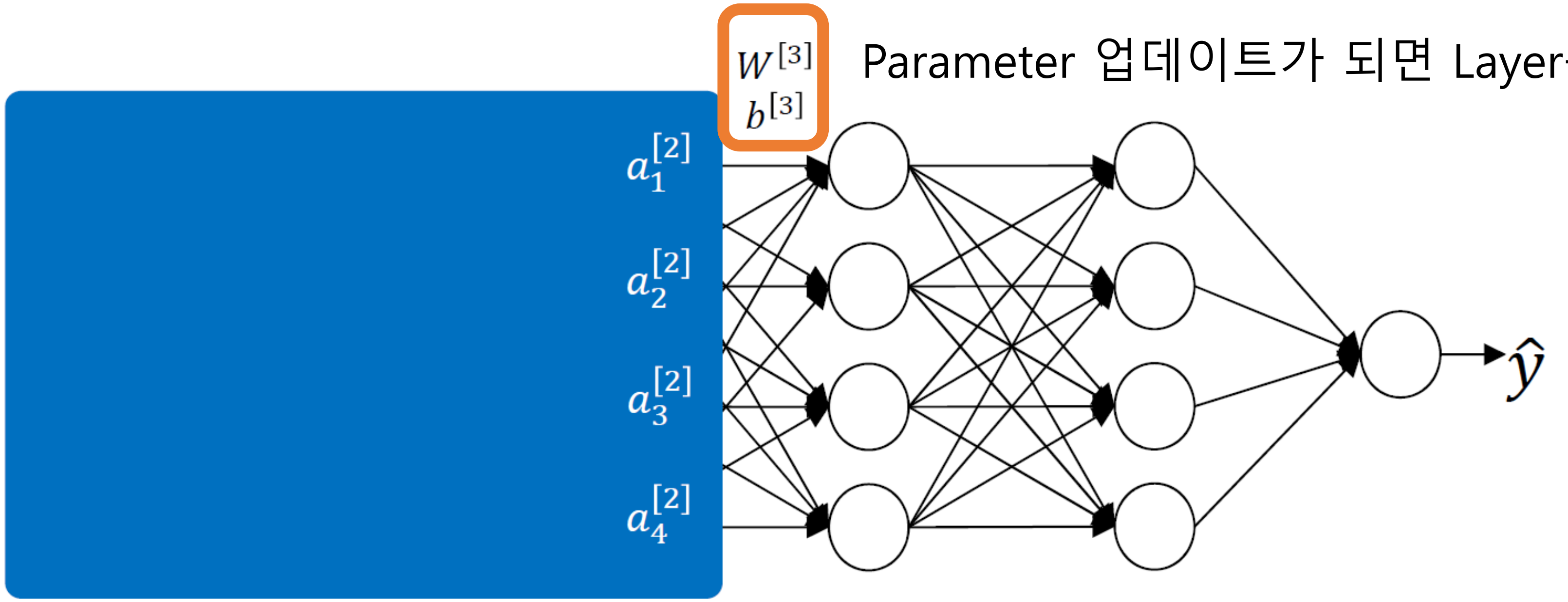

Parameter 업데이트가 되면 Layer는 다른 이전과 다른 값 표현

이런 error가 layer를 거칠수록 쌓아짐

Batch Normalization

- BATCHNORM1D
  - https://pytorch.org/docs/stable/generated/torch.nn.BatchNorm1d.html#torch.nn.BatchNorm1d

```
torch.nn.BatchNorm1d(num_features, eps=1e-05,
```

num_features : batch normalization을 적용할 input의 dimension size

Input: (N, C) or (N, C, L)

Applies Batch Normalization over a 2D or 3D input as described in the paper Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift .

$$y = \frac{x - \mathrm{E}[x]}{\sqrt{\mathrm{Var}[x] + \epsilon}} * \boxed{\gamma} + \boxed{\beta}$$

The mean and standard-deviation are calculated per-dimension over the mini-batches and γ and β are learnable parameter vectors of size C (where C is the number of features or channels of the input). By default, the elements of γ are set to 1 and the elements of β are set to 0. The standard-deviation is calculated via the biased estimator, equivalent to *torch.var(input, unbiased=False)*.

Batch Normalization

- Model code
  - 각 layer의 activation 이전에 불러줌
  - num_features에 올바른 값 선언

```
class Model(nn.Module):
  def __init__(self, drop_prob):
    super(Model, self).__init__()
    self.linear1 = nn.Linear(32*32*3, 256)
    self.linear2 = nn.Linear(256, 128)
    self.linear3 = nn.Linear(128, 10)
    self.dropout = nn.Dropout(drop_prob)
    self.activation = nn.Sigmoid()

    self.bn1 = nn.BatchNorm1d(256)
    self.bn2 = nn.BatchNorm1d(128)

  def forward(self, x):
    z1 = self.linear1(x)
    z1 = self.bn1(z1)
    a1 = self.activation(z1)
    al = self.dropout(a1)

    z2 = self.linear2(a1)
    z2 = self.bn2(z2)
    a2 = self.activation(z2)
    a2 = self.dropout(a2)

    z3 = self.linear3(a2)

    return z3
```

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    a2 = self.dropout(a2)

    z3 = self.linear3(a2)

    return z3
```

오늘 실습 내용

Batch normalization을 이전 실습 코드에 적용하여 성능 차이 확인해보기