MAPPING CONDITIONAL DISTRIBUTIONS FOR DOMAIN ADAPTATION UNDER GENERALIZED TARGET SHIFT

ICLR 2022

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Introduction

Problem definition

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Unsupervised Domain Adaptation (UDA)

Train a good classifier $h : \mathcal{X} \rightarrow \mathcal{Y}$ for an **unlabelled** target domain T given a labelled source domain S.

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Generalized Target Shift

We consider the most challenging UDA setting, Generalized target shift (`GeTarS`) Zhang et al. 2013 where:

$$p_S(X|Y) \neq p_T(X|Y), p_S(Y) \neq p_T(Y)$$

UDA under generalized target shift

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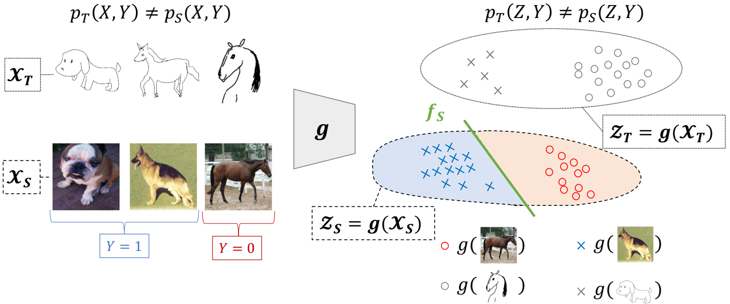

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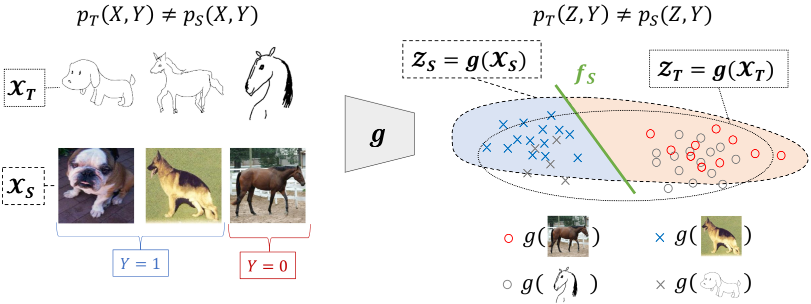

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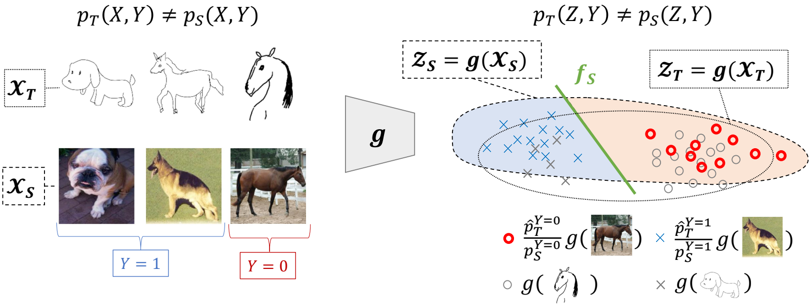
- Learn g to match encoded S and T samples.
- Under GeTarS, reweight S samples by estimated class-ratios.

Combes et al. 2020; Gong et al. 2016; Rakotomamonjy et al. 2021; Shui et al. 2021



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    - unicity of the solution.

OSTAR framework

Optimal Sample Transport and Reweight (OSTAR) (I)

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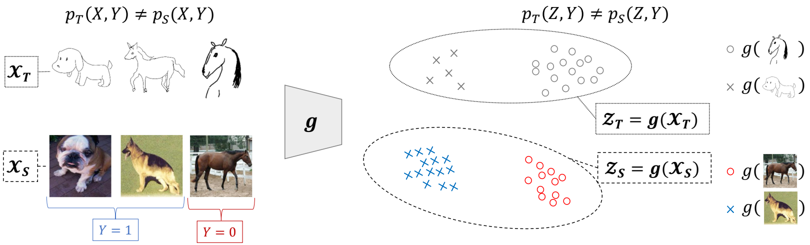
Objectives

- Encode input S and T samples with g



Optimal Sample Transport and Reweight (OSTAR) (I)

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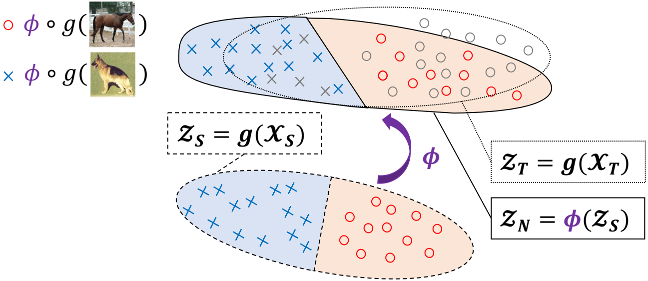
Objectives

- With fixed representations jointly
  1. Map encoded S samples onto T with ϕ under OT constraints.



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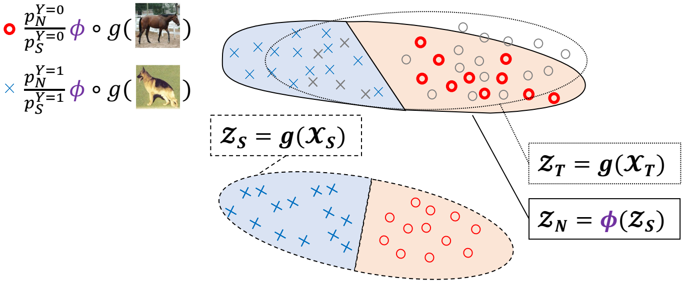
  2. Reweight mapped S samples with class-ratio estimates $\boldsymbol{p}_N^Y / \boldsymbol{p}_S^Y$.



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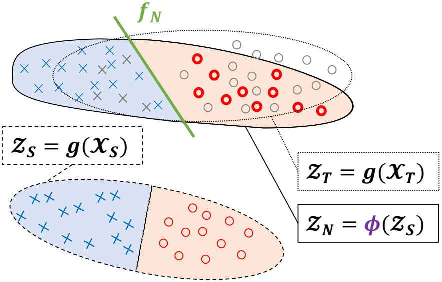
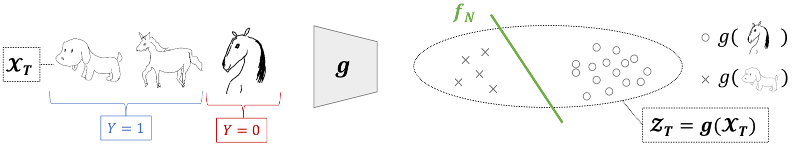
3. Train classifier f_N on reweighted and mapped S samples



Optimal Sample Transport and Reweight (OSTAR) (I)

Objectives

- Use f_N for inference on encoded T samples.



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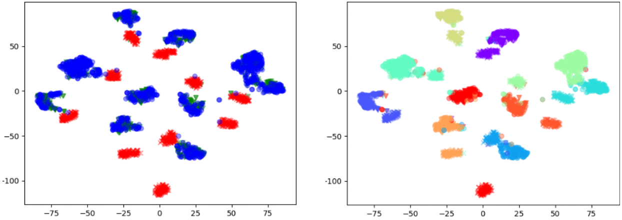
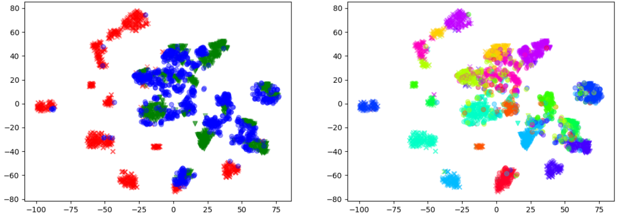
  - Its solution $(\phi, \boldsymbol{p}_N^Y)$ is unique.

Results

t-SNE feature visualizations



(a) USPS→MNIST



(b) VisDA

(left) source, target and mapped source. (right) classes in source and target.

Performance on visual UDA datasets

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Balanced accuracy (↑) over 10 runs with best performance in **bold**.
Results are aggregated over imbalance scenarios and datasets.

Setting	Source	DANN	$WD_{\beta=0}$	$WD_{\beta=1}$	$WD_{\beta=2}$	MARSg	MARSc	IW-WD	OSTAR+IM
					Digits				
balanced	74.98 ± 3.8	90.81 ± 1.3	92.63 ± 1.0	82.80 ± 4.7	76.07 ± 7.1	92.18 ± 2.2	94.91 ± 1.4	95.89 ± 0.5	**97.51 ± 0.3**
subsampled	75.05 ± 3.1	89.91 ± 1.5	89.45 ± 1.0	81.56 ± 4.8	77.77 ± 6.5	91.87 ± 2.0	93.75 ± 1.4	93.22 ± 1.1	**96.69 ± 0.7**
					VisDA12				
original	48.63 ± 1.0	53.72 ± 0.9	57.40 ± 1.1	47.56 ± 0.8	36.21 ± 1.8	55.62 ± 1.6	55.33 ± 0.8	51.88 ± 1.6	**59.24 ± 0.5**
subsampled	42.46 ± 1.4	47.57 ± 0.9	47.32 ± 1.4	41.48 ± 1.6	31.83 ± 3.0	55.00 ± 1.9	51.86 ± 2.0	50.65 ± 1.5	**58.84 ± 1.0**
					Office31				
subsampled	74.50 ± 0.5	76.13 ± 0.3	76.24 ± 0.3	74.23 ± 0.5	72.40 ± 1.8	80.20 ± 0.4	80.00 ± 0.5	77.28 ± 0.4	**82.61 ± 0.4**
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subsampled	50.56 ± 2.8	50.87 ± 1.05	53.47 ± 0.7	52.24 ± 1.1	49.48 ± 1.3	56.60 ± 0.4	56.22 ± 0.6	54.87 ± 0.4	**59.51 ± 0.4**

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Same trends for target label estimation error $\|\boldsymbol{p}_N^Y - \boldsymbol{p}_T^Y\|_1$.

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Domain-invariant baselines designed for:

- Covariate shift w/o reweighting (DANN Ganin et al. 2016, $WD_{\beta=0}$ Shen et al. 2018).
- GeTarS with reweighting ($WD_{\beta\in\{1,2\}}$ Wu et al. 2019, MARS Rakotomamonjy et al. 2021; IW-WD Combes et al. 2020).

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Thank you for your attention !

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