

P1 ReLU는 nonnegative homogeneousity. (by midterm)

Leaky ReLU는 nonnegative homogeneousity가 성립

Leaky ReLU

$$\sigma(x) = \begin{cases} \alpha x & x < 0 \\ x & x \geq 0 \end{cases}$$

$$\alpha \geq 0 \text{ 이면 } \sigma(\alpha x) = \begin{cases} \alpha \alpha x & x < 0 \\ \alpha x & x \geq 0 \end{cases}$$

$$\text{이므로 } \sigma(\alpha x) = \alpha \sigma(x)$$

dropout은 element에 0이 붙어있거나 $\frac{1}{1-p}$ 이 붙어있는 것으로 σ 가 nonnegative homogeneousity
dropout- σ 와 σ -dropout은 equivalent하다.

Sigmoid의 경우 linear로 확장한 것과 element 하나를 곱하면

dropout $\rightarrow \sigma$

$\sigma \rightarrow$ dropout

$$\text{non-drop } \frac{1}{1+e^{-\frac{x}{1-p}}} \neq \frac{1}{(1-p)(1+e^{-x})}$$

$$\text{drop } \frac{1}{1+e^{-0}} = \frac{1}{2} \neq 0$$

Sigmoid는 선형으로 확장한 equivalent하지 않다.

p2

default initialization

$$A_{1i} \sim \text{Uniform}\left(-\frac{1}{\sqrt{n_{k-1}}}, \frac{1}{\sqrt{n_{k-1}}}\right) \quad \text{mean: } 0, \text{Var: } \frac{1}{3n_{k-1}}$$

$$b_{1i} \sim \text{Uniform}\left(-\frac{1}{\sqrt{n_{k-1}}}, \frac{1}{\sqrt{n_{k-1}}}\right) \quad \text{mean: } 0, \text{Var: } \frac{1}{3n_{k-1}}$$

$$E[y_{1i}] = E[A_{1i} x_i + b_{1i}] = E[A_{1i}] E[x_i] + E[b_{1i}] = 0$$

$$E[y_{1i}] = 0 \quad \text{이랑 맞아요}$$

$$E[y_{k+1}] = E[A_{k+1}] E[y_k] + E[b_{k+1}] = 0$$

$$\therefore, E[y_k] = 0 \quad \text{이랑 맞아요}$$

$$\begin{aligned} \text{Var}(y_{k+1}) &= \text{Var}\left(\sum_{j=1}^{n_{k-1}} A_{k+1,j} y_{k,j}\right) + \text{Var}(b_{k+1}) \\ &= \sum_{j=1}^{n_{k-1}} \text{Var}(A_{k+1,j} y_{k,j}) + \text{Var}(b_{k+1}) \end{aligned}$$

$A_{k+1,j}$ 와 $y_{k,j}$ 는 zero mean 이고 독립

$$= \sum_{j=1}^{n_{k-1}} \text{Var}(A_{k+1,j}) \text{Var}(y_{k,j}) + \text{Var}(b_{k+1})$$

$$= n_{k-1} \cdot \frac{1}{3n_{k-1}} \text{Var}(y_{k,j}) + \frac{1}{3n_{k-1}}$$

$$= \frac{1}{3} \text{Var}(y_k) + \frac{1}{3n_{k-1}}$$

$$\text{Var}(y_i) = \frac{1}{3} + \frac{1}{3n_0}$$

$$\therefore \text{Var}(y_k) = \frac{1}{3^k} + \sum_{k=0}^{L-1} \frac{1}{3^{L-k} \cdot n_k}$$

$$\begin{aligned} \text{Var}(y_2) &= \frac{1}{3} \text{Var}(y_1) + \frac{1}{3n_1} \\ \text{Var}(y_3) &= \frac{1}{3} \text{Var}(y_2) + \frac{1}{3n_2} \\ &\vdots \end{aligned}$$

$$\begin{aligned} \text{Var}(y_k) &= \frac{1}{3^{k-1}} + \frac{1}{3 \cdot 3^{k-2}} + \dots + \frac{1}{3^{k-1} \cdot 3n_0} \\ &\quad + \frac{1}{3^k} \cdot \frac{1}{3} \left(\frac{1}{3} + \frac{1}{3n_0} \right) \end{aligned}$$

P 2. (i) $y_l = G(A_l y_{l-1} + b_l) + y_{l-1}$

$$y_l^* = G(A_l y_{l-1} + b_l) \quad \text{• 1st term}$$

$$y_{li}^* = G\left(\sum_{j=1}^m A_{lij} y_{l-1j} + b_{li}\right) \quad \text{• 1st}$$

$$\left(\frac{\partial y_l^*}{\partial y_{l-1j}}\right) = G'\left(\sum_{j=1}^m A_{lij} y_{l-1j} + b_{li}\right) \cdot A_{lij}$$

$$\left(\frac{\partial y_l^*}{\partial y_{l-1}}\right) = \text{diag}\left(G'(A_l y_{l-1} + b_l)\right) A_l$$

$$y_l = y_l^* + y_{l-1}$$

$$\frac{\partial y_l}{\partial y_{l-1}} = \text{diag}\left(G'(A_l y_{l-1} + b_l)\right) A_l + I$$

$$(ii) \frac{\partial Y_L}{\partial b_L} = \frac{\partial Y_L}{\partial Y_L} \frac{\partial Y_L}{\partial b_L}$$

$$= \frac{\partial Y_L}{\partial Y_L} \cdot \text{diag}(6'(A_L Y_{L-1} + b_L))$$

$$\left(\frac{\partial Y_L}{\partial A_L} \right)_{ij} = \frac{\partial Y_L}{\partial Y_L} \frac{\partial Y_L}{(\partial A_L)_{ij}} \left(\rightarrow \begin{bmatrix} 0 \\ \vdots \\ 6'(A_L Y_{L-1} + b_L)_i Y_{L-1,j} \\ \vdots \\ 0 \end{bmatrix} \right)$$

$$= \left(\frac{\partial Y_L}{\partial Y_L} \right)_i 6'(A_L Y_{L-1} + b_L)_i (Y_{L-1})_j$$

$$\therefore \frac{\partial Y_L}{\partial A_L} = \text{diag}(6'(A_L Y_{L-1} + b_L)) \left(\frac{\partial Y_L}{\partial Y_L} \right)^T Y_{L-1}^T$$

(iii)

$$\frac{\partial Y_L}{\partial Y_{L-1}} \text{ or } \frac{\partial Y_L}{\partial A_L} \text{ or } \frac{\partial Y_L}{\partial b_L} \text{ need not vanish.}$$

$$\frac{\partial Y_L}{\partial Y_{L-1}} \text{ or } \frac{\partial Y_L}{\partial A_L} \text{ or } \frac{\partial Y_L}{\partial b_L} \text{ need not vanish.}$$

$$\frac{\partial Y_L}{\partial b_i} \text{ or } \frac{\partial Y_L}{\partial A_i} \text{ or } \frac{\partial Y_L}{\partial Y_L} \text{ need not vanish.}$$

P4

(a) My Conv Layer

$$\text{conv1} \quad 256 \times 128 + 128$$

$$\text{conv2} \quad 126 \times 128 \times 7 + 128$$

$$\text{conv3} \quad 128 \times 256 + 256$$

$$\text{total} \quad 213504$$

STM Conv Layer:

$$256 \times 4 \times 32 + 4 \times 32$$

$$4 \times 4 \times 9 \times 32 + 4 \times 32$$

$$4 \times 256 \times 32 + 256 \times 32$$

$$\text{total} \quad 78512$$

(b)

```
import torch
import torch.nn as nn

class STMConv(nn.Module):
    def __init__(self):
        super(STMConv, self).__init__()
        self.layer1 = nn.ModuleList([nn.Conv2d(256, 4, kernel_size=1, stride=1) for _ in range(32)])
        self.layer2 = nn.ModuleList([nn.Conv2d(4, 4, kernel_size=3, stride=1, padding=1) for _ in range(32)])
        self.layer3 = nn.ModuleList([nn.Conv2d(4, 256, kernel_size=1, stride=1) for _ in range(32)])
    def forward(self, x):
        result = []
        for i in range(32):
            x = torch.nn.functional.relu(self.layer1[i](x))
            x = torch.nn.functional.relu(self.layer2[i](x))
            x = torch.nn.functional.relu(self.layer3[i](x))
            result.append(x)
        return sum(result)
```