

Open world semi supervised learning

Setting:

$$\mathcal{D}_l = \{(x_i, y_i)\}_{i=1}^n$$

$\in \mathcal{C}_l$

$$\mathcal{D}_u = \{(x_i)\}_{i=1}^m$$

$\in \mathcal{C}_u$

Dataset Assumption: Category / class Set:

$$\mathcal{C}_l \cap \mathcal{C}_u \neq \emptyset$$

Different from NCD

$$\mathcal{C}_l \neq \mathcal{C}_u$$

$$\mathcal{C}_S = \mathcal{C}_l \cap \mathcal{C}_u \quad // \text{ Seen classes.}$$

$$\mathcal{C}_u = \mathcal{C}_u \setminus \mathcal{C}_l \quad // \text{ unseen / novel classes.}$$

Notations:

$$f_\theta : \mathbb{R}^N \rightarrow \mathbb{R}^D$$

feature; $\mathbf{z}_l = \{z_i \in \mathbb{R}^D\}_{i=1}^n$

labeled

$$\mathbf{z}_u = \{z_i \in \mathbb{R}^D\}_{i=1}^m$$

classification head weight matrix.

$$W: \mathbb{R}^D \rightarrow \mathbb{R}^{|C_s \cup C_u|} \rightarrow \text{a softmax.}$$

final prediction: $C_i = \arg \max (w^T \cdot z_i)$
one of the $C_s \cup C_u$ classes.

for unknown no of classes we

initialize the head with large

Number of classes. [OVER CLUSTER
solution]

final optimization objective:

$$\mathcal{L} = \mathcal{L}_s + \eta_1 \mathcal{L}_p + \eta_2 \mathcal{L}$$

supervised

pairwise objective

regularization.

① Supervised Objective with Uncertainty Adaptive
 \mathcal{L}_s margin

- utilization of categorical annotated labels.

usual case

$$L_S = \frac{1}{n} \sum_{i \in \mathcal{Z}_k} -\log \left[\frac{e^{w_{y_i}^T \cdot z_i}}{e^{w_{y_i}^T \cdot z_i} + \sum_{j \neq i} e^{w_{y_j}^T \cdot z_i}} \right]$$

ith row.

- result in learning a classifier with larger margin.

- Result model bias towards the known classes [smaller intra-class variance for the known compared to novel classes]

introduce uncertainty Adaptive margin

[propose a normalization!]

$$L_S = \frac{1}{n} \sum_{z_i \in \mathcal{Z}_k} -\log \left[\frac{e^{s(w_{y_i}^T \cdot z_i + \lambda \bar{u})}}{e^{s(w_{y_i}^T \cdot z_i + \lambda \bar{u})} + \sum_{j \neq i} e^{s(w_{y_j}^T \cdot z_i)}} \right]$$

uncertainty $\bar{u} \rightarrow$ how?

scale s

$$\bar{u} = \frac{1}{|D_u|} \sum_{x \in D_u} \text{var}(y | x = x)$$

$$= \frac{1}{|D_u|} \sum_{x \in D_u} p_K(y=1|x) p_K(y=0|x)$$

$$\approx \frac{1}{|D_u|} \sum_{x_i \in D_u} 1 - \max p_K(y=K | x=x_i)$$

Group uncertainty.

Requirement

$$\begin{cases} z_i = \frac{z_i'}{|z_i'|} \\ w_j = \frac{w_j'}{|w_j'|} \end{cases}$$

① Pairwise Objective

Dot product

$$L_p = \frac{1}{n+n} \sum_{z_i, z_i' \in \{z_1 \cup z_n, z_1' \cup z_n'\}} -\log \langle \sigma(w^T z), \sigma(w^T z') \rangle$$

softmax

$$\{z_1 \cup z_n, z_1' \cup z_n'\}$$

Augmentation

works with positive only !!

(ii) regularizer term

$$\mathcal{R} = \text{KL} \left(\frac{1}{m+n} \sum_{z_i \in \mathcal{Z}_r \cup \mathcal{Z}_u} \sigma(w^T z_i) \parallel \mathcal{P}(y) \right)$$