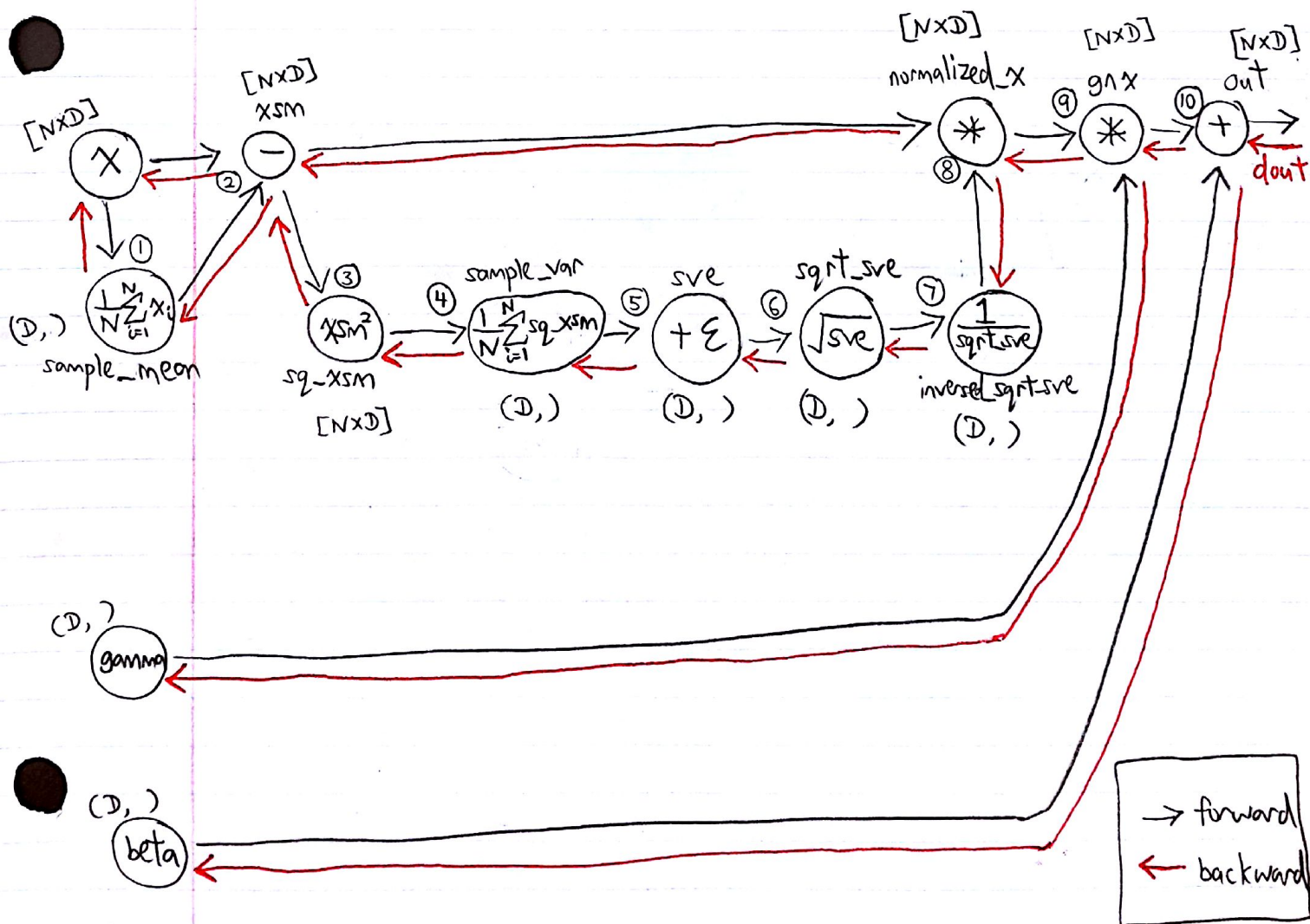


Forward propagation

- ① $\text{sample_mean} = E[X] = \frac{1}{N} \sum_{i=1}^N x_i$
- ② $x_{sm} = x - \text{sample_mean}$
- ③ $sq_xsm = x_{sm}^2$
- ④ $\text{sample_var} = \text{Var}[X] = \frac{1}{N} \sum_{i=1}^N (x_i - E(x_i))^2 = \frac{1}{N} \sum_{i=1}^N (x_{sm})^2$
- ⑤ $sve = \text{sample_var} + \epsilon$
- ⑥ $\text{sqr_sve} = \sqrt{sve}$
- ⑦ $\text{inversed_sqr_sve} = \frac{1}{\text{sqr_sve}}$
- ⑧ $\text{normalized_x} = x_{sm} * \text{inversed_sqr_sve}$
- ⑨ $gx = \text{gamma} * \text{normalized_x}$
- ⑩ $\text{out} = gx + \text{beta}$



Backward propagation

Recall Chain-Rule

Eg. $f(x, y, z) = (x+y)z$

Let $q = (x+y)$ and $f = qz$, then

$$\frac{\partial f}{\partial x} = \frac{\partial f}{\partial q} * \frac{\partial q}{\partial x} \quad , \quad \frac{\partial f}{\partial y} = \frac{\partial f}{\partial q} * \frac{\partial q}{\partial y} \quad , \quad \frac{\partial f}{\partial q} = z$$

Chain-Rule

$$\frac{\partial f}{\partial x} = \frac{\partial f}{\partial q} * \frac{\partial q}{\partial x} \quad , \quad \frac{\partial f}{\partial y} = \frac{\partial f}{\partial q} * \frac{\partial q}{\partial y} \quad , \quad \frac{\partial f}{\partial q} = z$$

short-hand

$$dx = dq * \frac{\partial q}{\partial x} \quad , \quad dy = dq * \frac{\partial q}{\partial y} \quad , \quad dq = z$$

$$= dq * 1 \quad , \quad = dq * 1 \quad , \quad = z$$

$$= \underline{\underline{z}} \quad , \quad = \underline{\underline{z}} \quad , \quad = \underline{\underline{z}}$$

⑩ $\begin{cases} d\gamma x = 1 * dout \\ d\beta q = 1 * dout \end{cases}$

⑨ $\begin{cases} d\gamma = normalized_x * d\gamma x \\ dnormalized_x = \gamma * d\gamma x \end{cases}$

⑧ $\begin{cases} dx_{sm1} = inversed_sqrt_sve * dnormalized_x \\ dinversed_sqrt_sve = x_{sm} * dnormalized_x \end{cases}$

⑦ $-dsqrt_sve = -\frac{1}{(sqrt_sve)^2} * dinversed_sqrt_sve$

⑥ $-dsve = \frac{1}{2} * \frac{1}{\sqrt{sve}} * dsqrt_sve$

⑤ $\begin{cases} dsample_var = 1 * dsve \\ deps \leftarrow \text{hyperparameter, so we don't backpropagate it} \end{cases}$

④ $dsq_xsm = \frac{1}{N} * np.ones((N, D)) * dsample_var$

③ $dx_{sm2} = 2 * x_{sm} * dsq_xsm$

Note: $dx_{sm} = \underbrace{dx_{sm1}}_{\text{from normalized_x}} + \underbrace{dx_{sm2}}_{\text{from sq_xsm}}$ [which is true since node "xsm" inputs to two other nodes (i.e. node "normalized_x" and node "sq_xsm")]

② $\begin{cases} dx_1 = 1 * dx_{sm} \\ dsample_mean = -1 * dx_{sm} \end{cases}$

① $dx_2 = \frac{1}{N} * np.ones((N, D)) * dsample_mean$

Note $dx = \underbrace{dx_1}_{\text{from xsm}} + \underbrace{dx_2}_{\text{from sample_mean}}$