Supplementary for Unknown-Oriented Learning for Open Set Domain Adaptation

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In the supplementary material, we first provide the extensive implementation details. Then some additional experiment results are presented with qualitative and quantitative performance analysis. This supplementary is organized as follows:

1 Implementation details

1.1 Experimental settings

Apart from the mentioned details in Section 4.1 of manuscript, we warm up the model with source data for all benchmarks. The scale weight in GRL [3] is set as 1 for digital recognition and set as 0.2 for other two benchmarks. The conjugate gradient method is implemented using sklearn [1]. For *digital recognition*, we convert all images to RGB format and resize them into 28×28. Then, they are normalize with $(0.5, 0.5, 0.5)$ mean and $(0.5, 0.5, 0.5)$ variance. For *Office-Home* and *Endo-c2k*, we resize images into 256×256 and horizontally flip the image with 0.5 probability. Then, they are randomly cropped into 224×224 and normalized with $(0.485, 0.456, 0.406)$ mean and $(0.229, 0.224, 0.225)$ variance. During test stage, they are resize into 256×256 and cropped into 224 at the center. The parameter are tuned in $Ar \rightarrow Cp$ task and fixed for all other tasks. We tune the μ, λ and N resulting in $\mu : \{10^{-4}, 10^{-3}, 10^{-2}\} - \{64.19, \mathbf{65.17}, 63.34\}$ (%, *HOS*), λ: $\{0.85, 0.90, 0.95, 1.00\} - \{64.71, 64.82, \mathbf{65.17}, 65.15\}$ (%, *HOS*) and N: $\{5, 10, 15, 20\} - \{62.81, \mathbf{65.18}, 63.92, 64.85\}$ (%, *HOS*). Hence we empirically set μ, λ and N as $10^{-3}, 0.95$ and 10. As for training strategy of three stages, the first and third stages are stopped at the 30^{th} and 50^{th} epoch separately. The second stage does not require a termination signal.

1.2 Dataset

We elaborate on the division of benchmark *Endo-c2k* in this section. The source CAD-CAP dataset [2] consists of three class, i.e. normal, inflammatory and vascular lesions. For the target KID dataset [4], the normal-colon, normal-esophagus, normal-small-bowel and norm-stomach are merged into normal while the polypoids and ampulla-of-vater are set as unknown. Due to the complexity of normal class in the target domain, it is non-trivial to classify the normal samples.

2 Experimental results

2.1 Graph Visualization

To visualize the graphs constructed in *false unknown suppression*, we utilize the pyecharts package[1]. The results in MNIST $\rightarrow$ USPS task are shown in Fig. 1. In the S2TAG, most of known samples in target domain are connected with the same category samples in source domain, while the unknown samples are associated with source samples belonging to different categories. These results validate the rationality of super confidence criteria. As for the T2TAG, the gradient manifold of target samples is neat, where samples of the same category are prone to be arranged together. Hence, we can obtain confident pseudo labels based on the gradient manifold.

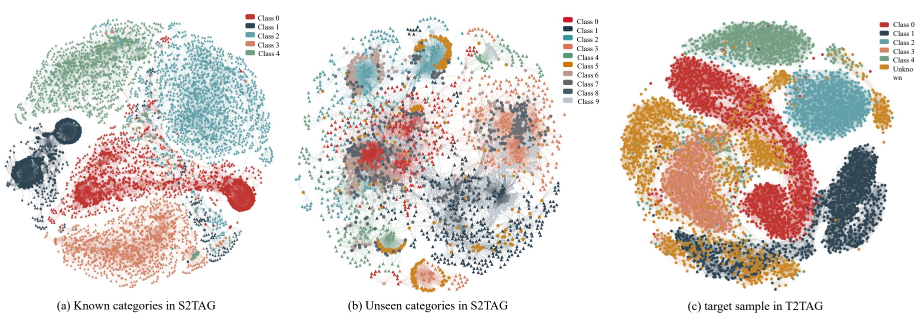

Fig. 1: The visualization of (a) known categories in S2TAG, (b) unseen categories in S2TAG and (c) target samples in T2TAG. Circles represent target samples and triangles represent source samples.

2.2 Ablation for k

We analyze the sensitivity to the number of neighbors k in *false unknown suppression*, as shown in Fig. 2. We set different k with 5, 10, 20, 30 and 40. It is

[1] https://github.com/pyecharts/pyecharts-gallery

reported that the *HOS* score is highest when the k is set as 20 or 30. Considering the trade-off of computational complexity and performance, 20 is selected for our experiments. Notably, three metrics are stable to the k within a range.

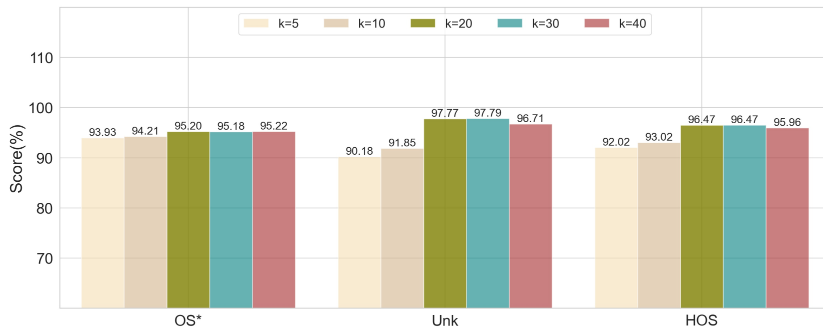

Fig. 2: Results of different numbers of neighbors k.

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