Source-free Few-shot Semi-supervised Domain Adaptation

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Motivation

The application of deep learning techniques in medical imaging is emerging. However, the medical data is hard to obtain and may be subject to privacy and confidential issues. The labeling process can also be costly due to the requirement of domain knowledge. It is crucial to develop semi-supervised algorithms that can be trained with very few data. In this work, we focus on classifying body part from CT images

Related Work

- Test-time domain adaptation (Tent) (2020)
- Unsupervised Black-box Domain Adaptation
- Meta Learning
- Pseudo-labeling

References

[1] J. Liang, D. Hu, and J. Feng. Do we really need to access the source data? source hypothesis transfer for unsupervised domain adaptation. In International Conference on Machine Learning, pages 6028–6039. PMLR, 2020

[2] D. Wang, E. Shelhamer, S. Liu, B. Olshausen, and T. Darrell. Tent: Fully test-time adaptation by entropy minimization. arXiv preprint arXiv:2006.10726, 2020

Technique

- We propose a semi-supervised few-shot learning algorithm to classify body parts based on pseudo-label propagation and early stopping
- We performed experiments on different pretrained models to demonstrate that our proposed method outperforms the fine-tuning baseline
- Our method does not require any source data, while uses only few target domain data, which is a significant advantage over other methods
- The presentation video can be found at this link: https://youtu.be/7WvNc2STs5A

Algorithm and Experiments

Algorithm 1 Source-free Few-shot Semi-supervised CT

Classification

Input: labeled data x_0 , y_0 , unlabeled data x_1 , pretrained model g_{θ} , confidence level t, number of iterations *iter*, learning rate λ

while There are new psuedo-labels do

for i from 0 to *iter* **do** $\phi \leftarrow \phi - \lambda \nabla_{\phi} \sum_{j}^{D} CE(f_{\phi}(g_{\theta}, x_{0j}), y_{0j})$

end for

 $\hat{d} \leftarrow \arg\min_{train} \frac{VAR(l_{train})}{E[l_{train}^2]}$

 $\phi \leftarrow \phi_{\hat{d}}$ for $x \in x_1$ do

> if $f_{\phi}(x) > t$ then Append x and $f_{\phi}(x)$ to the training set

end if

end for

end while

Table 1. Results

Method	VGG-16	ResNet-50	ResNet-18
No-pretrain	0.51	0.59	0.57
Fine-tuning	0.77	0.82	0.81
Psuedo-label Propogation (Ours)	0.85	0.93	0.90