1.对齐,点乘,加lias:卷起来!

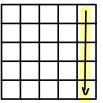
2.1	2.	4.
۱،د	4.1	7,
4.1	2.	3.

2. Normalization是解决训练过程中不同 layer的形状、nom等"不-较"面提出的规范化层输入方法。

它能提高训练速度,增强不同 initialization is robustness.

本来最重览的角度是layer normalization,但是考虑到有时候一层的形状、norm等也是重要feature (想象 MNISTios

笔迹粗细等), 好以来用"同类型"正则化, 即 batch normalization (BN). 其实视方坛是,加入一层:Zi+1 = Ci(ZiWi+ biT) 飞则比矩阵的Column,



这可能带来不必要的dependency on the entire batch, 因此是底对所有层feature 计算实对 mean. variance为 スピークストン・シート エー (ヹー) = (ヹー) - (ヹー)

附上我曾经的定视:

```
def __init__(self, dim, eps=1e-5, momentum=0.1, device=None, dtype="float32"):
   super().__init__()
    self.dim = dim
    self.eps = eps
    self.momentum = momentum
    self.weight = Parameter(init.ones(dim, requires_grad=True))
    self.bias = Parameter(init.zeros(dim, requires_grad=True))
    self.running mean = init.zeros(dim)
    self.running_var = init.ones(dim)
def forward(self, x: Tensor) -> Tensor:
       batch_mean = (x.sum((0,)) / x.shape[0])
       batch var = ((x - batch mean.broadcast to(x.shape)) ** 2).sum((0,)) / x.shape[0]
       # Update the running statistics using momentum technic.
       self.running_mean = (1 - self.momentum) * self.running_mean + self.momentum * batch_me (function) data: Any
       {\tt self.running\_var = (1 - self.momentum) * self.running\_var + self.momentum * batch\_var.data}
       norm = (x - batch_mean.broadcast_to(x.shape)) / (batch_var.broadcast_to(x.shape) + self.eps) ** 0.5
       return self.weight.broadcast_to(x.shape) * norm + self.bias.broadcast_to(x.shape)
       norm = (x - self.running_mean.broadcast_to(x.shape)) \
                   / (self.running_var.broadcast_to(x.shape) + self.eps) ** 0.5
        return self.weight.broadcast_to(x.shape) * norm + self.bias.broadcast_to(x.shape)
```

$$y = \omega \circ \frac{z_i - E[x]}{(Var(x) + \xi)^{\frac{1}{2}}} + b$$

$$y = \frac{x - \hat{\mu}}{(v_{i+1}^2)_{j-1}^2 + \xi}$$

$$\hat{\chi} := (1 - m) \hat{x} + m \times_{obs}$$

3. 關摩nlr:abdefcq 中存Inr: dbfeage 石库 Irn

=> d, f, e, b, g, c, a