20240212 (월)

Python HW7.

layer	input	output.	func
1	32x32x3	28x28x6	Conv.
2	28x28x6	14x14x6	pool
3	14x14x6	10x10x16	conv
4	10x10x16	5x5x16	pool
5	5x5x16 = 400	120	fc
6	120	84	fc
7	84	10 //	fc

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FreeMatch thesis.

2.

X : input

Y : label (equally likely to -1 or +1)

binary classification problem : even mixture of two Gaussians.

$$X \mid Y = -1 \sim N(\mu_1, \sigma_1^2)$$
$$X \mid Y = +1 \sim N(\mu_2, \sigma_2^2)$$

$$\mu_1 < \mu_2$$

classifer outputs confidence score $s(x)$

$$s(x) = \frac{1}{\left[1 + e^{-\beta\left(x - \frac{\mu_1+\mu_2}{2}\right)}\right]}$$: confidence score

β : positive parameter.

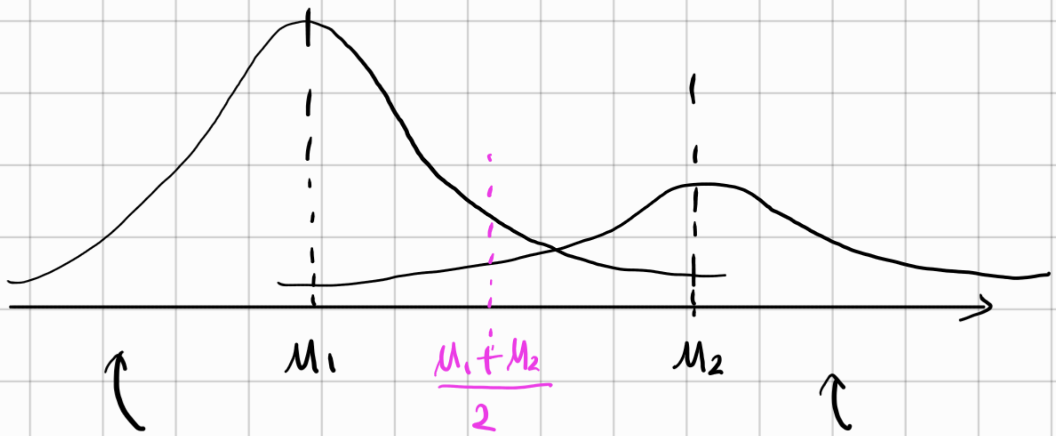
reflects model learning status.

train $\uparrow$ $\Rightarrow$ model confident $\uparrow$ $\Rightarrow$ $\beta \uparrow$

$\frac{\mu_1+\mu_2}{2}$: Bayes' optimal linear decision boundary.

fixed threshold $\tau \in (\frac{1}{2}, 1)$: used to generate pseudo labels.

S		X		Y_p
if $s(x) > \tau$	, then	sample x	is assigned	pseudo label $+1$. 너야
if $s(x) < 1-\tau$	, then	〃	〃	pseudo label -1. 너는 아냐
if $1-\tau \le s(x) \le \tau$	, then	〃	〃	pseudo label 0 (masked). 아몰라



$Y=-1 \sim N(\mu_1, \sigma_1^2)$

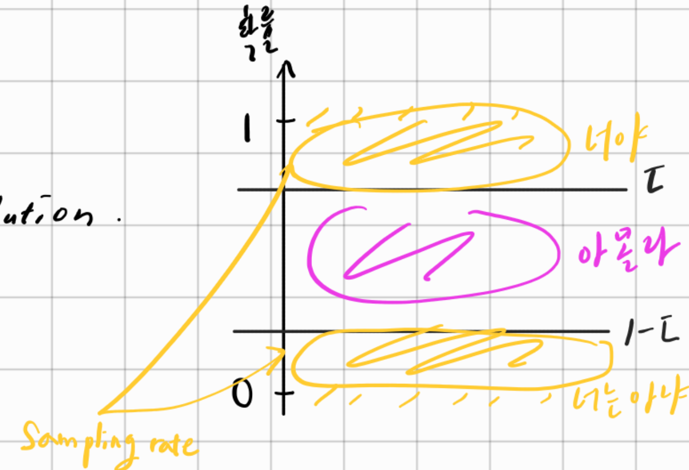
$Y=+1 \sim N(\mu_2, \sigma_2^2)$

Theorem 2.1.

$$P(Y_p = 1) = \frac{1}{2}\Phi\left(\frac{\left(\frac{\mu_2-\mu_1}{2}\right) - \frac{1}{\beta}\cdot\log\left(\frac{\tau}{1-\tau}\right)}{\sigma_2}\right) + \frac{1}{2}\Phi\left(\frac{\left(\frac{\mu_1-\mu_2}{2}\right) - \frac{1}{\beta}\cdot\log\left(\frac{\tau}{1-\tau}\right)}{\sigma_1}\right)$$

$$P(Y_p = -1) = \frac{1}{2}\cdot\Phi\left(\frac{\left(\frac{\mu_2-\mu_1}{2}\right) - \frac{1}{\beta}\log\left(\frac{\tau}{1-\tau}\right)}{\sigma_1}\right) + \frac{1}{2}\cdot\Phi\left(\frac{\left(\frac{\mu_1-\mu_2}{2}\right) - \frac{1}{\beta}\cdot\log\left(\frac{\tau}{1-\tau}\right)}{\sigma_2}\right)$$

$$P(Y_p = 0) = 1 - P(Y_p = 1) - P(Y_p = -1)$$



Φ : cdf of standard normal distribution.

$(\mu_2-\mu_1)\downarrow \Rightarrow P(Y_p=0)\uparrow$

3.

training data $\begin{cases} \text{labeled data} & : D_L \\ \text{unlabeled data} & : D_U \end{cases}$

$D_L = \{(x_b, y_b) : b \in [N_L]\}$

$D_U = \{u_b : b \in [N_U]\}^2$

N_L, N_U : # of samples.

L_s : supervised loss for labeled data

$$L_s = \frac{1}{B} \sum_{b=1}^{B} H\left(y_b, p_m(y \mid w(x_b))\right)$$

정답과 대답 간 거리 평균.

B : batch size

$H(\cdot,\cdot)$: cross-entropy loss

$w(\cdot)$: stochastic data augmentation function.

$p_m(\cdot)$: output probability from the model.

L_U : unsupervised training objective for unlabeled data.

$$L_U = \frac{1}{\mu B} \sum_{b=1}^{B} \mathbb{1}\left(\max(q_b) > \tau\right) \cdot H(\hat{q}_b, Q_b).$$

pseudo 정답과 대답 간 거리 평균

단, pseudo 정답 > τ 인것만 살려.

q_b : $p_m(y \mid w(u_b))$

Q_b : $p_m(y \mid \Omega(u_b))$

$\hat{q}_b$: one-hot label converted from q_b

μ : ratio of unlabeled data batch size to labeled data batch size.

$\mathbb{1}(\cdot > \tau)$: indicator function for confidence-based thresholding with τ.

$w(\cdot)$: weak augmentation

$\Omega(\cdot)$: strong augmentation

L_f : fairness objective.

: encourage model to predict each class at the same frequency.

$$L_f = U \cdot \log(\mathbb{E}_{\mu B}[q_b])$$

U : uniform prior distribution

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4.

4.1. SAT

$T_t(c)$: threshold for class c at t-th iteration.

* SAGT

T_t : average confidence from the model on unlabeled data

은 ↳ t : t-th time step (iteration)

EMA 방식.

예

$$T_t = \begin{cases} \frac{1}{C} & , t=0 \\ \lambda \cdot T_{t-1} + (1-\lambda) \cdot \frac{1}{\mu B} \sum_{b=1}^{\mu B} \max(q_b) & , \text{o/w} \end{cases}$$

C : # of classes

$\lambda \in (0, 1)$: momentum decay of EMA

* SALT