

① Theoretical understanding of CL

Theoretical Understanding of CL

framework:

setup

- $\mathcal{X} \rightarrow \text{dataset}$
- $D_{sim} \sim (x, x^+)$
- $D_{neg} \sim x_1^-, x_2^-, \dots, x_k^-$
- Encoder family \mathcal{F}
- $\therefore f: \mathcal{X} \rightarrow \mathbb{R}^d$ such that, $\|f(\cdot)\| \leq R$; $R > 0$

Latent class:

more setup

- $(x, x^+) \rightarrow \text{similar pair}$
- family of latent class \mathcal{C}
- $c \in \mathcal{C}$
- D_c over the \mathcal{X}
- $D_c(x)$: How relevant x to c ??
- ρ : how class occurs naturally.

Semantic Similarity:

$$D_{sim}(x, x^+) = \mathbb{E}_{c \sim p} [D_c(x) D_c(x^+)]$$

$$D_{neg}(x^-) = \mathbb{E}_{c \sim p} [D_c(x^-)]$$

Supervised Tasks: for a labeled pair (x, c) ; $c \in \{c_1, \dots, c_{K+1}\}$

$$D_{\mathcal{F}}(x, c) = D_c(x) D_{\mathcal{F}}(c)$$

①

Ⓣ Theoretical understanding of CL

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$D_c(x)$: how relevant x to c ?

p : how class occurs naturally.

Semantic Similarity:

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Supervised Tasks: for a labeled pair (x, y) ; $c \in \{c_1, \dots, c_{c+1}\}$

$$D_{\mathcal{F}}(x, y) = D_c(x) D_c(y)$$

Evaluation metric for representation:

$$\text{Task } \mathcal{T} = \{y \dots y_{k+1}\}$$

function $g: \mathcal{X} \rightarrow \mathbb{R}^{k+1}$ // linear classifier.

$$\text{point } (x, y) \in \mathcal{X} \times \mathcal{T}$$

$$\text{loss} \triangleq L(\{g(x)_y - g(x)_{y'}\}_{y \neq y'}) \quad \left[\begin{array}{l} \text{Different from} \\ \text{true class should} \\ \text{be high} \end{array} \right]$$

\swarrow (k dim vector of difference in coordinate)

By considering standard hinge loss:

$$L(v) = \max\{0, 1 + \max_i \{-v_i\}\}$$

$$\text{logistic loss } l(v) = \log_2(1 + \sum_i \exp(-v_i)) ; v \in \mathbb{R}^k$$

$$L_{\text{sup}}(\mathcal{T}, g) := \mathbb{E}_{(x, y) \sim \mathcal{D}_\mathcal{X}} \left[L\{g(x)_y - g(x)_{y'}\}_{y \neq y'} \right]$$

For linear Classifier: $g(x) = W f(x)$

finally (k+1)

$$\text{Further, } L_{\text{sup}}(\mathcal{T}, f) = \inf_{W \in \mathbb{R}^{(k+1) \times d}} L_{\text{sup}}(\mathcal{T}, Wf)$$

TP: w_j mean for each class representation:

mean classifier: w^k

$$\text{c.th row} \Rightarrow \mu_c = \mathbb{E}_{x \sim \mathcal{D}_c} [f(x)]$$

$$\text{Now, } L_{\text{sup}}^u(\mathcal{T}, f) = L_{\text{sup}}(\mathcal{T}, W^k f)$$

⑦ Theore. understanding of CL

Arg Supervised loss:

$$L_{\text{sup}}(f) := \mathbb{E}_{\{c_i\}_{i=1}^{k+1} \sim p^{k+1}} \left[L_{\text{sup}}(\{c_i\}_{i=1}^{k+1}, f) \mid c_i \neq y \right]$$

for mean class

$$L_{\text{sup}}^{\mu}(f) := \mathbb{E}_{\{c_i\}_{i=1}^{k+1} \sim p^{k+1}} \left[L_{\text{sup}}^{\mu}(\{c_i\}_{i=1}^{k+1}, f) \mid c_i \neq y \right]$$

CL Algorithm:

unsupervised loss: Population loss:

neg number
↑

$$L_{\text{un}}(f) := \mathbb{E} \left[L \left(\{f(x)^T (f(x^+) - f(x_i))\}_{i=1}^k \right) \right]$$

Empirical counterparts: $(x_j^+, x_j^-, \bar{x}_j, \dots, x_{j,k}^-) \in \mathcal{D}_{\text{sim}} \times \mathcal{D}_{\text{neg}}^k$
 $j=1$

$$\hat{L}_{\text{un}}(f) = \frac{1}{n} \sum_{j=1}^n L \left(\{f(x_j)^T (f(x_j^+) - f(x_{j,i}^-))\}_{i=1}^k \right)$$

Now,

$$L_{\text{un}}(f) = \mathbb{E}_{\substack{x^+, \bar{c} \\ \sim p^{k+1}}} \mathbb{E}_{\substack{x, x^+ \sim \mathcal{D}_{C^+} \\ x_i \sim \mathcal{D}_{C^-}}} \left[L \left(\{f(x)^T (f(x^+) - f(x_i^-))\} \right) \right]$$

(iv)

Results and theorem:Th. 1.

$$L_{\text{sup}}(\hat{f}) \leq \alpha L_{\text{un}}(f) + \eta \text{Gen}_m + \delta \quad \forall f \in \mathcal{F}$$

upper bound?? generalization
error.

$$M \rightarrow \infty, \text{Gen}_m \rightarrow 0$$

$$\alpha, \eta \rightarrow 1, \delta \rightarrow 0$$

[if α is large, $L_{\text{un}}(f)$ can be small]

$$L_{\text{sup}}(\hat{f}) \leq L_{\text{un}}^{\rho}(f) + \beta s(f) + \eta \text{Gen}_m \quad \forall f \in \mathcal{F}$$

ρ dependent.

$$\rho \rightarrow \text{uniform}, |E| \rightarrow \infty \text{ then } \beta \rightarrow 0, \eta \rightarrow 1$$

Ideal result should be:
$$L_{\text{sup}}(\hat{f}) \leq \alpha L_{\text{sup}}(f) + \eta \text{Gen}_m \quad \forall f \in \mathcal{F}$$

However not true??