UC San Diego

Visual Intelligence Lab

Instance Level Affinity-Based Transfer for Unsupervised Domain Adaptation

Astuti Sharma, Tarun Kalluri, Manmohan Chandraker

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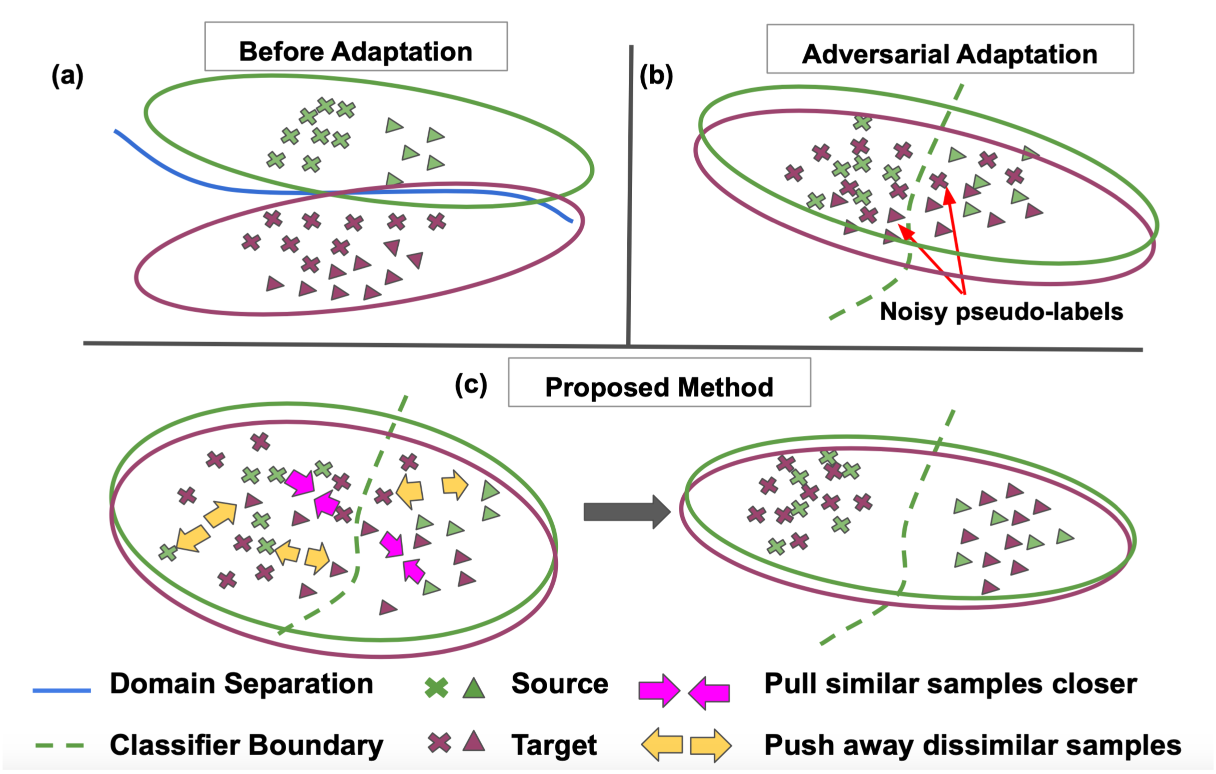
Overview: Instance Level Affinity-Based Transfer

Improve transferability and increase accuracy on unlabeled target domain of a model trained on labelled source domain and unlabeled target domain.

- ✓ Complementary improvements to adversarial domain adaptation methods.
- ✓ Leverages sample level relationships useful for adaptation.



Challenges

This work addresses the following challenges-

- ➢ Domain Adaptation: Prior works on this only align global distributions. This does not guarantee alignment between the respective categories which might lead to negative transfer.
- ➢ Class Specific Adaptation: The performance of these methods is dependent on the pseudo-labeling hypothesis, leading to noisy predictions near the classifier boundaries.
- ➢ Metric Learning for Unsupervised Domain Adaptation: Prior works require complex sample strategies or do not leverage instance level relations.

Approach

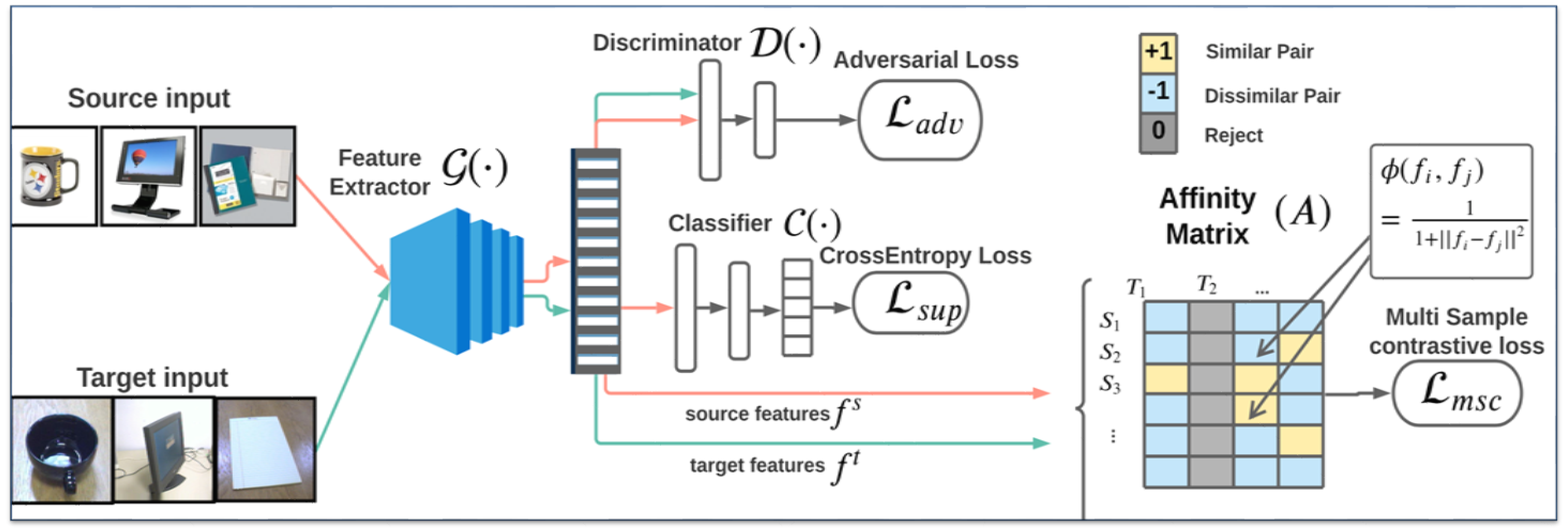
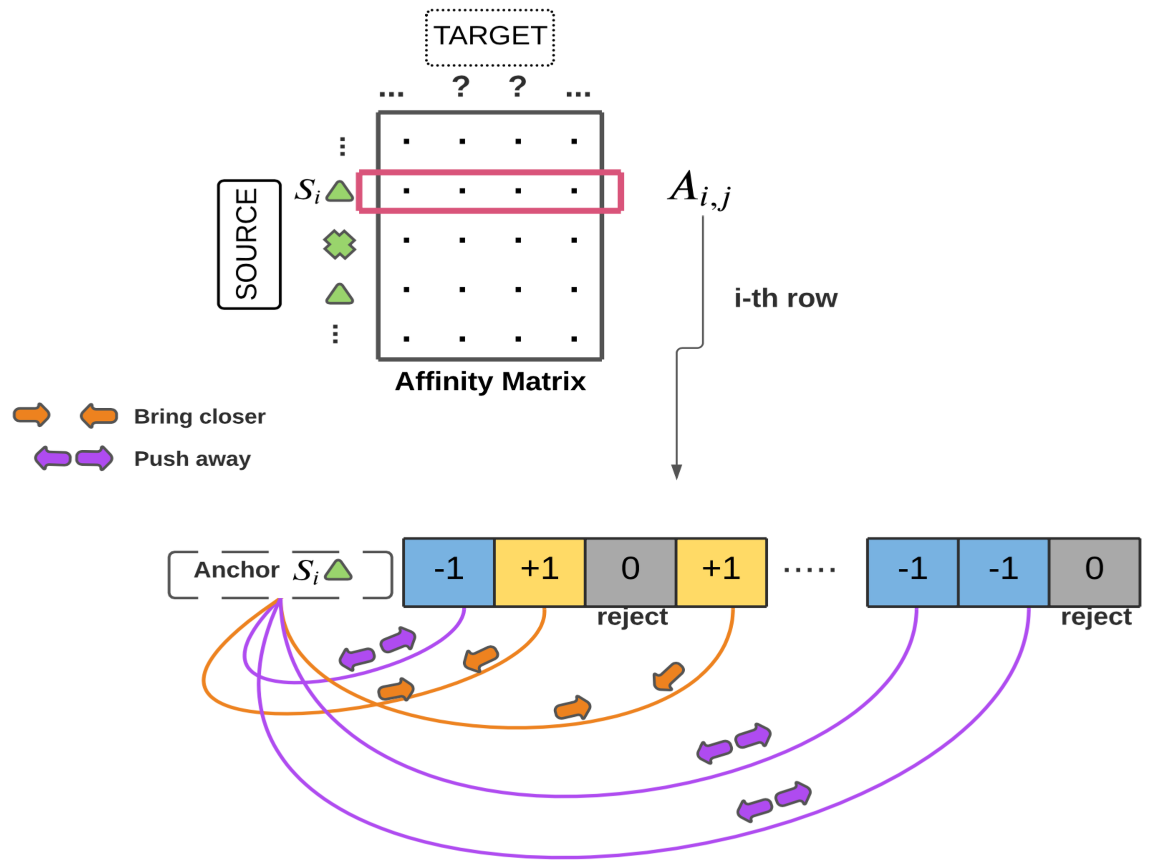


Illustration of Instance Affinity Matrix



I^{th} row of affinity matrix A contains similarity information of I^{th} source sample with every target sample in a mini-batch. MSC loss uses these relations to attract positive sample from target while separating negative ones.

Training Objective

Total Loss

$$\min_{\mathcal{G},\mathcal{C}} \mathcal{L}_{sup} + \lambda_1 \mathcal{L}_{adv} + \lambda_2 \mathcal{L}_{MSC}$$

$$\min_{\mathcal{D}} \mathcal{L}_D$$

$$\mathcal{L}_D = -\mathbb{E}_{x\sim\mathcal{D}^s}[\log \mathcal{D}(\mathcal{G}(x))] - \mathbb{E}_{x\sim\mathcal{D}^t}[\log(1-\mathcal{D}(\mathcal{G}(x)))].$$

$$\mathcal{L}_{adv} = \mathbb{E}_{x\sim\mathcal{D}^t}[-\log \mathcal{D}(\mathcal{G}(x))],$$

$$\mathcal{L}_{MSC} = \frac{1}{|B_S|}\sum_{i \in B_S} \mathcal{L}^i_{MSC}.$$

$$\mathcal{L}^i_{MSC} = -\log \frac{\sum_{j\in B_T^{i+}} e^{\phi(f_i,f_j)}}{\sum_{j\in B_T^{i+}} e^{\phi(f_i,f_j)} + \sum_{j\in B_T^{i-}} e^{\phi(f_i,f_j)}},$$

$$\mathcal{L}_{sup} = \mathbb{E}_{(x,y)\sim\mathcal{D}^s}[-\log[\mathcal{C}(\mathcal{G}(x))]_y]$$

Datasets

Office-31
3 Domains, 6 Tasks

Digits
3 Domains
3 Tasks

Datasets with various domains

Birds-31
3 Domains, 6 Tasks

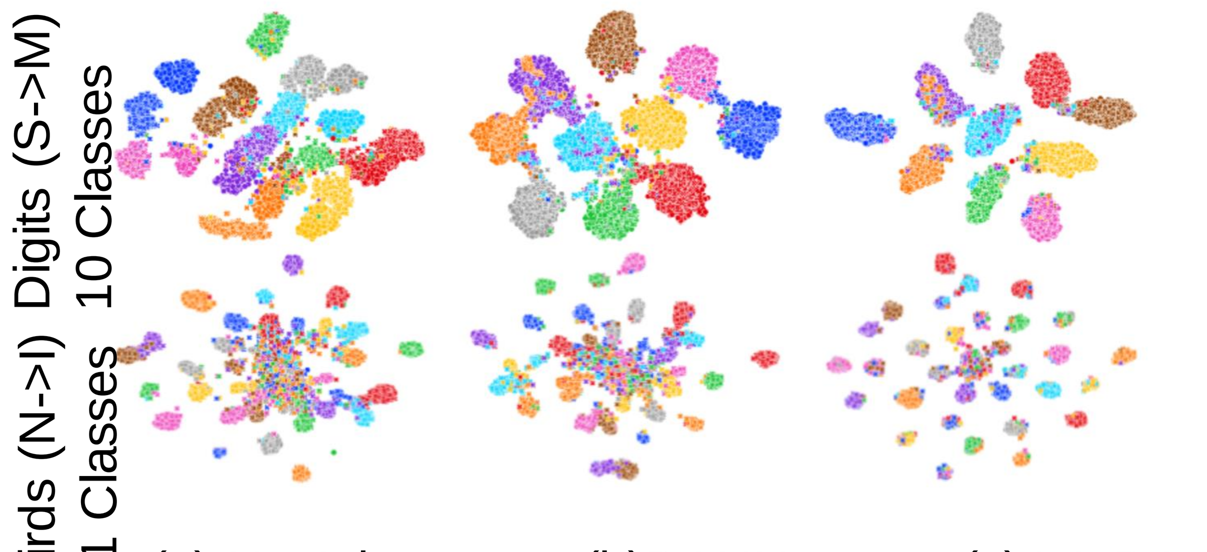
Experimental Results

Method	Office-31	Birds-31	Digits
Source Only	76.1	79.14	69.1
DANN	82.2	78.44	89.29
CDAN	86.6	82.18	93.1
ILA-DA (DANN)	85.54	83.63	93.83
ILA-DA (CDAN)	89.30	**86.03**	94.88

New SOTA results on Birds-31

Consistent improvements over baseline methods.

tSNE Visualization



(a) No Adapt (b)DANN (c)ILA-DA

While DANN is only successful in domain alignment, our proposed ILA-DA approach additionally improves category separation on target domain.