CLDA: Contrastive Learning for Semi-Supervised Domain Adaptation

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ML in Practice Reading Group

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Introduction

This paper presents a single-stage contrastive learning framework for semi-supervised domain adaptation -- CLDA

- Domain shift
- Have some labeled data from the target domain -- Semi-Supervised
  - Few labeled data from the target domain can significantly boost the performance
  - Direct application of unsupervised approaches only gives sub-optimal performance
- Contrastive learning
- Intra-domain discrepancy & inter-domain discrepancy

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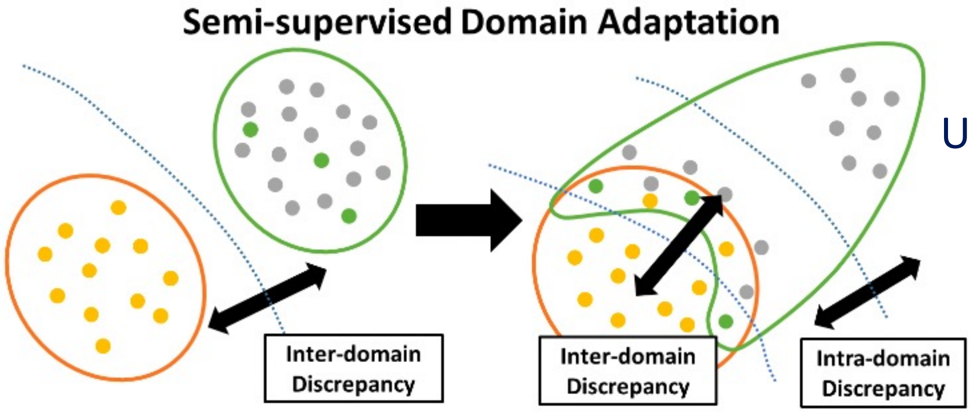
Background

- Intra-domain discrepancy (Kim & Kim, 2020, APE approach)
  - Only partial alignment between two domain distributions



Unaligned sub-distribution

Aligned sub-distribution

Background

Related SSDA approaches

- MME (Saito et al., 2019)
  - Adversarial learning
  - Assume a single domain-invariant prototype for each class for both domains
- APE (Kim & Kim, 2020)
  - Attract, perturb, and explore
  - Intra-domain discrepancy

Intuition

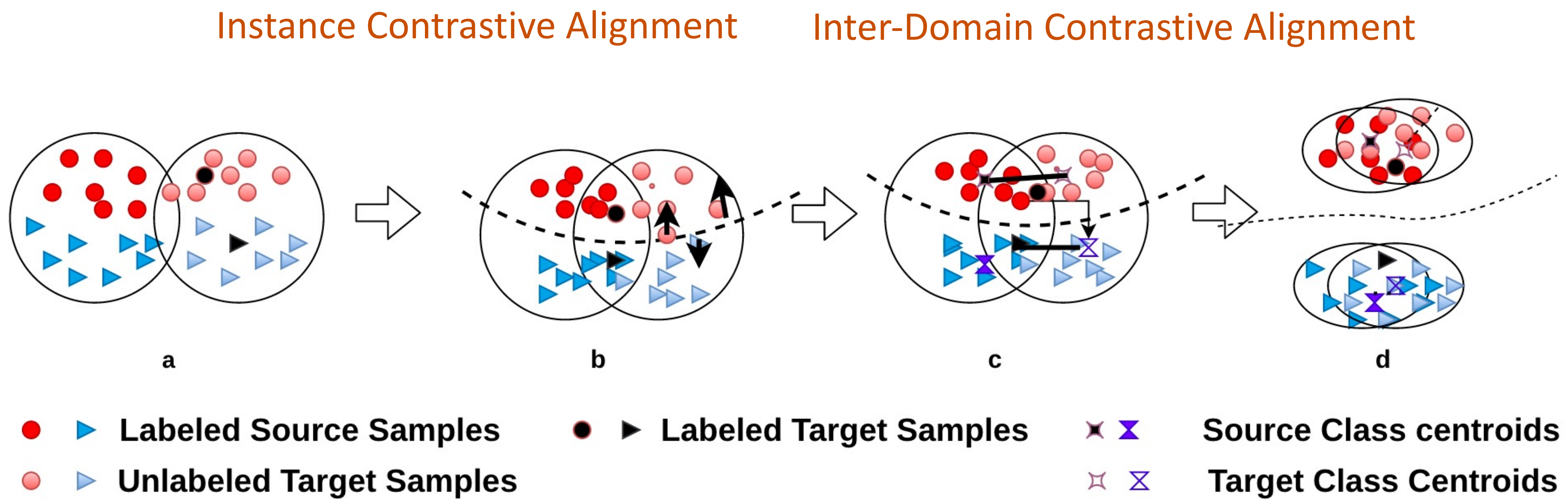


Figure 1 from Singh (2021)

Methods – Problem Formulation

Source dataset contains labeled images

- $\mathcal{D}_s = \{(x_i^s, y_i^s)_{i=1}^{N_s}\} \subset \mathcal{R}^d \times \mathcal{Y}$ from distribution $P_S(X, Y)$

Target dataset contains two sets of data from distribution $P_T(X, Y)$

- Labeled set $\mathcal{D}_{lt} = \left\{\left(x_i^{lt}, y_i^{lt}\right)_{i=1}^{N_{lt}}\right\}$
- Unlabeled set $\mathcal{D}_t = \left\{\left(x_i^t, y_i^t\right)_{i=1}^{N_t}\right\}$ where $N_t \gg N_{lt}$

Labeled data from both domains

- $\mathcal{D}_l = \mathcal{D}_s \cup \mathcal{D}_{lt}$
- $Y = \{1,2, \ldots K\}$

Goal: Lean a task specific classifier using $\mathcal{D}_s$, $\mathcal{D}_{lt}$ and $\mathcal{D}_t$ to accurately predict labels on test data from target domain

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Methods -- Supervised Learning on Labeled Source and Target

CNN-based **feature extractor** $\mathcal{G}(.)$, **classifier** $\mathcal{F}(.)$

Cross-entropy loss:

$$\mathcal{L}_{sup} = -\sum_{k=1}^{K} \left(y^i\right)_k \log(\mathcal{F}\left(\mathcal{G}\left(x_l^i\right)_k\right))$$

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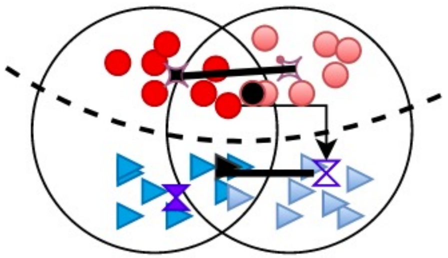
Methods -- Inter-Domain Contrastive Alignment

- Samples from the same category across domains must cluster in the latent space
- Aligning the centroids (mean of features) of each class of source and target domain
- Centroids of class k of source C_k^s

$$C_k^s = \frac{\sum_{i=1}^{i=B} \mathbb{1}_{\{y_i^s = k\}} \mathcal{F}(\mathcal{G}(x_i^s))}{\sum_{i=1}^{i=B} \mathbb{1}_{\{y_i^s = k\}}}$$



- Update centroid values $C_k^s = \rho(C_k^s)_{step} + (1-\rho)(C_k^s)_{step-1}$
- For unlabeled target samples, use pseudo labels and calculate target centroid C_k^t

$$\hat{y_i^t} = argmax((\mathcal{F}(\mathcal{G}(x_i^t)))$$

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Methods -- Inter-Domain Contrastive Alignment

- Maximize the similarity between the cluster representation of each class k from the source and the target domain
- Positive pair: C_i^t and C_i^s
- Negative pair: Other cluster centroids
- Modified NT-Xent (normalized temperature-scaled cross-entropy) contrastive loss (Chen et al. 2020, SimCLR)

$$\mathcal{L}_{clu}(C_i^t, C_i^s) = -\log \frac{h\big(C_i^t, C_i^s\big)}{h\big(C_i^t, C_i^s\big) + \sum\limits_{\substack{r=1 \\ q\in\{s,t\}}}^{K} \mathbb{1}_{\{r\neq i\}} h\big(C_i^t, C_r^q\big)}$$

$$h(\mathbf{u}, \mathbf{v}) = \exp\left(\frac{\mathbf{u}^\top \mathbf{v}}{||\mathbf{u}||_2 ||\mathbf{v}||_2} / \tau\right)$$

cosine similarity

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Methods -- Instance Contrastive Alignment

- Strong augmented unlabeled target image $\tilde{x}_i^t$
- Positive sample: Variants of the same image
- Negative sample: All other images
- Only perturb the unaligned sub-distribution (unlabeled target)
- Force the unaligned target sub-distribution to move away from the low density region towards aligned distribution
- NT-Xent loss

$$\mathcal{L}_{ins}(\tilde{x}_i^t, x_i^t) = -\log \frac{h\big(\mathcal{F}(\mathcal{G}(\tilde{x}_i^t), \mathcal{F}(\mathcal{G}(x_i^t))\big)}{\sum_{r=1}^{B} h\big(\mathcal{F}(\mathcal{G}(\tilde{x}_i^t)), \mathcal{F}(\mathcal{G}(x_r^t))\big) + \sum_{r=1}^{B} \mathbb{1}_{\{r \neq i\}} h\big(\mathcal{F}(\mathcal{G}(\tilde{x}_i^t)), \mathcal{F}(\mathcal{G}(\tilde{x}_r^t))\big)}$$

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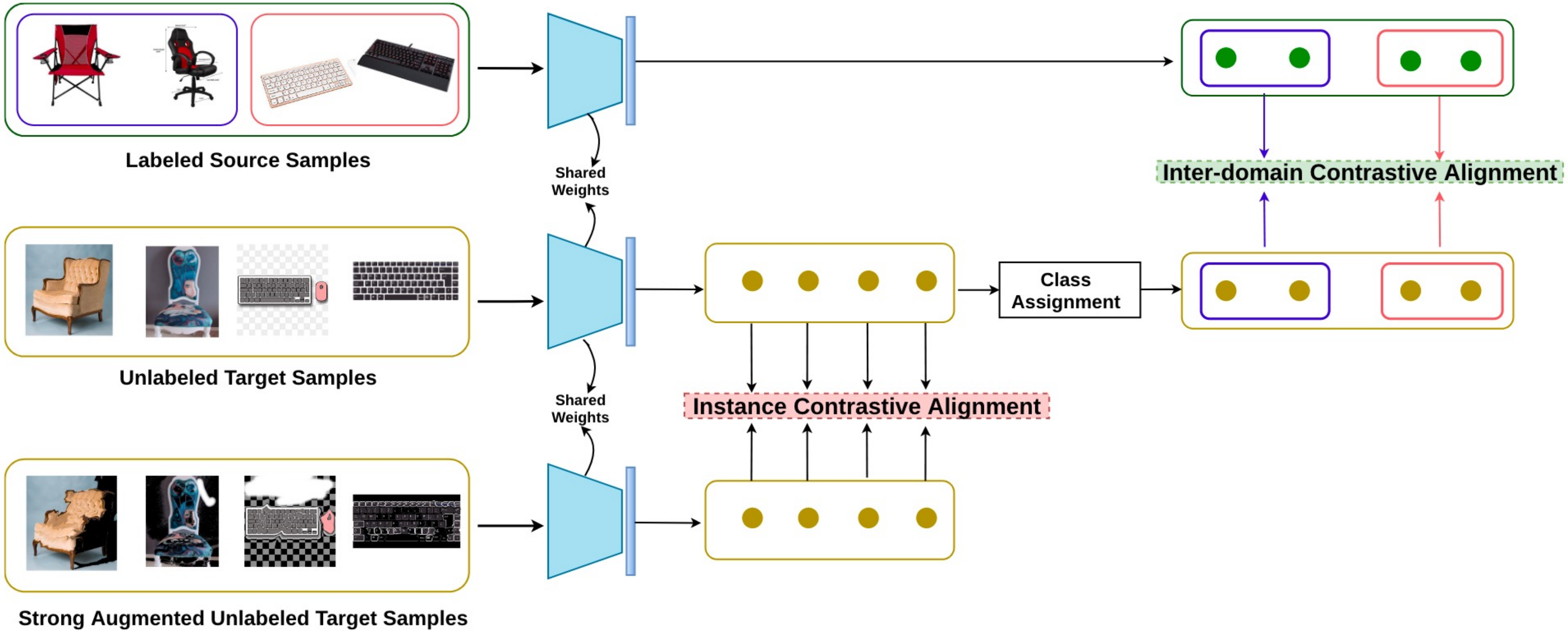
Methods – Overall Training Objective

$$\mathcal{L}_{tot} = \mathcal{L}_{sup} + \alpha\mathcal{L}_{clu} + \beta\mathcal{L}_{ins}$$

- Supervised loss
- Inter-Domain Contrastive Alignment
- Instance Contrastive Alignment



Implementation

Algorithm 1: CLDA - **C**ontrastive **L**earning for Semi-Supervised **D**omain **A**daptation

Input: Source dataset $\{\mathcal{D}_s\}$, Labeled Target dataset $\{\mathcal{D}_{lt}\}$, Unlabeled Target dataset $\{\mathcal{D}_t\}$, and Model $\{\mathcal{G}, \mathcal{F}\}$

for *steps* 1 *to totalsteps* **do**

- Load a mini-batch of source samples $\{(\mathbf{x}_i^s, y_i^s)\}_{i=1}^{i=B}$ from source dataset $\mathcal{D}_s$ and target labeled samples $\{(\mathbf{x}_i^{lt}, y_i^{lt})\}_{i=1}^{i=B}$ from labeled target dataset $\mathcal{D}_{lt}$
- Compute $\mathcal{L}_{sup}$ *cross-entropy loss* on both source and labeled target samples.
- Load a mini-batch of unlabeled target samples $\{(\mathbf{x}_i^t\}_{i=1}^{i=\mu \times B}$ from target dataset
- Compute $\mathcal{L}_{ins}$ *Instance Contrastive Alignment* on input and strongly augmented unlabeled input images.
- Assign the class to the unlabeled target samples based on their pseudo-label.
- Update source centroids
- Compute $\mathcal{L}_{clu}$ *Inter-Domain Contrastive Alignment* between unlabeled target samples and source samples.
- Update $\{\mathcal{G}, \mathcal{F}\}$ using total loss $\mathcal{L}_{tot} = \mathcal{L}_{sup} + \alpha * \mathcal{L}_{ins} + \beta * \mathcal{L}_{clu}$

https://github.com/Griffintaur/CLDA_NeurIPS21

Experimental Results

Office-Home (65 classes, 4 domains)
3-shot setting (randomly selected 3 labeled samples per class for training target samples)

Net	Method	Rl→Cl	Rl→Pr	Rl→Ar	Pr→Rl	Pr→Cl	Pr→Ar	Ar→Pl	Ar→Cl	Ar→Rl	Cl→Rl	Cl→Ar	Cl→Pr	Mean
Alexnet	S+T	44.6	66.7	47.7	57.8	44.4	36.1	57.6	38.8	57.0	54.3	37.5	57.9	50.0
	DANN	47.2	66.7	46.6	58.1	44.4	36.1	57.2	39.8	56.6	54.3	38.6	57.9	50.3
	ADR	37.8	63.5	45.4	53.5	32.5	32.2	49.5	31.8	53.4	49.7	34.2	50.4	44.5
	CDAN	36.1	62.3	42.2	52.7	28.0	27.8	48.7	28.0	51.3	41.0	26.8	49.9	41.2
	ENT	44.9	70.4	47.1	60.3	41.2	34.6	60.7	37.8	60.5	58.0	31.8	63.4	50.9
	MME	51.2	73.0	50.3	61.6	47.2	40.7	63.9	43.8	61.4	59.9	44.7	64.7	55.2
	Meta-MME	50.3	-	-	-	48.3	40.3	-	44.5	-	-	44.5	-	-
	BiAT	-	-	-	-	-	-	-	-	-	-	-	-	56.4
	APE	**51.9**	**74.6**	51.2	61.6	47.9	42.1	65.5	44.5	60.9	58.1	44.3	64.8	55.6
	CLDA(ours)	51.5	74.1	**54.3**	**67.0**	**47.9**	**47.0**	**65.8**	**47.4**	**66.6**	**64.1**	**46.8**	**67.5**	**58.3**
Resnet34	S+T	55.7	80.8	67.8	73.1	53.8	63.5	73.1	54.0	74.2	68.3	57.6	72.3	66.2
	DANN	57.3	75.5	65.2	69.2	51.8	56.6	68.3	54.7	73.8	67.1	55.1	67.5	63.5
	ENT	62.6	85.7	70.2	79.9	60.5	63.9	79.5	61.3	79.1	76.4	64.7	79.1	71.9
	MME	64.6	85.5	71.3	80.1	64.6	65.5	79.0	63.6	79.7	76.6	67.2	79.3	73.1
	Meta-MME	65.2	-	-	-	64.5	66.7	-	63.3	-	-	67.5	-	-
	APE	**66.4**	86.2	73.4	82.0	**65.2**	66.1	81.1	**63.9**	80.2	76.8	66.6	79.9	74.0
	CLDA (ours)	66.0	**87.6**	**76.7**	**82.2**	63.9	**72.4**	**81.4**	63.4	**81.3**	**80.3**	**70.5**	**80.9**	**75.5**

Experimental Results

DomainNet (total 345 classes across 6 domains, use subset with 126 classes across 4 domains

Net	Method	R→C		R→P		P→C		C→S		S→P		R→S		P→R		Mean	
		1-shot	3-shot	1-shot	3-shot	1-shot	3-shot	1-shot	3-shot	1-shot	3-shot	1-shot	3-shot	1-shot	3-shot	1-shot	3-shot
Alexnet	S+T	43.3	47.1	42.4	45.0	40.1	44.9	33.6	36.4	35.7	38.4	29.1	33.3	55.8	58.7	40.0	43.4
	DANN	43.3	46.1	41.6	43.8	39.1	41.0	35.9	36.5	36.9	38.9	32.5	33.4	53.5	57.3	40.4	42.4
	ADR	43.1	46.2	41.4	44.4	39.3	43.6	32.8	36.4	33.1	38.9	29.1	32.4	55.9	57.3	39.2	42.7
	CDAN	46.3	46.8	45.7	45.0	38.3	42.3	27.5	29.5	30.2	33.7	28.8	31.3	56.7	58.7	39.1	41.0
	ENT	37.0	45.5	35.6	42.6	26.8	40.4	18.9	31.1	15.1	29.6	18.0	29.6	52.2	60.0	29.1	39.8
	MME	48.9	55.6	48.0	49.0	46.7	51.7	36.3	39.4	39.4	43.0	33.3	37.9	56.8	60.7	44.2	48.2
	Meta-MME	-	56.4	-	50.2		51.9	-	39.6	-	43.7	-	38.7	-	60.7	-	48.8
	BiAT	54.2	58.6	49.2	50.6	44.0	52.0	37.7	41.9	39.6	42.1	37.2	42.0	56.9	58.8	45.5	49.4
	APE	47.7	54.6	49.0	50.5	46.9	52.1	38.5	42.6	38.5	42.2	33.8	38.7	57.5	61.4	44.6	48.9
	CLDA (ours)	**56.3**	**59.9**	**56.0**	**57.2**	**50.8**	**54.6**	**42.5**	**47.3**	**46.8**	**51.4**	**38.0**	**42.7**	**64.4**	**67.0**	**50.7**	**54.3**
Resnet34	S+T	55.6	60.0	60.6	62.2	56.8	59.4	50.8	55.0	56.0	59.5	46.3	50.1	71.8	73.9	56.9	60.0
	DANN	58.2	59.8	61.4	62.8	56.3	59.6	52.8	55.4	57.4	59.9	52.2	54.9	70.3	72.2	58.4	60.7
	ADR	57.1	60.7	61.3	61.9	57.0	60.7	51.0	54.4	56.0	59.9	49.0	51.1	72.0	74.2	57.6	60.4
	CDAN	65.0	69.0	64.9	67.3	63.7	68.4	53.1	57.8	63.4	65.3	54.5	59.0	73.2	78.5	62.5	66.5
	ENT	65.2	71.0	65.9	69.2	65.4	71.1	54.6	60.0	59.7	62.1	52.1	61.1	75.0	78.6	62.6	67.6
	MME	70.0	72.2	67.7	69.7	69.0	71.7	56.3	61.8	64.8	66.8	61.0	61.9	76.1	78.5	66.4	68.9
	UODA	72.7	75.4	70.3	71.5	69.8	73.2	60.5	64.1	66.4	69.4	62.7	64.2	77.3	80.8	68.5	71.2
	Meta-MME	-	73.5	-	70.3	-	72.8	-	62.8	-	68.0	-	63.8	-	79.2	-	70.1
	BiAT	73.0	74.9	68.0	68.8	71.6	74.6	57.9	61.5	63.9	67.5	58.5	62.1	77.0	78.6	67.1	69.7
	APE	70.4	76.6	70.8	72.1	**72.9**	**76.7**	56.7	63.1	64.5	66.1	63.0	67.8	76.6	79.4	67.6	71.7
	CLDA (ours)	**76.1**	**77.7**	**75.1**	**75.7**	71.0	76.4	**63.7**	**69.7**	**70.2**	**73.7**	**67.1**	**71.1**	**80.1**	**82.9**	**71.9**	**75.3**

Experimental Results

Office 31 (31 classes across 3 domain)

	Alexnet						VGG					
	W→A		D→A		Mean		W→A		D→A		Mean	
Method	1-shot	3-shot	1-shot	3-shot	1-shot	3-shot	1-shot	3-shot	1-shot	3-shot	1-shot	3-shot
S+T	50.4	61.2	50.0	62.4	50.2	61.8	169.2	73.2	68.2	73.3	68.7	73.25
DANN	57.0	64.4	54.5	65.2	55.8	64.8	69.3	75.4	70.4	74.6	69.85	75.0
ADR	50.2	61.2	50.9	61.4	50.6	61.3	69.7	73.3	69.2	74.1	69.45	73.7
CDAN	50.4	60.3	48.5	61.4	49.5	60.8	65.9	74.4	64.4	71.4	65.15	72.9
ENT	50.7	64.0	50.0	66.2	50.4	65.1	69.1	75.4	72.1	75.1	70.6	75.25
MME	57.2	67.3	55.8	67.8	56.5	67.6	73.1	76.3	73.6	**77.6**	73.35	76.95
BiAT	57.9	68.2	54.6	68.5	56.3	68.4	-	-	-	-	-	-
APE	-	67.6	-	69.0	-	68.3	-	-	-	-	-	-
CLDA	**64.6**	**70.5**	**62.7**	**72.5**	**63.6**	**71.5**	**76.2**	**78.6**	**75.1**	76.7	**75.6**	**77.6**

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Comments

- Straightforward paper, easy to follow
- Instance contrastive alignment uses augmented image data – different approach for tabular data (e.g. add noise)
- Inter-domain contrastive alignment uses centroid of images – interpretation for tabular data
- Have labels in each classes for target domain

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