Reliable Weighted Optimal Transport for Unsupervised Domain Adaptation

Renjun Xu*, Pelen Liu, Liyan Wang, Chao Chen
Zhejiang University, China

Jindong Wang
Microsoft Research

1. Experiment

The residual experiment results of *ImageNet-Caltech* are reported in Table 1. Our proposal outperforms the comparison methods on most transfer tasks, indicating that weighted optimal transport strategy based on shrinking subspace reliability can achieve intra-class compactness and inter-class separability. The unsupervised adaptation results of *Office-Home* are reported in Table 2. We can observe that RWOT significantly outperforms all previous methods on most tasks. It is worth noting that our proposal improves the classification accuracy substantially on hard transfer tasks, *e.g.* **Ar** $\rightarrow$ **Cl** and **Ar** $\rightarrow$ **Rw** that the source and target domains are remarkably different. It is noteworthy that our model outperforms CDAN [5] and TPN [6] that indicates the efficacy of our approach. Since the four domains in *Office-Home* are visually more dissimilar with each other, the difficulties still exist in the intra-domain alignment, as shown in Figure 1. Category agnostic may lead to the imperfect marginal alignment and subspace breakdown of the conditional alignment. Indeed, our proposal yields larger boosts on such difficult domain adaptation tasks, which demonstrates the power of discriminative subspace matching based on reliable intra-domain probability information.

Feature visualization To show the feature transferability, we visualize the t-SNE embeddings [4] of the bottleneck representation by TPN and CDAN on **A**$\rightarrow$**D** task in *Office-31*. Figure 2(a)-2(b) show that the features learned by TPN that indicates that the prototypical distance improves the performance of domain adaptation. However, without exploiting intra-domain structure for the pseudo label, some target samples near the decision boundary are mixed up, leading to negative transfer. Figure 2(c)-2(d) shows that deep features learned by CDAN, which indicates that the conditional adversarial network can achieve high accuracy. Nevertheless, indiscriminative representations of scattered target samples cause misclassification. The significant visualization results suggest that our proposal can match the complex structures of the source and target domains and maximize the margin between different classes.

*Corresponding author: rux@zju.edu.cn

Figure 1. The sample images from the *Office-Home* dataset. The dataset consists of 4 domains of 65 categories. Art: paintings, sketches or artistic depictions. Clipart: clipart images. Product: images without background and Real-World: regular images captured with a camera.

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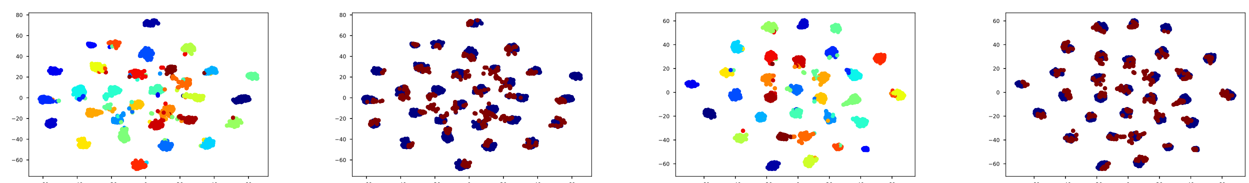
Table 1. Classification accuracy (%) on *ImageNet-Caltech* for unsupervised domain adaptation (ResNet)

Method	C→I	C→P	I→C	I→P	P→C	P→I	Avg
ResNet [3]	78.0±0.3	65.5±0.4	91.5±0.3	74.8±0.3	91.2±0.1	83.9±0.2	80.8
DeepCORAL [7]	85.5±0.2	69.0±0.2	92.0±0.4	75.1±0.2	91.7±0.2	85.5±0.2	83.1
DANN [1]	87.0±0.1	74.3±0.2	96.2±0.3	75.0±0.4	91.5±0.2	86.0±0.3	85.0
ADDA [8]	89.1±0.2	75.1±0.4	96.5±0.3	75.5±0.3	92.0±0.3	88.2±0.2	86.0
CDAN [5]	91.3±0.3	74.2±0.2	97.7±0.3	77.7±0.1	94.3±0.3	90.7±0.2	88.0
TPN [6]	90.8±0.3	76.2±0.4	96.1±0.2	78.2±0.2	95.1±0.2	92.1±0.1	88.1
DeepJDOT [2]	88.3±0.2	74.9±0.4	95.0±0.1	77.5±0.2	94.2±0.1	90.5±0.1	86.7
RWOT	**92.7**±0.1	**79.1**±0.2	**97.9**±0.1	**81.3**±0.2	**96.5**±0.3	**92.9**±0.2	**90.0**

Table 2. Classification accuracy (%) on *Office-Home* for unsupervised domain adaptation (ResNet)

Method	Ar→Cl	Ar→Pr	Ar→Rw	Cl→Pr	Cl→Pr	Cl→Rw	Pr→Ar	Pr→Cl	Pr→Rw	Rw→Ar	Rw→Cl	Rw→Pr	Avg
ResNet [3]	34.9	50.0	58.0	37.4	41.9	46.2	38.5	31.2	60.4	53.9	41.2	59.9	46.1
DANN [1]	43.6	57.0	67.9	45.8	56.5	60.4	44.0	43.6	67.7	63.1	51.5	74.3	56.3
CDAN [5]	50.7	70.6	76.0	57.6	70.0	70.0	57.4	**50.9**	77.3	**71.1**	**56.7**	81.6	65.8
TPN [6]	51.2	71.2	76.0	**65.1**	**72.9**	72.8	55.4	48.9	76.5	70.9	53.4	80.4	66.2
DeepJDOT [2]	48.2	69.2	74.5	58.5	69.1	71.1	56.3	46.0	76.5	68.0	52.7	80.9	64.3
RWOT	**55.2**	**72.5**	**78.0**	63.5	72.5	**75.1**	**60.2**	48.5	**78.9**	69.8	54.8	**82.5**	**67.6**



(a) TPN (b) TPN (c) CDAN (d) CDAN

Figure 2. The t-SNE visualization of **A**→**D** tasks. Figure (a-d) represents category information (Each color denotes a class). Figure (e-h) represents domain information (Blue: Source domain; Red: Target domain).

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