Meta Self-Learning for Multi-Source Domain Adaptation: A Benchmark

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https://github.com/bupt-ai-cz/Meta-SelfLearning

Background & Introduction

Text recognition task suffers from the problems below

- Labor-intensive to collect and label the data.
- Text images from different domains have domain shift.

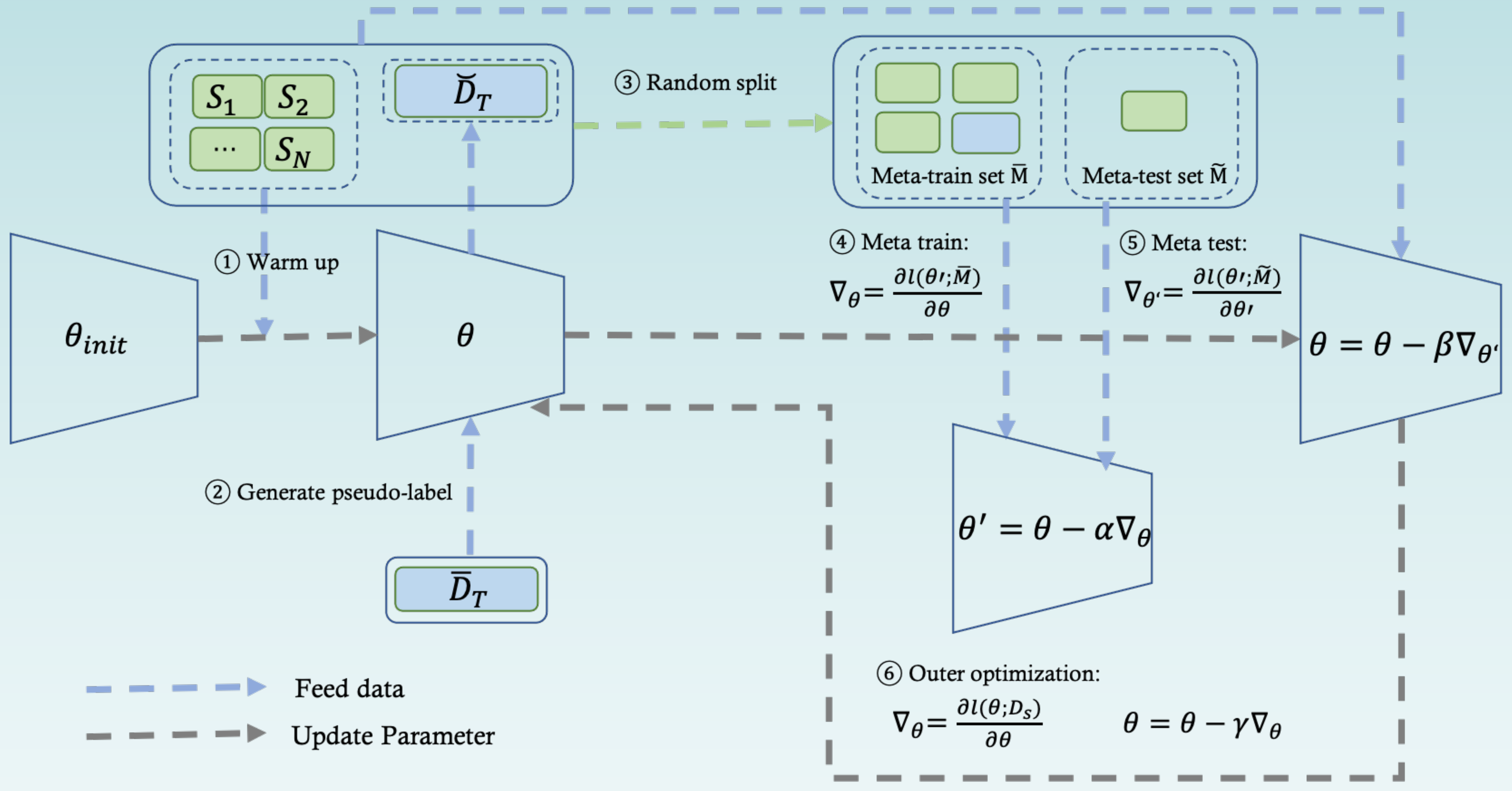
In this paper, we focus on the multi-source domain adaptation in text recognition area and mainly make three contributions:

- First, we collect a multi-source domain adaptation dataset for text recognition, which is the first multi-domain text recognition dataset to our best knowledge.
- Secondly, we propose a new method called Meta Self-Learning, which achieves a better recognition result under the scene of multi-domain adaptation.
- Thirdly, extensive experiments are conducted on the dataset to provide a benchmark and also show the effectiveness of our method.

Dataset

- First dataset for multi-domain text recognition with 5 million images
- Five different domains: synthetic domain, document domain, street view domain, handwritten domain and car license domain.
- A wide variety of length, appearance and corpus.

Meta Self-Learning Method



Algorithm Description

① The data from source domains with labels $\boldsymbol{D_s}$ are used for warm-up, which is very important for self-learning method.

② The model is evaluated on the target domain data without labels $\bar{\boldsymbol{D}}_{\boldsymbol{T}}$ and generates pseudo-labels.

③ The target domain data with pseudo-labels $\breve{\boldsymbol{D}}_{\boldsymbol{T}}$ and $\boldsymbol{D_s}$ are split randomly as $\bar{\boldsymbol{M}}$ and $\tilde{\boldsymbol{M}}$.

④ Use $\bar{\boldsymbol{M}}$ for meta-train, the parameter is updated as $\theta' = \theta - \alpha \frac{\partial l(\theta; \bar{M})}{\partial \theta}$

⑤ Use $\tilde{\boldsymbol{M}}$ for meta-test, the parameter is updated as $\theta = \theta - \beta \frac{\partial l(\theta'; \tilde{M})}{\partial \theta'}$

⑥ Use a subet of $\boldsymbol{D_s}$ and $\breve{\boldsymbol{D}}_{\boldsymbol{T}}$ for outer optimization, $\theta = \theta - \gamma \frac{\partial l(\theta; D_s)}{\partial \theta}$

Experiment Result

	St,Sy,D,H→C	St,Sy,D,C→H	St,Sy,C,H→D	C,St,D,H→Sy	C,Sy,D,H→St	Average
Source Only	22.43%	3.50%	29.39%	24.75%	9.24%	17.86%
MLDG [16]	23.85%	3.39%	30.31%	25.11%	12.46%	19.02%
Pseudo-Label [14]	44.97%	3.77%	51.60%	54.11%	15.00%	33.89%
Meta Self-Learning (Ours)	**58.64%**	**5.41%**	**64.09%**	**65.33%**	**16.52%**	**42.00%**

Fig 1. Experiment results of different methods on our dataset

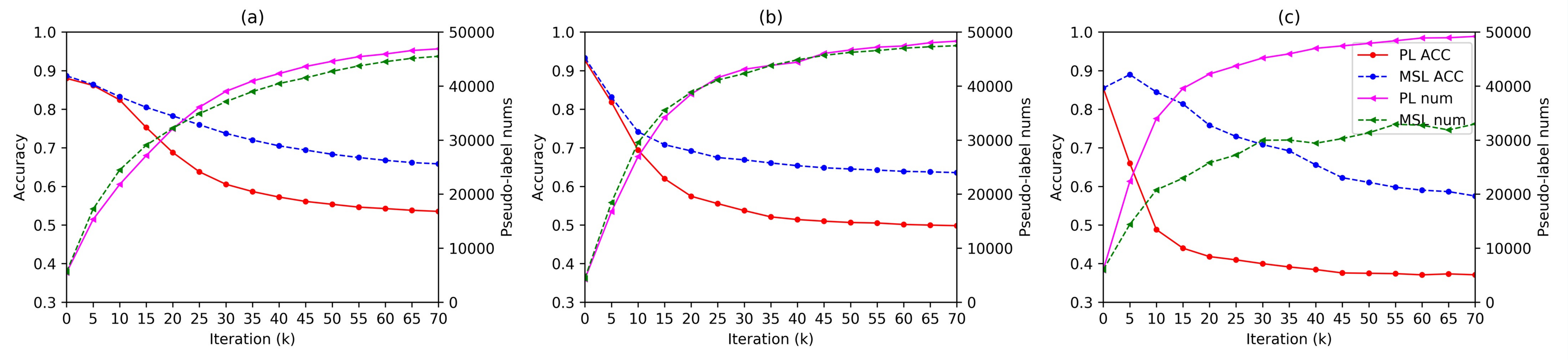


Fig 2. Accuracy of pseudo-label during training of our method and baseline

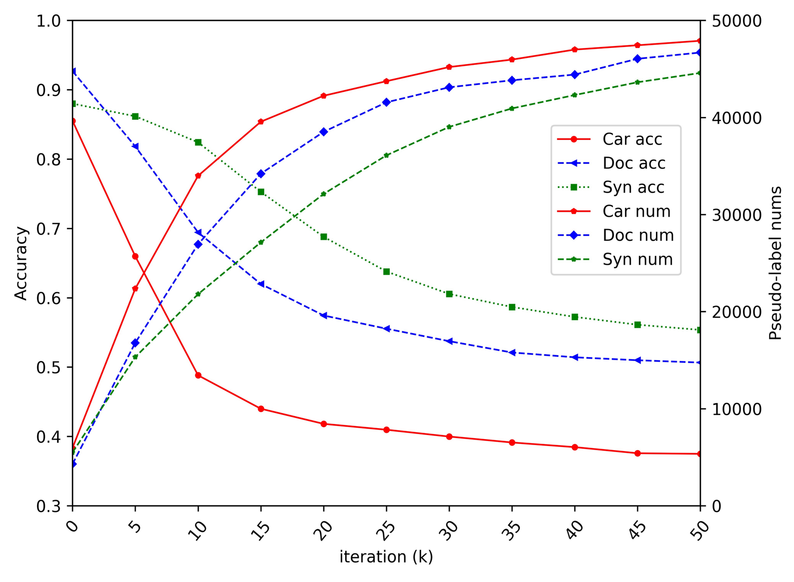


Fig 3. Accuracy of pseudo-label during training for different domain

- Figure 1 shows that our method brings up to 13.67% gain and 8.11% gain on average accuracy compared with the vanilla pseudo-label method
- Figure 2 shows that our method greatly improves the accuracy of pseudo-label compared with the baseline.
- Figure 3 shows the difference of pseudo-label quality among different domains

Application & Future Work

- Our method is a self-learning framework and is model-agnostic, therefore can be easily applied to any task.
- Our dataset is still challenging in some domains (the average accuracy is only 42.00%), therefore remains room for improvement for researchers.