Distilling and Refining Domain-Specific Knowledge for Semi-Supervised Domain Adaptation

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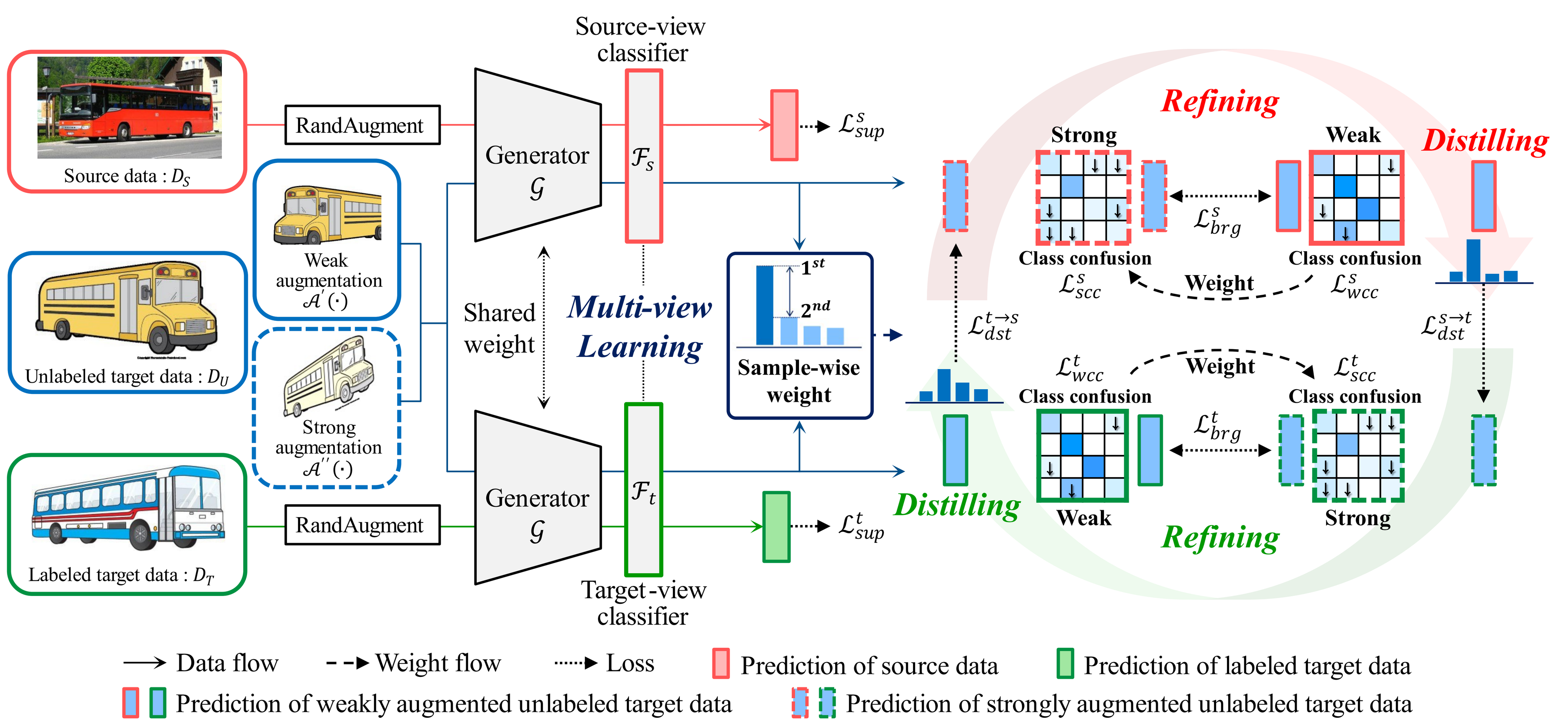
Introduction

▶ **Key factors that determine the performance of semi-supervised domain adaptation (SSDA)**

- **1. The efficiency of using partially labeled target samples**
  - When the model is trained with the mixed labeled samples from different domains, an imbalance problem in which the labeled source samples dominate the training can occur.
- **2. Quality of domain alignment between the source and target domains (Inter-and intra-domain alignment)**
  - If only the inter-domain alignment is considered without intra-domain alignment, the performance can not increase successfully since low-density distributions for each class in the target domain can be generated.

Proposed method



▶ **Multi-view learning for domain-specific knowledge**

- To prevent a bias problem from imbalanced data and to extract the domain-specific knowledge from the labeled data, we separate the training pipeline of D_S and D_T into <u>the source-and target-view classifiers</u>, respectively.

▶ ***Distilling* strategy for inter-and intra-domain alignment**

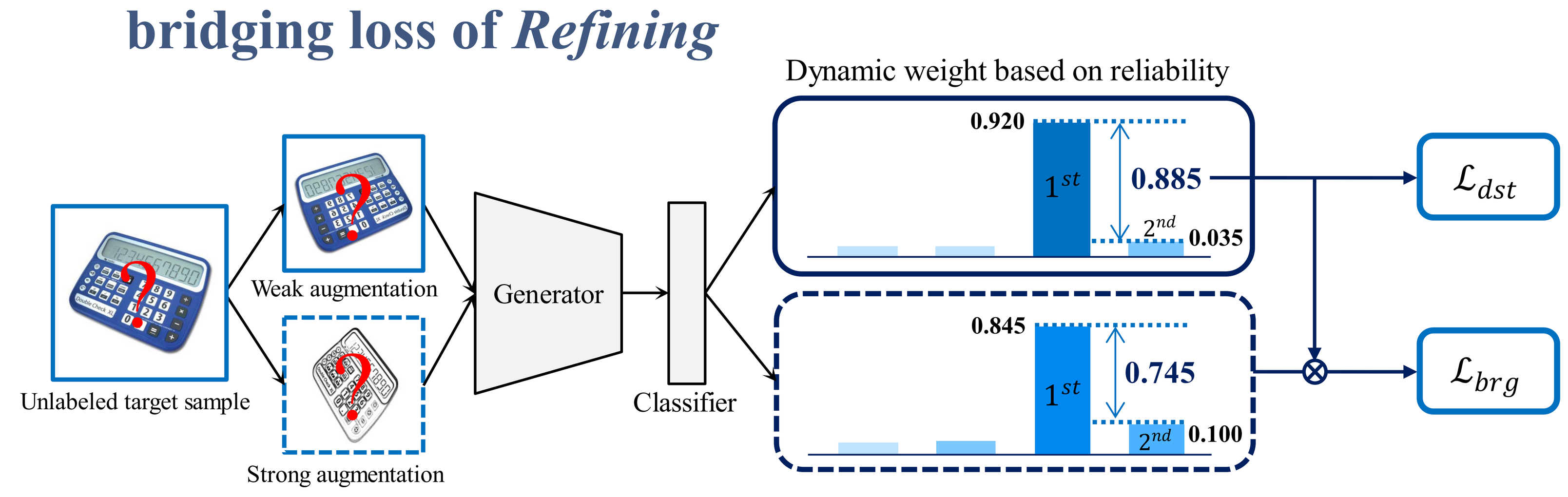
- The classifiers $\mathcal{F}_s$ and $\mathcal{F}_t$ exchange each domain-specific knowledge using <u>cross-view consistency regularization</u>.
  - We use <u>soft labels</u> for pseudo labels to deliver the inter-and intra-class information without information loss for flexibility.
  - We apply <u>label smoothing</u> to reduce the negative effects caused by of uncertain training at the beginning of training.
  - We utilize <u>proposed sample-wise dynamic weights</u> for each sample are applied to utilize information from low-reliability data with a reduced negative effect.

▶ ***Refining* strategy for intra-domain alignment**

- *Distilling* → The model can have class confusion by large intra-class variance and small inter-class variance.
- We propose *Refining* to perform evolutional intra-domain alignment through a class-wise alignment to use <u>minimizing class confusion loss for differently augmented unlabeled target data</u>.
  - To alleviate the negative effect of dark knowledge of strongly augmented unlabeled target data, we employ <u>bridging loss</u> and <u>dynamic weight for progressive activation</u>.

▶ **Dynamic weight based on reliability**

- **We propose a novel sample-wise dynamic weight based on prediction reliability (SDWR) for the loss functions of unlabeled samples using the first and second largest prediction values of classes.**
  - Information from low-confidence samples for *Distilling*
  - Progressive weight based on the model performance for bridging loss of *Refining*



Experimental Results

▶ **Comparison with State-of-the-art Methods**

- **Tables shows classification accuracies of DARK and benchmark methods for DomainNet.**

Methods	R → C	R → P	P → C	C → S	S → P	R → S	P → R	Mean
MME [30]	70.0	67.7	69.0	56.3	64.8	61.0	76.1	66.4
APE [9]	70.4	70.8	72.9	56.7	64.5	63.0	76.6	67.8
PAC [20]	74.9	73.0	72.6	65.8	67.9	68.7	76.7	71.4
CDAC [13]	77.4	74.2	75.5	67.6	71.0	69.2	80.4	73.6
ASDA [28]	77.0	75.4	75.5	66.5	72.1	70.9	79.7	73.9
CLDA [32]	76.1	75.1	71.0	63.7	70.2	67.1	80.1	71.9
DECOTA [38]	**79.1**	74.9	76.9	65.1	72.0	69.7	79.6	73.9
DARK (ours)	78.3	**77.9**	**79.1**	**71.8**	**75.1**	**72.5**	**84.4**	**77.0**

Quantitative results on DomainNet of 1-shot setting using ResNet-34.

Methods	R → C	R → P	P → C	C → S	S → P	R → S	P → R	Mean
MME [30]	72.1	69.7	71.7	61.8	66.8	61.9	78.5	68.9
APE [9]	76.6	72.1	76.7	63.1	66.1	67.8	79.4	71.7
PAC [20]	78.6	74.3	76.0	69.6	69.4	70.2	79.3	73.9
CDAC [13]	79.6	75.1	79.3	69.9	73.4	72.5	81.9	76.0
ASDA [28]	79.4	76.7	78.3	70.2	74.2	72.1	82.3	76.2
CLDA [32]	77.7	75.7	76.4	69.7	73.7	71.1	82.9	75.3
DECOTA [38]	**80.4**	75.2	78.7	68.6	72.7	71.9	81.5	75.6
DARK (ours)	79.4	**78.6**	**81.0**	**74.8**	**77.4**	**73.8**	**85.4**	**78.6**

Quantitative results on DomainNet of 3-shot setting using ResNet-34.

▶ **Visualization**

- **The effectiveness of the *Distilling* and *Refining* startegies**

Before domain adaptation — *Distilling* — *Distilling* and *Refining*

Conclusion

▶ **We introduce DARK for SSDA tasks with *distilling* and *Refining* domain-specific knowledge strategy.**

▶ **We prove that the components of our method are necessary to improve the performance of each other and that our approach is more effective compared with other benchmark methods.**

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