Indian Institute of Science
Bangalore, India
भारतीय विज्ञान संस्थान
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Balancing Discriminability and Transferability for Source-Free Domain Adaptation

Jogendra Nath Kundu*[1] Akshay Kulkarni*[1] Suvaansh Bhambri*[1]
Deepesh Mehta[1] Shreyas Kulkarni[1]
Varun Jampani[2] R. Venkatesh Babu[1]

[1]Indian Institute of Science [2]Google Research

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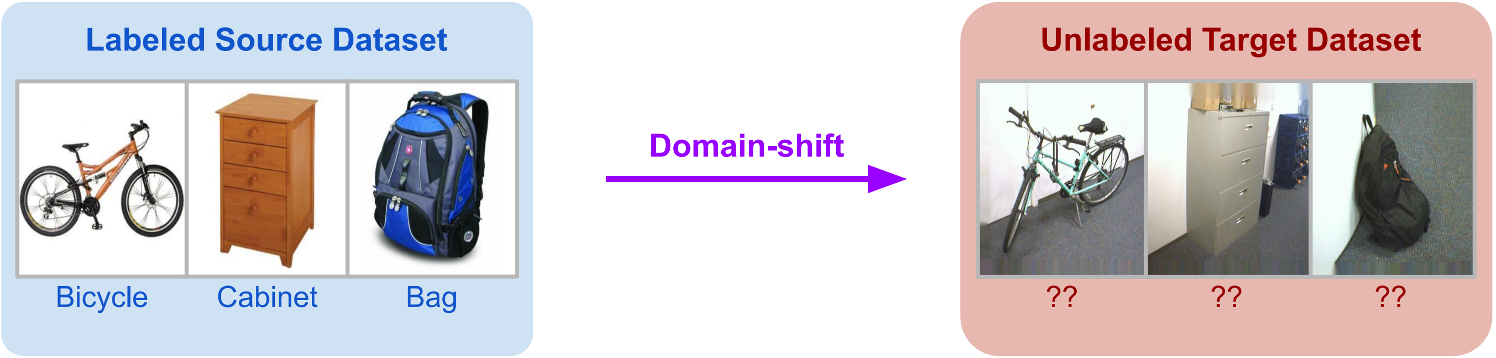
VIDEO ANALYTICS LAB

* Equal contribution

Google

Unsupervised Domain Adaptation (DA)[1]

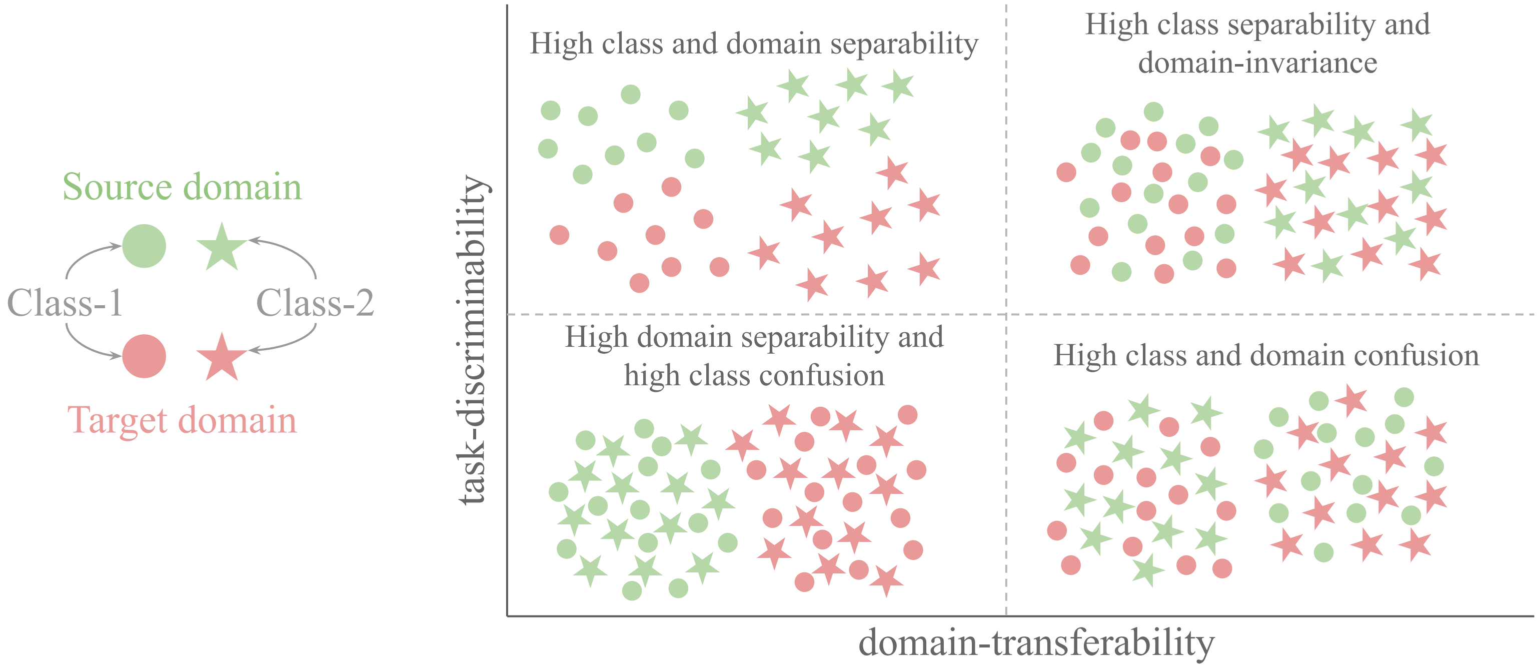
- Problem: Transfer of knowledge from a *labeled* source domain to an *unlabeled* target domain under domain-shift



[1] Long *et al.*, "Learning Transferable Features with Deep Adaptation Networks", ICML '15

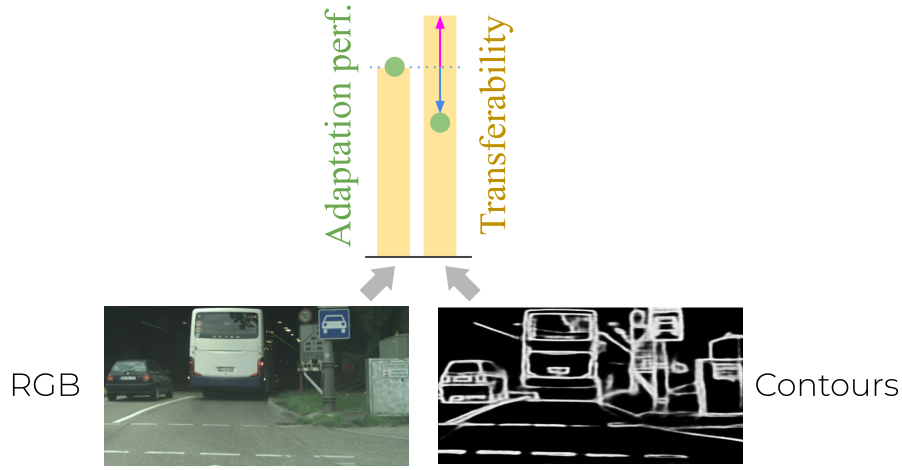
Preliminaries: Discriminability and Transferability

- Task-Discriminability → Ease of separating different task-category features with a supervised classifier
- Domain-Transferability → Invariance of feature representations across domains



Preliminaries: Discriminability and Transferability tradeoff

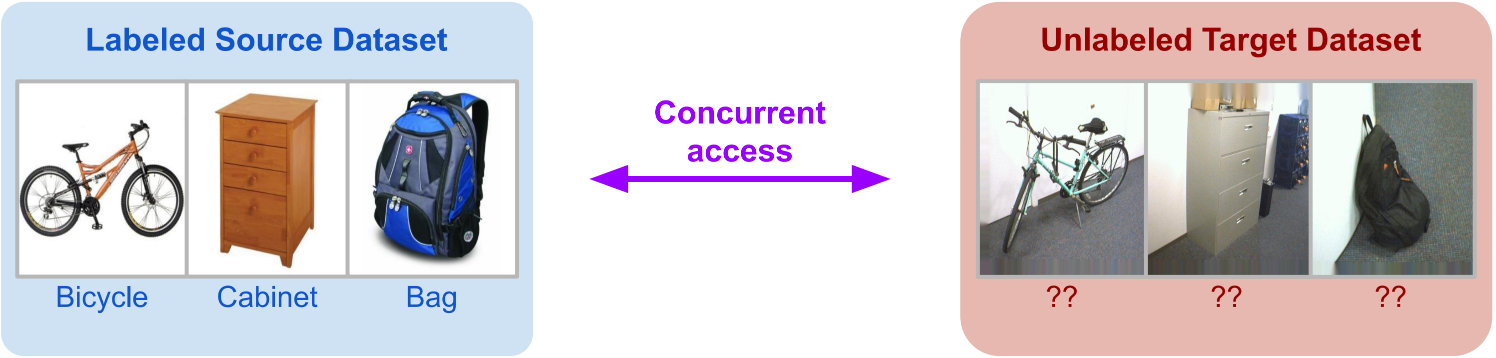
- Removing domain-specific info for better transferability may also lead to loss of entangled task-specific info
- Thus, exclusively improving transferability hurts discriminability and vice versa[3]
- Example: In semantic segmentation DA, contour features improve transferability but reduce discriminability



[3] Chen *et al.*, “Harmonizing Transferability and Discriminability for Adapting Object Detectors”, CVPR ‘20

Can we balance Discriminability and Transferability?

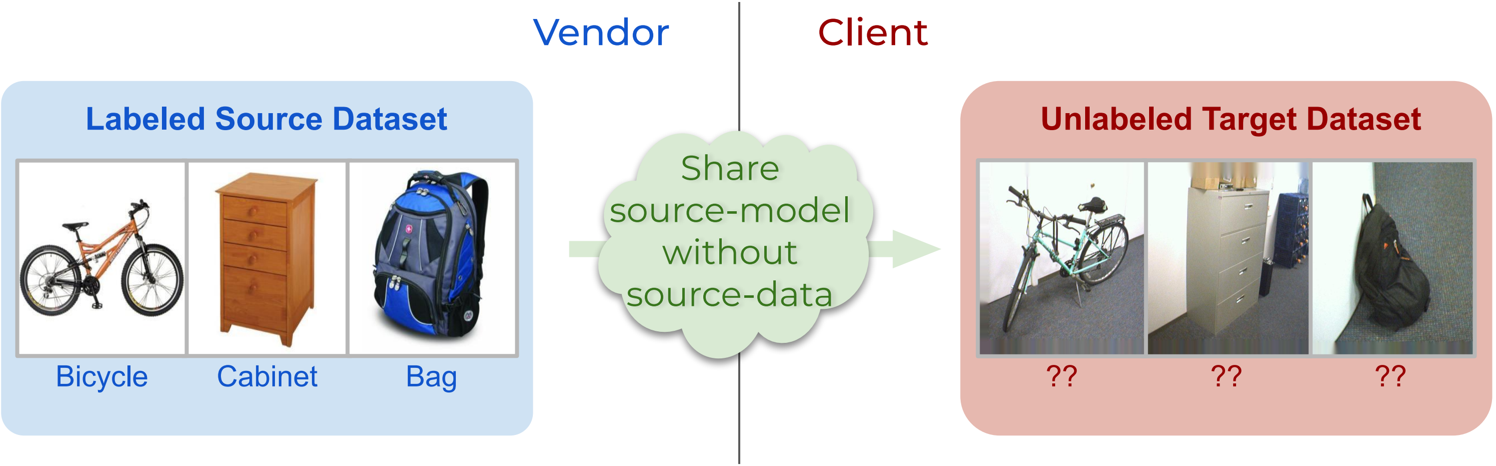
- Prior works[4, 5] propose modified adversarial DA to balance discriminability and transferability
- However, they require concurrent access to both source and target datasets



[4] Chen *et al.*, "Transferability vs. Discriminability: Batch Spectral Penalization for Adversarial DA", ICML '19
[5] Yang *et al.*, "Mind the Discriminability: Asymmetric Adversarial Domain Adaptation", ECCV '20

Can we balance Discriminability and Transferability?

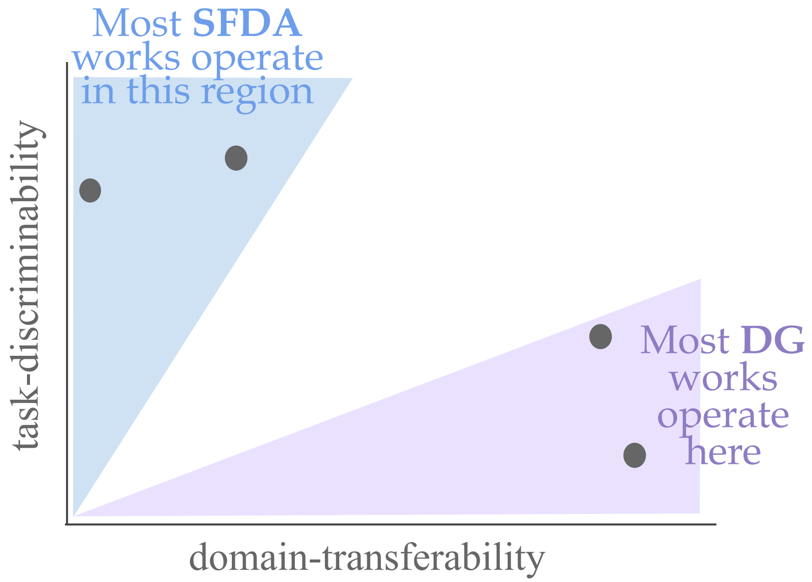
- Prior works[4, 5] propose modified adversarial DA to balance discriminability and transferability
- However, they require concurrent access to both source and target datasets
- These solutions are unsuitable for privacy-oriented source-free DA[6, 7] where data-sharing is restricted



[6] Li *et al.*, "Unsupervised Domain Adaptation without Source Data", CVPR '20
[7] Kundu *et al.*, "Towards Inheritable Models for Open-Set Domain Adaptation", CVPR '20

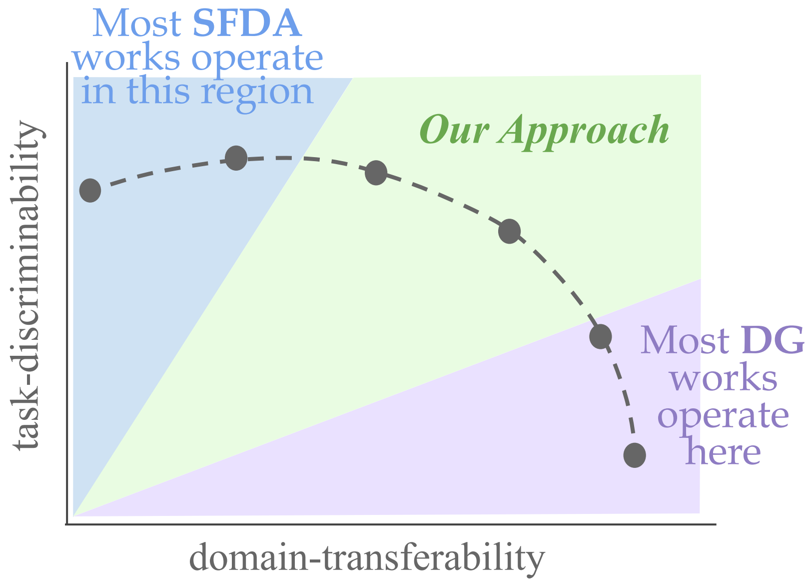
Analyzing existing Domain Generalization (DG) and Source-Free DA works

- SFDA works focus on preserving task-discriminability in the absence of labeled source data
- DG works focus on maximizing domain-transferability in the absence of target data



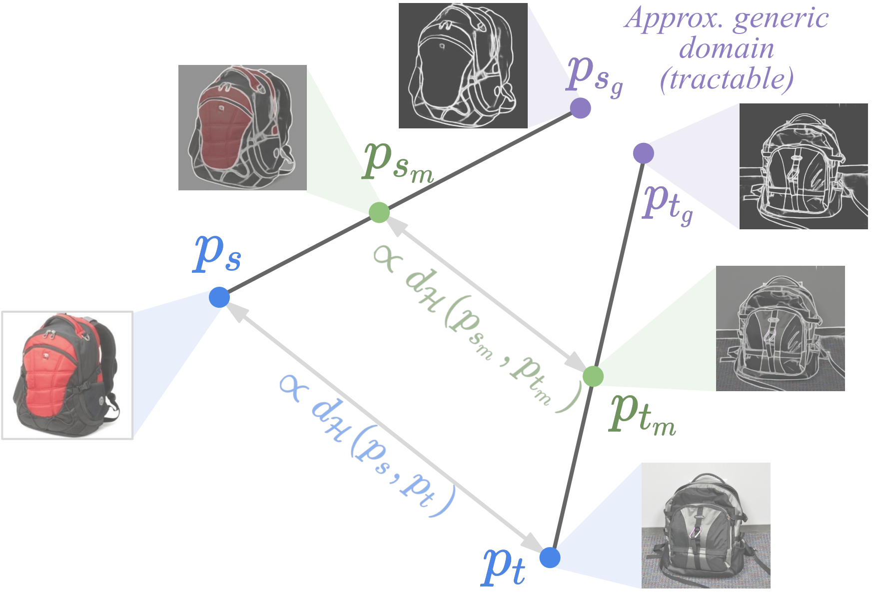
Why is striking a balance crucial in Source-Free DA (SFDA)?

- In the source-free setting, task-discriminability can only be gathered on the source-side
- The tradeoff becomes more severe as discriminability cannot be preserved with only unlabeled target data
- An explicit effort to improve the tradeoff (green region) could considerably benefit Source-Free DA



What are the key design aspects to improve the tradeoff in SFDA?

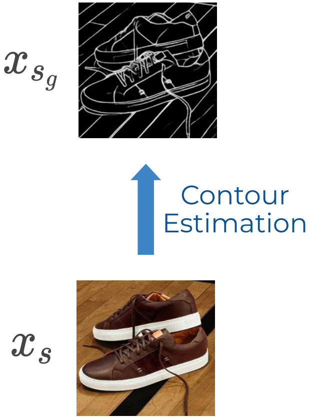
- Translate source and target to a generic-domain with both high transferability and discriminability
- In practice, source-to-generic and target-to-generic translations would result in a loss of discriminability
- We propose mixup between original domain samples and corresponding generic-domain translated samples



How to obtain the generic-domain samples?

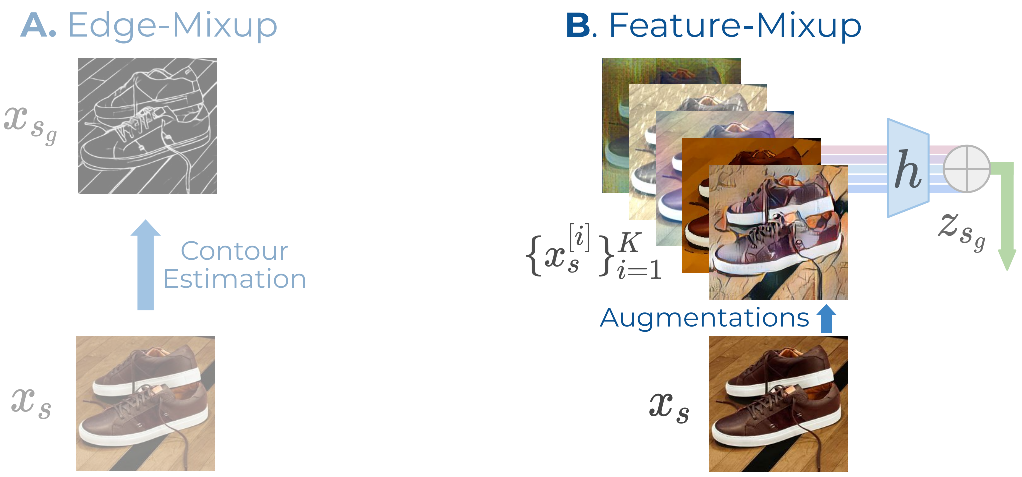
- A realizable generic-domain must possess features with high domain-transferability
- Edge representation as a generic-domain
  - Intuitively, edge representation preserves the shape information
  - And removes domain-variant information like color and texture

A. Edge-Mixup



How to obtain the generic-domain samples?

- A realizable generic-domain must possess features with high domain-transferability
- Feature-space generic-domain representation
  - We use a set of task-preserving image augmentations to simulate novel sub-domains
  - Augm. feature mean diffuses the domain-variance and is used as the generic-domain features

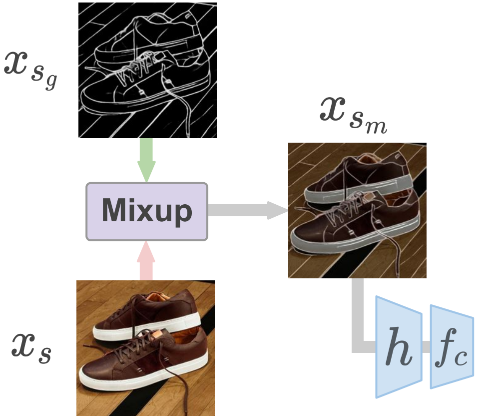


How to perform the mixup?

- Mixup of generic-domain samples with original samples
- Perform mixup as a convex combination with fixed mixup-ratio λ

$$x_{s_m} = \lambda x_{s_g} + (1 - \lambda) x_s \qquad\qquad z_{s_m} = \lambda z_{s_g} + (1 - \lambda) z_s$$

A. Edge-Mixup



B. Feature-Mixup

Training algorithm

- Our approach can be combined with any existing Source-Free DA algorithm
- Assume a vendor-side algorithm $\texttt{VsAlgo}(\mathcal{D}_s)$ that uses the original source dataset
- Assume a client-side algorithm $\texttt{CsAlgo}(\mathcal{D}_t)$ that uses the original target dataset
- We simply replace the original datasets with our proposed mixup datasets

$$\texttt{VsAlgo}(\mathcal{D}_{s_m}) \qquad \texttt{CsAlgo}(\mathcal{D}_{t_m})$$

Quantitative results (Image Classification DA)

- Single source domain adaptation
- Multi source domain adaptation

Method	SF	Office-31	VisDA
CDAN+RADA (Jin et al., 2021)	✗	91.1	76.3
FAA (Huang et al., 2021a)	✗	90.8	82.7
FixBi (Na et al., 2021)	✗	91.4	87.2
HCL (Huang et al., 2021b)	✓	87.6	83.5
CPGA (Qiu et al., 2021)	✓	89.9	84.1
A^{2}Net (Xia et al., 2021)	✓	90.1	84.3
VDM-DA (Tian et al., 2021)	✓	89.7	85.1
NRC (Yang et al., 2021a)	✓	89.4	85.9
Ours (edge-mixup) + NRC	✓	90.3 (+0.9)	86.4 (+0.5)
Ours (feat-mixup) + NRC	✓	90.5 **(+1.1)**	87.3 **(+1.4)**
SHOT++ (Liang et al., 2021)	✓	89.2	87.3
Ours (edge-mixup) + SHOT++	✓	90.2 (+1.0)	87.5 (+0.2)
Ours (feat-mixup) + SHOT++	✓	**90.7** **(+1.5)**	**87.8** **(+0.5)**

We demonstrate gains over SOTA across single-source, multi-source and also multi-target DA

Quantitative results (Image Classification DA)

- Single source domain adaptation
- Multi source domain adaptation

Method	SF	w/o Domain Labels	**DomainNet**	**Office-Home**
SImpAl_{50} (Venkat et al., 2020)	✗	✗	48.6	72.2
CMSDA (Scalbert et al., 2021)	✗	✗	50.4	76.6
DRT (Li et al., 2021b)	✗	✗	51.3	-
STEM (Nguyen et al., 2021)	✗	✗	53.4	-
Source-combine	✗	✓	44.4	66.9
SHOT (Liang et al., 2020)-Ens	✓	✗	46.2	74.3
DECISION (Ahmed et al., 2021)	✓	✗	45.9	75.5
CAiDA (Dong et al., 2021)	✓	✗	-	76.2
NRC (Yang et al., 2021a)*	✓	✓	47.4	74.7
Ours (edge-mixup) + NRC	✓	✓	49.6 (+2.2)	76.6 (+1.9)
Ours (feature-mixup) + NRC	✓	✓	**51.0 (+3.6)**	**77.4 (+2.7)**

We demonstrate gains over SOTA across single-source, multi-source and also multi-target DA

Quantitative results (Semantic Segmentation DA)

- Single source domain adaptation

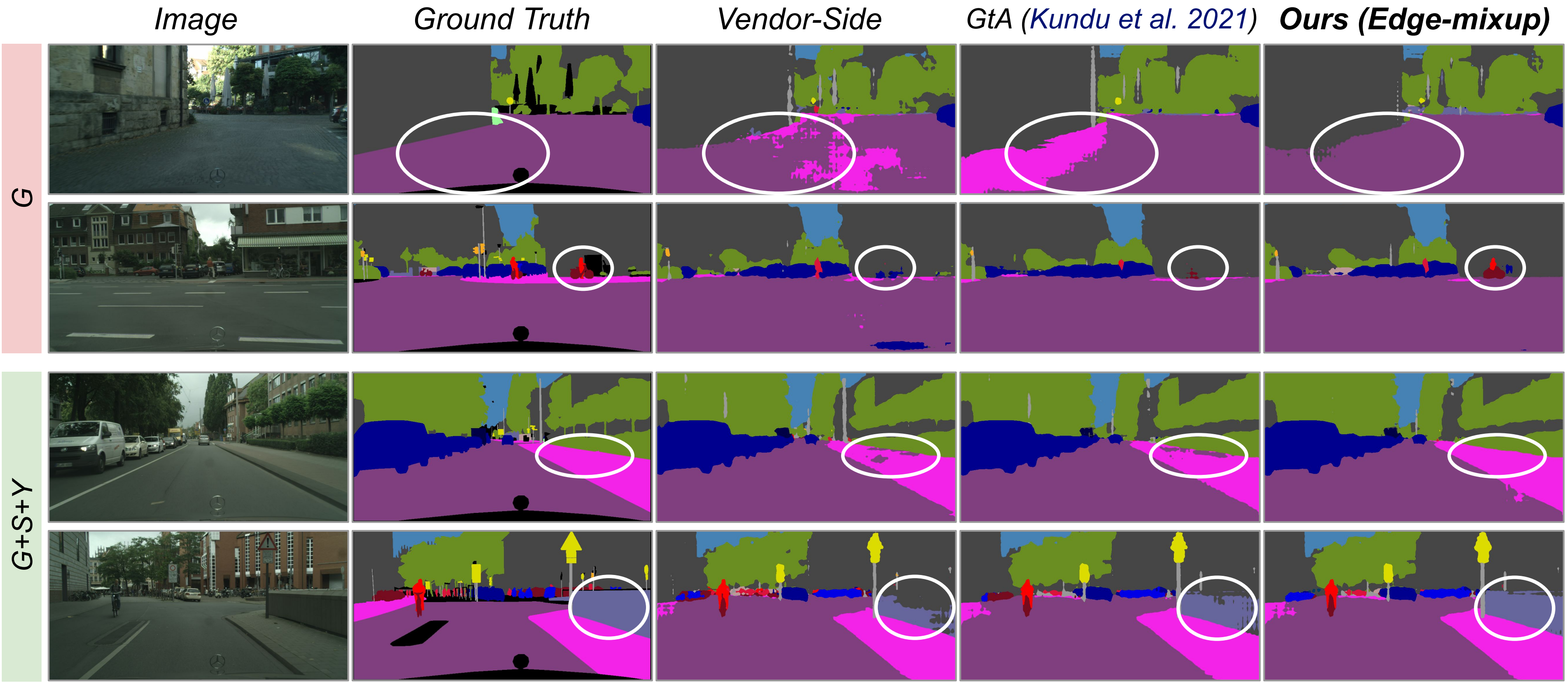
- Multi source domain adaptation

Method (→ **Cityscapes**)	SF	**SSDA**		**MSDA**				
		G	Y	G+S	S+Y	G+Y	G+S+Y	Avg
FDA (Yang et al. 2020)	✗	50.5	52.5	-	-	-	-	-
ProDA (Zhang et al., 2021)	✗	57.5	62.0	-	-	-	-	-
Src-combine (He et al., 2021)	✗	-	-	57.2	53.6	55.5	58.0	56.1
MSDA-CL (He et al., 2021)	✗	-	-	**65.8**	63.1	59.4	**67.1**	63.8
SFDA (Liu et al., 2021)	✓	43.1	45.9	-	-	-	-	-
URMA (Teja et al., 2021)	✓	45.1	45.0	-	-	-	-	-
SFUDA (Ye et al., 2021)	✓	49.4	51.9	-	-	-	-	-
GtA (Kundu et al., 2021)	✓	51.6	55.5	63.5	62.8	58.3	63.4	62.0
Ours (feature-mixup)	✓	51.9 +0.3	55.6 +0.1	63.6 +0.1	63.2 +0.4	61.4 +3.1	64.3 +0.9	63.1 +1.1
Ours (edge-mixup)	✓	**52.6** **+1.0**	**56.7** **+1.2**	64.6 **+1.1**	**65.4** **+2.6**	**61.8** **+3.5**	64.9 **+1.5**	**64.2** **+2.2**

Source datasets
- G ⟶ GTA5
- S ⟶ Synscapes
- Y ⟶ SYNTHIA

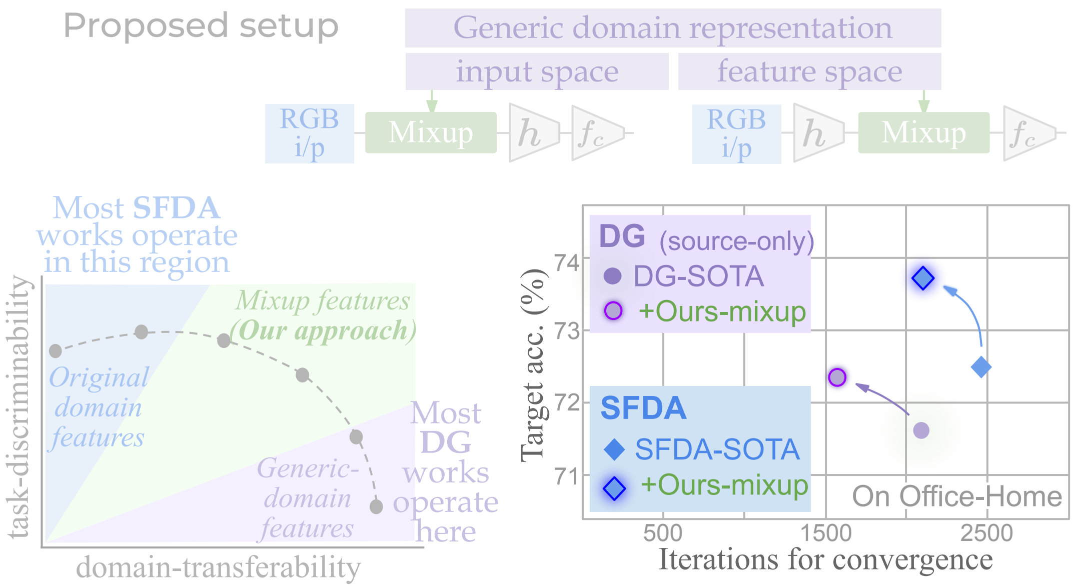
Unlike in Clsf-DA, Edge-Mixup is better suited for dense prediction DA tasks

Qualitative results (Semantic Segmentation DA)



Balancing Discriminability and Transferability in Source-Free DA

- We analyze existing DG and SFDA works in terms of Discriminability and Transferability
- To strike a balance, we propose mixup between discriminable original samples and transferable generic samples
- We achieve SOTA performance with faster convergence across multiple source-free DA settings and tasks



Thanks!

Balancing Discriminability and Transferability for Source-Free Domain Adaptation

Please check our project page for more details

https://sites.google.com/view/mixup-sfda

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