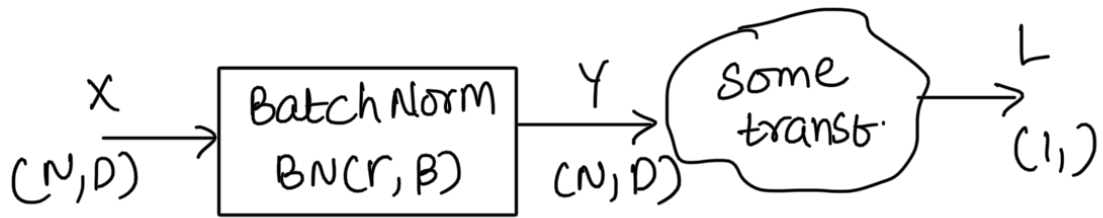


Batch Norm computational graph:-



$$\mu = \frac{1}{N} \sum_{i=1}^N x_i$$

↑  
(D,)

$$\sigma^2 = \frac{1}{N} \sum_{i=1}^N (x_i - \mu)^2$$

↑  
(D,)

$$\hat{x} = \frac{x - \mu}{\sqrt{\sigma^2 + \epsilon}}$$

↑  
(N, D)

$$y = r \hat{x} + \beta$$

↑      ↑  
(N, D)   (D,)

where  $r, \beta$  are learnable params of a BN layer

problem:-  $\frac{\partial L}{\partial y}$  is known/available, of shape (N, D)

calculate  $\frac{\partial L}{\partial x}$ ,  $\frac{\partial L}{\partial r}$ ,  $\frac{\partial L}{\partial \beta}$

(N, D)      (D,)      (D,)

$$\frac{\partial L}{\partial \beta} = \frac{\partial L}{\partial y} \frac{\partial y}{\partial \beta} \rightarrow \text{since } \frac{\partial y}{\partial \beta} = 1, \quad \frac{\partial L}{\partial \beta} = \sum_{i=1}^N \frac{\partial L}{\partial y_i}, \text{ where } y_i \text{ is the } i\text{-th row of } y$$

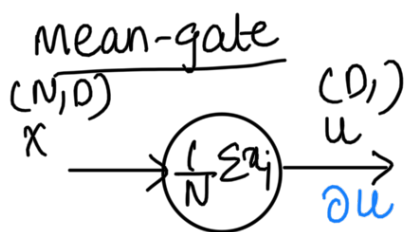
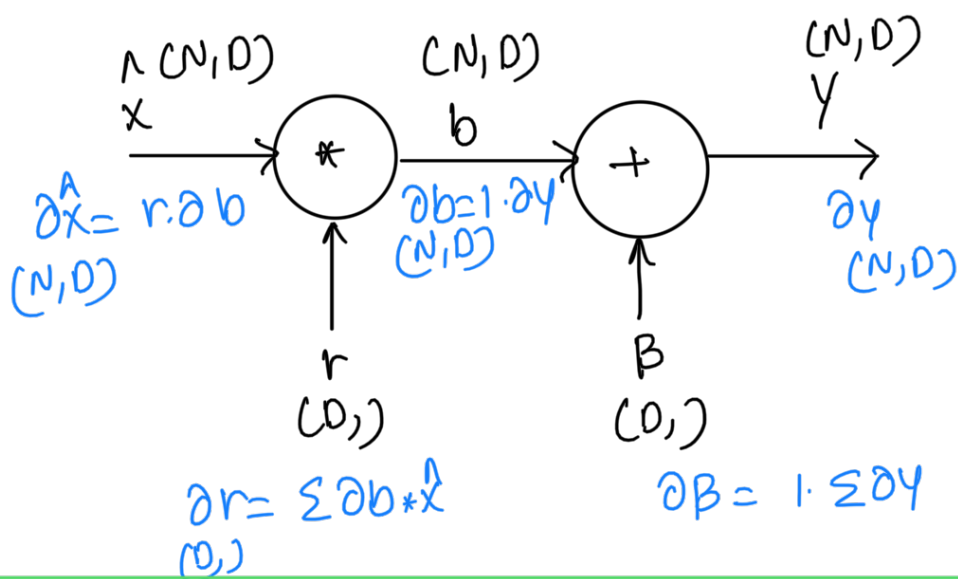
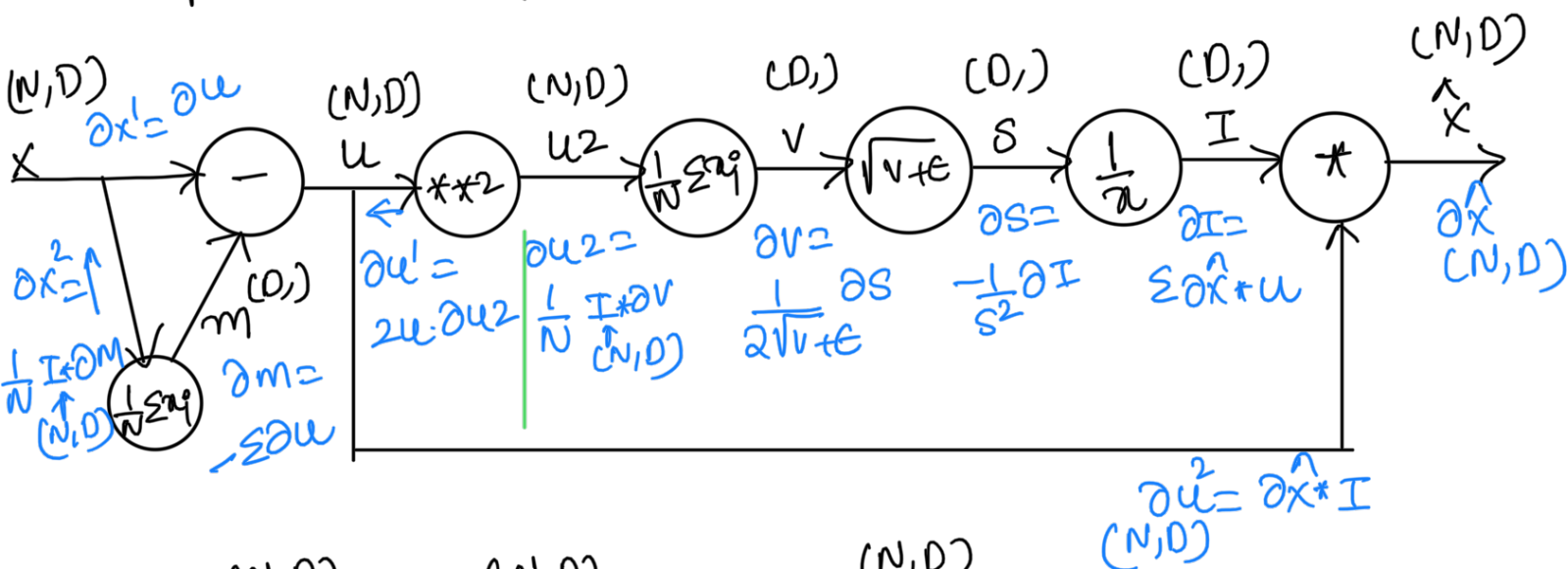
similarly,  $\frac{\partial L}{\partial r} = \frac{\partial L}{\partial y} \frac{\partial y}{\partial r}$  and since  $\frac{\partial y}{\partial r} = \hat{x}$ ,

$$\frac{\partial L}{\partial r} = \sum_{i=1}^N \frac{\partial L}{\partial y_i} * \hat{x}_i \quad \text{where } y_i \in y \text{ \& } \hat{x}_i \in \hat{x} \text{ are } i\text{-th rows of } y \text{ \& } \hat{x}, \text{ respectively.}$$

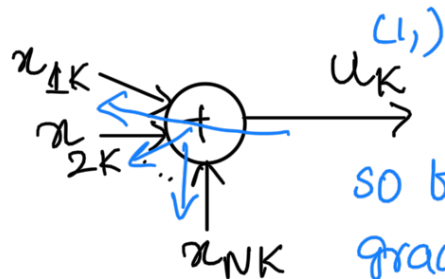
$\frac{\partial L}{\partial r} \in \frac{\partial L}{\partial \beta}$  are relatively straight forward to calculate.

$\frac{\partial L}{\partial x}$  is easier to calculate using a computational graph.

a computational graph is shown below:-



mean-gate can be thought of as D sum-gates in parallel, each with N inputs corresponding to the N examples of a given feature.



$$\partial x = \frac{1}{N} I \frac{du}{(N, D)}$$

$K = \{1 \dots D\}$ , for D features  
so for each feature  $u_k$ , the gradient is copied to the N samples  
⇒ essentially copy u vector N times so it is of shape (N, D) and divide by N

