Supplementary Material for
Adaptive Label Noise Cleaning with Meta-Supervision for Deep Face Recognition

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Abstract

In this supplementary material, we present fully detailed information on 1) derivation of the meta-learning update (formula 11) in the paper; 2) the threshold-aware loss; 3) network structure of the GCN cleaner.

1. Meta-Learning Update

In the paper, we combine the meta-train and meta-test loss to get the final meta update loss as

$$\mathcal{L}^{\text{meta}} = \gamma \mathcal{L}^{\text{train}}(\theta) + (1-\gamma)\mathcal{L}^{\text{test}}(\theta') \tag{1}$$

Recall the update equation of SGD, the parameter θ is updated as

$$\theta \leftarrow \theta - \alpha \frac{1}{B} \sum_{b=1}^{B} \nabla_{\theta} \mathcal{L}_b^{\text{meta}}(\theta, \theta') \tag{2}$$

The computation of Eq. 11 in the paper by backpropagation can be understood by the following derivation:

$$\begin{aligned} \alpha \tfrac{1}{B} \sum_{b=1}^{B} \nabla_{\theta} \mathcal{L}_b^{\text{meta}}(\theta, \theta') &= \alpha \tfrac{1}{B} \sum_{b=1}^{B} \left(\gamma \tfrac{\partial \mathcal{L}_b^{\text{train}}(\theta)}{\partial \theta} + (1-\gamma) \tfrac{\partial \mathcal{L}_b^{\text{test}}(\theta')}{\partial \theta} \right) \\ &= \tfrac{\gamma \cdot \alpha}{B} \sum_{b=1}^{B} \tfrac{\partial \mathcal{L}_b^{\text{train}}(\theta)}{\partial \theta} + \tfrac{(1-\gamma)\cdot \alpha}{B} \sum_{b=1}^{B} \tfrac{\partial \mathcal{L}_b^{\text{test}}(\theta')}{\partial \theta'} \cdot \tfrac{\partial \theta'}{\partial \theta} \end{aligned} \tag{3}$$

where $\frac{\partial \theta'}{\partial \theta}$ is determined in the meta-training phase and can be extracted from the sum, therefore the second term

$$\begin{aligned} \tfrac{(1-\gamma)\cdot \alpha}{B} \sum_{b=1}^{B} \tfrac{\partial \mathcal{L}_b^{\text{test}}(\theta')}{\partial \theta'} \cdot \tfrac{\partial \theta'}{\partial \theta} &= \tfrac{(1-\gamma)\cdot \alpha}{B} \cdot \tfrac{\partial \theta'}{\partial \theta} \sum_{b=1}^{B} \tfrac{\partial \mathcal{L}_b^{\text{test}}(\theta')}{\partial \theta'} \\ &= \tfrac{(1-\gamma)\cdot \alpha}{B} \left(1 - \tfrac{\alpha}{B} \sum_{b=1}^{B} \tfrac{\partial^2 \mathcal{L}_b^{\text{train}}(\theta)}{\partial \theta^2} \right) \cdot \sum_{b=1}^{B} \tfrac{\partial \mathcal{L}_b^{\text{test}}(\theta')}{\partial \theta'} \\ &= \tfrac{(1-\gamma)\cdot \alpha}{B} \sum_{b=1}^{B} \tfrac{\partial \mathcal{L}_b^{\text{test}}(\theta')}{\partial \theta'} - \tfrac{(1-\gamma)\cdot \alpha^2}{B^2} \sum_{b=1}^{B} \tfrac{\partial^2 \mathcal{L}_b^{\text{train}}(\theta)}{\partial \theta^2} \sum_{b=1}^{B} \tfrac{\partial \mathcal{L}_b^{\text{test}}(\theta')}{\partial \theta'} \end{aligned} \tag{4}$$

By substituting Eq. 3 and Eq. 4 into Eq. 2, the meta-update formula is as shown in the paper:

$$\theta \leftarrow \theta - \frac{\gamma \cdot \alpha}{B} \sum_{b=1}^{B} \frac{\partial \mathcal{L}_b^{\text{train}}(\theta)}{\partial \theta} - \frac{(1-\gamma)\cdot \alpha}{B} \sum_{b=1}^{B} \frac{\partial \mathcal{L}_b^{\text{test}}(\theta')}{\partial \theta'} + \frac{(1-\gamma)\cdot \alpha^2}{B^2} \sum_{b=1}^{B} \frac{\partial^2 \mathcal{L}_b^{\text{train}}(\theta)}{\partial \theta^2} \sum_{b=1}^{B} \frac{\partial \mathcal{L}_b^{\text{test}}(\theta')}{\partial \theta'} \tag{5}$$

It can be seen that three terms control the gradient descent of parameter θ. The first term optimize meta-train set with learning rate $\gamma \cdot \alpha$ towards θ', then the second term optimize meta-test set on the updated model parameter θ' with learning rate $(1-\gamma)\cdot\alpha$. So that the parameter is trained to perform well on both meta-train and meta-test domains. The third term applies gradient ascent on parameter θ' with learning rate $\frac{(1-\gamma)\cdot\alpha^2}{B}\sum_{b=1}^{B}\frac{\partial^2\mathcal{L}_b^{\text{train}}(\theta)}{\partial\theta^2}$, which is constrained by the second-order derivative from meta-train domain. For instance, when the model reaches the local-minimum of the meta-train set, which means the second-order derivative is positive, then the third term corrects the second term to step less on the meta-test set to retain the learned knowledge from the meta-train set and to ensure convergence. Inversely, if the model is not stable on the meta-train set, then it follows more on the meta-test set to find the space that is fitted to both domains.

2. Threshold-Aware Loss

To effectively train the threshold adapter $\mathbf{T}$, a threshold-aware loss $\mathcal{L}^{\text{th}}$ is designed in the paper as below:

$$\mathcal{L}^{\text{th}} = -\frac{1}{n}\sum_{i=1}^{n}\left[\hat{\boldsymbol{y}}_i^t \cdot \log\left(1 - \left[1 - \boldsymbol{p}_i^t - [1 - \boldsymbol{t} - m_{\text{fn}}]_+\right]_+\right) + \left(1 - \hat{\boldsymbol{y}}_i^t\right) \cdot \log\left(1 - \left[\boldsymbol{p}_i^t - [\boldsymbol{t} - m_{\text{fp}}]_+\right]_+\right)\right] \tag{6}$$

For sample $\left(\boldsymbol{x}_i^t, \hat{\boldsymbol{y}}_i^t\right)$ in class (X^t, Y^t), we discuss the form of $\mathcal{L}^{\text{th}}$ in different situation in Algorithm 1. In fact, there are only two cases (Eq. 7 and Eq.10) where the gradients with repect to $\boldsymbol{t}$ are valid. In Figure 1, we show a simplified situation

Algorithm 1 Deviation of the threshold-aware loss.

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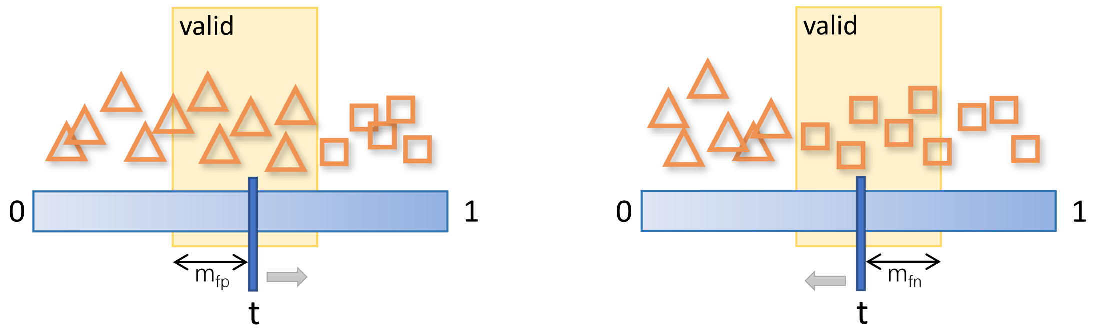
Require: Threshold-aware loss $\mathcal{L}^{\text{th}}$, a sample $\left(\boldsymbol{x}_i^t, \hat{\boldsymbol{y}}_i^t\right)$ in class $(X^t, Y^t)$.
  if $\hat{\boldsymbol{y}}_i^t = 0$ then
    if $\boldsymbol{t} > m_{\text{fp}}$ then
      if $\boldsymbol{p}_i^t > (\boldsymbol{t} - m_{\text{fp}})$ then
        $$\mathcal{L}^{\text{th}} = -\log\left(1 - \left(\boldsymbol{p}_i^t - (\boldsymbol{t} - m_{\text{fp}})\right)\right) \tag{7}$$
      else
        $$\mathcal{L}^{\text{th}} = 0 \tag{8}$$
      end if
    else
      $$\mathcal{L}^{\text{th}} = -\log\left(1 - \boldsymbol{p}_i^t\right) \tag{9}$$
    end if
  else
    if $\boldsymbol{t} + m_{\text{fn}} < 1$ then
      if $\boldsymbol{p}_i^t < (\boldsymbol{t} + m_{\text{fn}})$ then
        $$\mathcal{L}^{\text{th}} = -\log\left(1 - \left(\boldsymbol{t} + m_{\text{fn}} - \boldsymbol{p}_i^t\right)\right) \tag{10}$$
      else
        $$\mathcal{L}^{\text{th}} = 0 \tag{11}$$
      end if
    else
      $$\mathcal{L}^{\text{th}} = -\log \boldsymbol{p}_i^t \tag{12}$$
    end if
  end if
```



(a) Negative samples

(b) Positive samples

Figure 1: Training of threshold adaptor.

that the negative (triangle) and positive (rectangle) samples are well separated, but the threshold $\boldsymbol{t}$ is biased. For a noise sample, which means $\hat{\boldsymbol{y}}_i^t = 0$, if the predicted threshold $\boldsymbol{t}$ is greater than m_{fp} and the predicted score for the sample $\boldsymbol{p}_i^t$ is greater than $\boldsymbol{t} - m_{\text{fp}}$, we treat it as a false positive sample. As shown in Figure 1a, the gradients of false negatives pull the threshold $\boldsymbol{t}$ along the arrow in the positive direction. The threshold-aware loss is designed in cross-entropy way as in Eq. 7, and the gradient to the parameter ϕ in the threshold adapter is

$$\nabla_\phi \mathcal{L}^{\text{th}} = -\frac{\nabla_\phi \boldsymbol{t}}{1 - (\boldsymbol{p}_i^t - (\boldsymbol{t} - m_{\text{fp}}))} \tag{13}$$

Similarly, for a signal sample, if the predicted threshold $\boldsymbol{t}$ is less than $1 - m_{\text{fn}}$ and the predicted score for the sample $\boldsymbol{p}_i^t$ is less than $\boldsymbol{t} + m_{\text{fn}}$, we treat it as a false negative sample. As shown in Figure 1b, the gradients of false positives pull the threshold $\boldsymbol{t}$ along the arrow in the negative direction. The threshold-aware loss is designed in cross-entropy way as in Eq. 10, and the gradient to the parameter ϕ in the threshold adapter is

$$\nabla_\phi \mathcal{L}^{\text{th}} = \frac{\nabla_\phi \boldsymbol{t}}{1 - (\boldsymbol{t} + m_{\text{fn}} - \boldsymbol{p}_i^t)} \tag{14}$$

3. Graph Convolutional Network

In this paper, the GCN cleaner is designed as a binary vertex classification network, of which structure is designed similar to a recent GCN-based data cleaning work [4]. Specifically, the GCN forward propagation function [1, 2] from layer l to layer $l+1$ of one sample vertex i on the graph is

$$\boldsymbol{h}_i^{(l+1)} = \sigma\left[F_{j\in\mathcal{N}_i}\left(\boldsymbol{h}_j^{(l)}\right)\mathbf{W}^{(l)}\right] \tag{15}$$

where $\boldsymbol{h}_i^{(l)}$ is the embedding representation of vertex i in the l-th layer, $\mathbf{W}^{(l)}$ is a learnable linear transformation in the l-th layer, and σ denotes the activation function, where sigmoid is used in the last layer, and ReLU is used in the other layers. F is designed as the transforming function that aggregates vertex i and its neighbors with the similarity between vertices as the weight, and outputs a new expression of the vertex:

$$F_{j\in\mathcal{N}_i}\left(\boldsymbol{h}_j^{(l)}\right) = \left[\boldsymbol{h}_i^{(l)} \| \sum_{j\in\mathcal{N}_i} \sigma\left(\tilde{s}_{ij}\boldsymbol{h}_j^{(l)}\mathbf{A}^{(l)} + \mathbf{b}^{(l)}\right)\right] \tag{16}$$

where $\mathcal{N}_i$ is a collection of all neighbors of vertex i, $\tilde{s}_{ij} = \frac{s_{ij}}{\sum_{k\in\mathcal{N}_i} s_{ik}}$ is the normalized similarity score between vertex i and vertex j, $\|$ is the concatenation operator, $\mathbf{A}^{(l)}$ and $\mathbf{b}^{(l)}$ are deployed to learn the face aggregating principle in the l-th layer. Therefore, there are three learnable parameters $\mathbf{W}^{(l)}$, $\mathbf{A}^{(l)}$ and $\mathbf{b}^{(l)}$ in one layer of the cleaner. The network is implemented with DGL [3] by PyTorch deep learning framework.

References

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