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② Intriguing Properties of CL loss

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generalized loss function.

$$L_{gen CL} = L_{align} + \lambda L_{dist'n}$$

$$L^{NTXent} = -\frac{1}{N} \sum_{i,j} \text{sim}(z_i, z_j) + \frac{\tau}{2} \sum_i \log \sum_{k=1}^{2n} \frac{1}{[k \neq i]} \exp(\text{sim}(z_i, z_k))$$

$$L^{NTXent} = -\frac{1}{n} \sum_{i,j \in \mathcal{D}} \frac{\exp[\text{sim}(z_i, z_j)/\tau]}{\sum_{k=1}^{2n} \frac{1}{[k \neq i]} \exp[\text{sim}(z_i, z_k)/\tau]}$$

by some calculation, log breaking

$$L^{NTXent} = \underbrace{-\frac{1}{n} \sum_{i,j} \text{sim}[\cancel{\exp(z_i, z_j/\tau)}]}_{\text{Alignment}} + \underbrace{\frac{\tau}{2} \sum_i \log \sum_{k=1}^{2n} \frac{1}{[k \neq i]} \exp(\text{sim}(z_i, z_k/\tau))}_{\text{Distribution.}}$$

normalised.

[match hidden dist'n uniform in hypersphere]

✓ [Pairwise potential of gaussian kernel.]

✓ [minimized by perfect uniform encoder]

② Introducing CL Loss

(u)

sliced Wasserstein Distance (SWD) loss

Activation vectors. $H \in \mathbb{R}^{b \times d}$, a prior distribution S

Draw prior vector $P \in \mathbb{R}^{b \times d}$ using S

Generate random orthogonal vector matrix $W \in \mathbb{R}^{d \times d}$

$\begin{matrix} \boxed{d} \\ \boxed{d} \end{matrix}$
??

Projection $H^T = HW$; $P^T = PW$ // rotation.

initialize $L = 0$ // SWD

for $j' \in \{1, 2, \dots, d'\}$ do projection for all.

$$L = L + \left\| \underset{\substack{\downarrow \\ \text{column}}}{\text{sort}(H_{:,j'})} - \text{sort}(P_{:,j'}) \right\|^2$$

end for

return $L/(d')$

where it fits ??