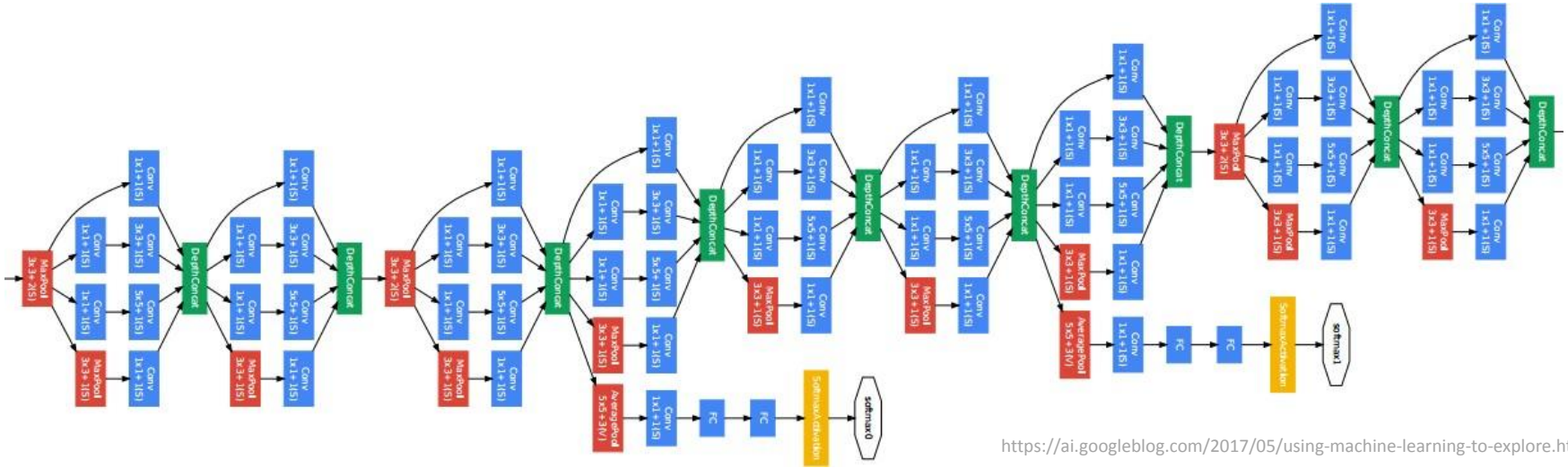
AutoGrad & Optimizer

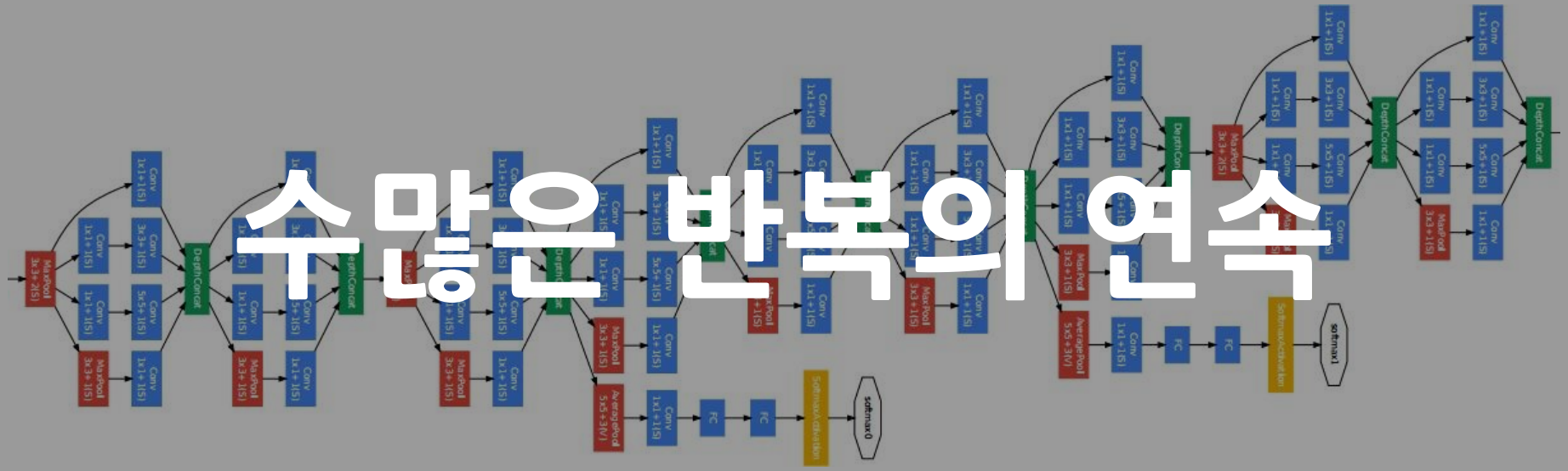
TEAMLAB director

최성철

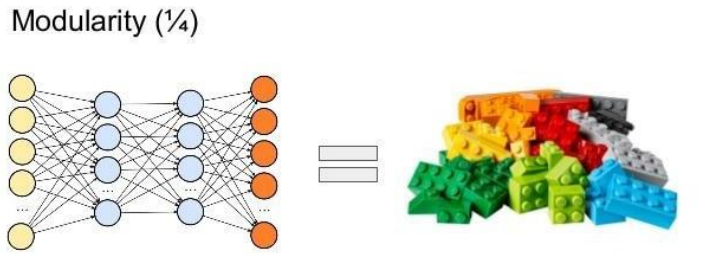
논문을 구현해 보자!



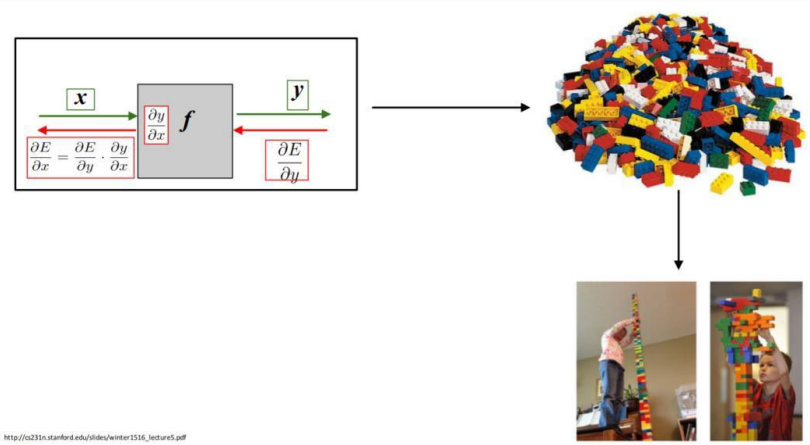
https://ai.googleblog.com/2017/05/using-machine-learning-to-explore.html



Layer = Block



https://bit.ly/3lv0eAJ



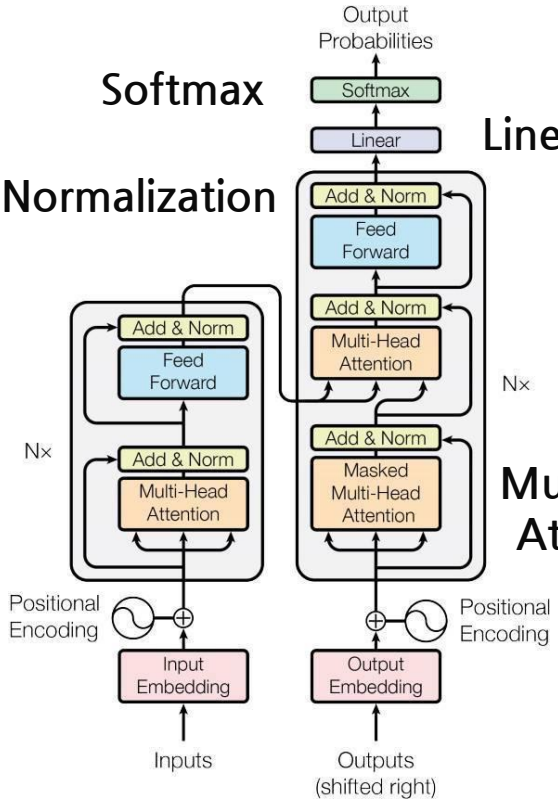
https://bit.ly/3lxGTPe

Softmax

Linear

Normalization

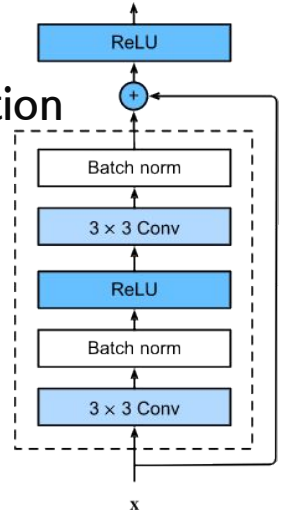
Multi-Head Attention

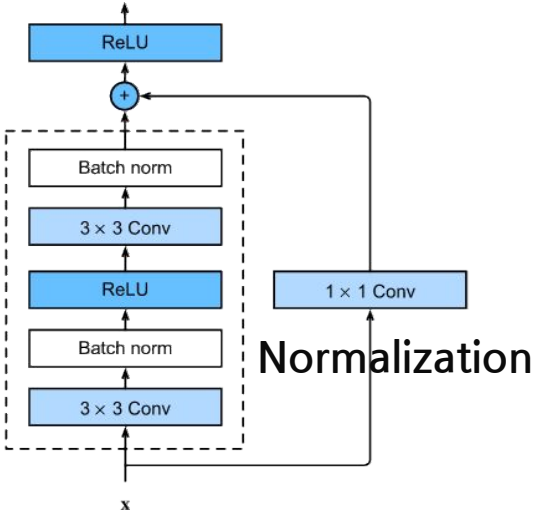


https://machinelearningmastery.com/the-transformer-model/

Normalization

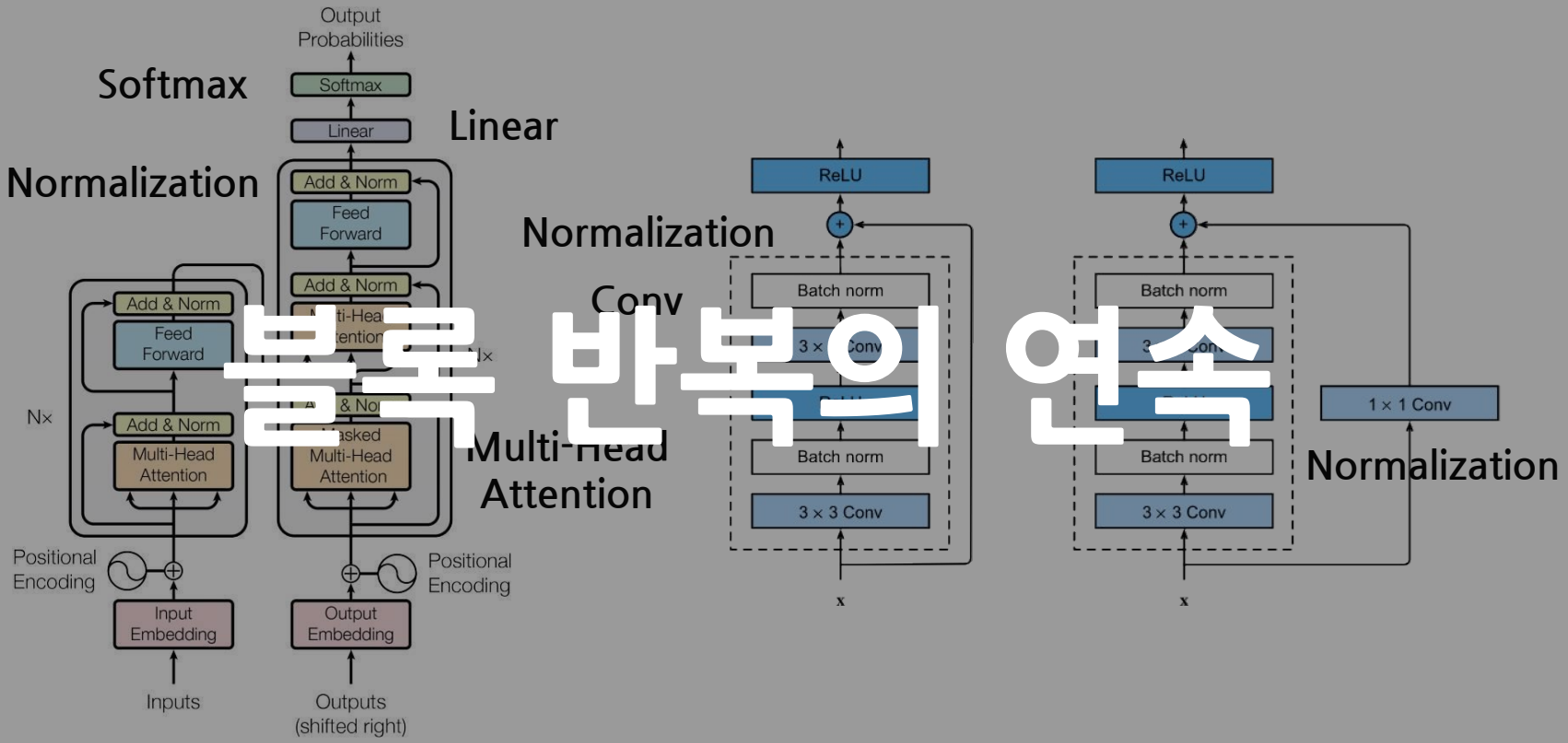
Conv





Normalization

https://d2l.djl.ai/chapter_convolutional-modern/resnet.html



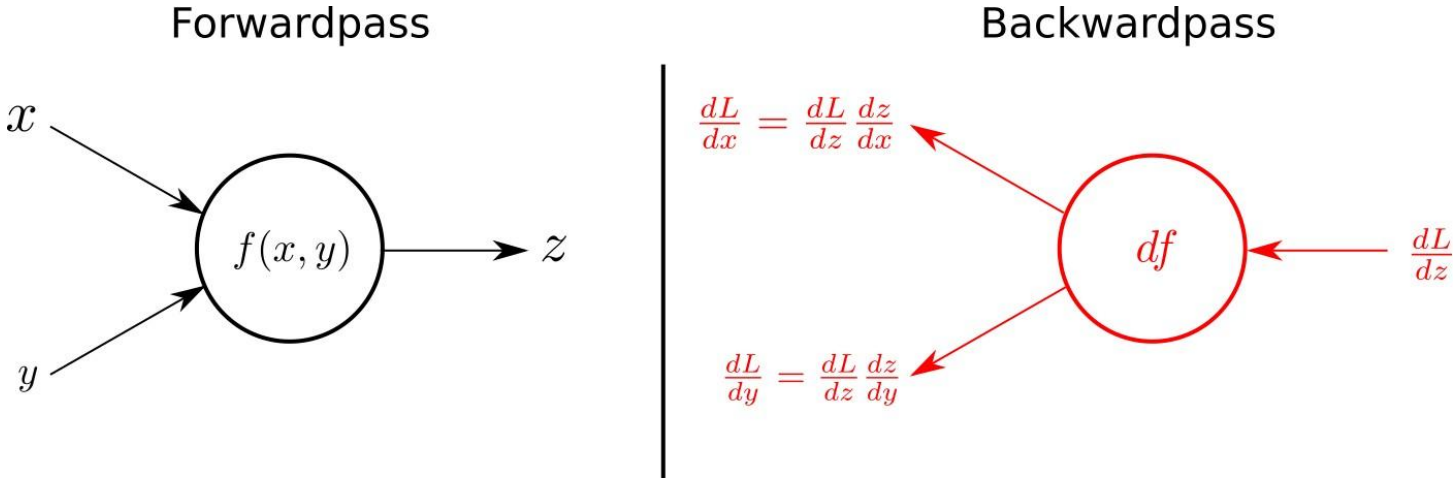
블록 반복의 연속

torch.nn.Module

torch.nn.Module

- 딥러닝을 구성하는 **Layer의 base class**
- **Input, Output, Forward, Backward 정의**
- 학습의 대상이 되는 **parameter(tensor)** 정의

torch.nn.Module



https://github.com/Vercaca/NN-Backpropagation

nn.Parameter

- **Tensor 객체의 상속 객체**
- **nn.Module 내에 attribute가 될 때는 required_grad=True**

  로 지정되어 학습 대상이 되는 Tensor
- **우리가 직접 지정할 일은 잘 없음**

  : 대부분의 layer에는 weights 값들이 지정되어 있음

nn.Parameter


```
class MyLinear(nn.Module):
    def __init__(self, in_features, out_features, bias = True):
        super().__init__()
        self.in_features = in_features
        self.out_features = out_features
        self.weights = nn.Parameter(
                            torch.randn(in_features, out_features))
        self.bias = nn.Parameter(torch.randn(out_features))

    def forward(self, x: Tensor):
        return x @ self.weights + self.bias
```

Backward

- **Layer에 있는 Parameter들의 미분을 수행**
- **Forward의 결과값 (model의 output=예측치)과 실제값간의 차이(loss) 에 대해 미분을 수행**
- **해당 값으로 Parameter 업데이트**

Backward


```
for epoch in range(epochs):
    … …
    # Clear gradient buffers because we don’t want any gradient from previous epoch to carry forward
    optimizer.zero_grad()

    # get output from the model, given the inputs
    outputs = model(inputs)

    # get loss for the predicted output
    loss = criterion(outputs, labels)
    print(loss)
    # get gradients w.r.t to parameters
    loss.backward()

    # update parameters optimize
    optimizer.step()
    … …
```

Backward from the scratch

- 실제 backward는 Module 단계에서 직접 지정가능
- Module에서 backward 와 optimizer 오버라이딩
- 사용자가 직접 미분 수식을 써야하는 부담

  → 쓸 일은 없으나 순서를 이해할 필요는 있음

```
class LR(nn.Module):
    def __init__(self, dim, lr = torch.scalar_tensor(0.01)):
        super(LR, self).__init__()
        # initialize parameters
        self.w = torch.zeros(dim, 1, dtype = torch.float).to(device)
        self.b = torch.scalar_tensor(0).to(device)
        self.grads = {'dw': torch.zeros(dim, 1, dtype = torch.float).to(device),
                      'db': torch.scalar_tensor(0).to(device)}

        self.lr = lr.to(device)

    def forward(self, x):
        # compute forward
        z = torch.mm(self.w.T, x)
        a = self.sigmoid(z)
        return a
```

$$h_\theta(x) = \frac{1}{1 + e^{-\theta^T \mathbf{x}}}$$

```
    def sigmoid(self, z):
        return 1 / (1 + torch.exp(-z))

    def backward(self, x, yhat, y):
        ## compute backward
        self.grads['dw'] = (1 / x.shape[1]) * torch.mm(x, (yhat - y).T)
        self.grads['db'] = (1/ x.shape[1]) * torch.sum(yhat - y)

    def optimize(self):
        ## optimization step
        self.w = self.w - self.lr * self.grads['dw']
        self.b = self.b - self.lr * self.grads['db']
```

$$\frac{\partial}{\partial \theta_j} J(\theta) = \frac{1}{m} \sum_{i=1}^{m} (h_\theta(x^i) - y^i) x_j^i$$

$$\begin{aligned} \theta_j &:= \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta) \\ &:= \theta_j - \alpha \sum_{i=1}^{m} (h_\theta(x^i) - y^i) x_j^i \end{aligned}$$

End of Document
Thank You.