

① Meta learning for Semi-Supervised FSL

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k-shot N-way episodes.

total k example from classes.

1) support (training) set $\mathcal{S} = \{(x_1, y_1), (x_2, y_2) \dots (x_{N \times k}, y_{N \times k})\}$

2) Query / test set $\mathcal{Q} = \{(x_1, y_1), (x_2, y_2) \dots (x_T, y_T)\}$

Prototype, p_c of class c

$$p_c = \frac{\sum_i h(x_i) z_{ic}}{\sum_i z_{ic}}; \quad z_{ic} = \mathbb{1}[y_i = c]$$

$$P(c | x^*, \{p_c\}) = \frac{\exp(-\|h(x^*) - p_c\|_2^2)}{\sum_{c'} \exp(-\|h(x^*) - p_{c'}\|_2^2)}$$

Loss function: to minimize

argmax
 $y_i = c$

$$-\frac{1}{T} \sum_i \log P(y_i^* | x_i^*, \{p_c\})$$

for test data (query)

Prototypical Net with Soft K-means: Extra terms [softmax]

$$\hat{p}_c = \frac{\sum_i h(x_i) z_{ic} + \sum_j h(\tilde{x}_j) \tilde{z}_{j,c}}{\sum_i z_{ic} + \sum_j \tilde{z}_{j,c}}; \quad \tilde{z}_{j,c} = \frac{\exp(-\|h(\tilde{x}_j) - p_c\|_2^2)}{\sum_{c'} \exp(-\|h(\tilde{x}_j) - p_{c'}\|_2^2)}$$

labeled

unlabeled

Refinement prototypes: \tilde{p}_c

Protop. Net with k-means [A distractor class]

assumption: $p_c = \begin{cases} \frac{\sum_i h(x_i) z_{ic}}{\sum_i z_{ic}} ; \text{ for } c=1 \dots N \\ 0 ; \text{ for } c=N+1 \end{cases}$

$$\tilde{z}_{j,c} = \frac{\exp\left(-\frac{1}{\sigma_c^2} \| \tilde{x}_j - p_c \|^2 - A(\sigma_c)\right)}{\sum_{c'} \exp\left(-\frac{1}{\sigma_c^2} \| \tilde{x}_j - p_{c'} \|^2 - A(\sigma_{c'})\right)}$$

length scale for distractor class.

$A(x) = \frac{1}{2} \log(k\pi) + \log(\pi)$

Here this paper, $\pi_1, \dots, \pi_N = 1$
learn $\sigma_{N+1} = ??$

PN soft k-means & masking:

Normalized Distance, $\tilde{d}_{j,c} = \frac{\|h(x_j) - p_c\|_2^2}{\frac{1}{n} \sum_j d_{j,c}}$

soft threshold \uparrow
 $[\beta_c, \delta_c] = \text{MLP}\left(\left[\min_j(\tilde{d}_{j,c}), \max_j(\tilde{d}_{j,c}), \text{var}_j(\tilde{d}_{j,c}), \text{skew}_j(\tilde{d}_{j,c}), \text{kurt}_j(\tilde{d}_{j,c})\right]\right)$
 slope \downarrow

$$\tilde{p}_c = \frac{\sum_i h(x_i) z_{ic} + \sum_j h(\tilde{x}_j) \tilde{z}_{j,c} m_{j,c}}{\sum_i z_{ic} + \sum_j \tilde{z}_{j,c} m_{j,c}} ; m_{j,c} = \sigma\left(-\gamma_c(\tilde{d}_{j,c} - \beta_c)\right)$$

\downarrow
 modified cluster.