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Domain Consensus Clustering for Universal Domain Adaptation

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ReLER

Recognition, LEarning, Reasoning

Background: Domain Adaptation

Deep Neural Network (DNN) has achieved promising performance in various vision tasks.

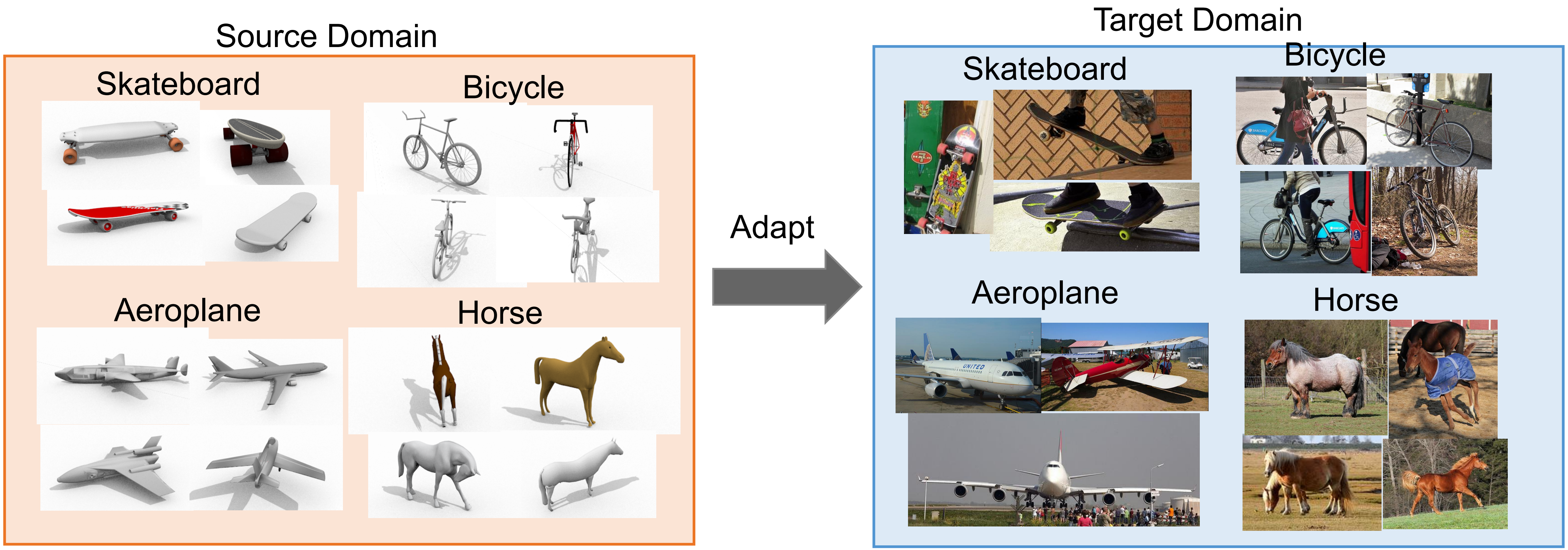
A DNN model may fail to generalize across different domains.

As a data-driven technique, it is unrealistic to collect and annotate the data from various domains.

Background: Domain Adaptation

As a feasible solution, Domain Adaptation is proposed:

transfer representations from a **labeled** domain (Source Domain) to an **unlabeled** domain (Target Domain).



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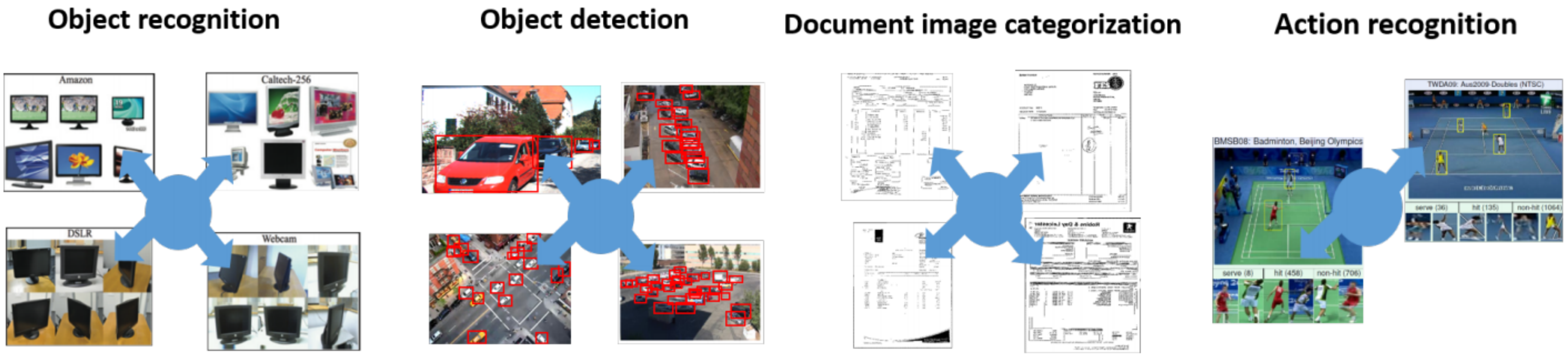
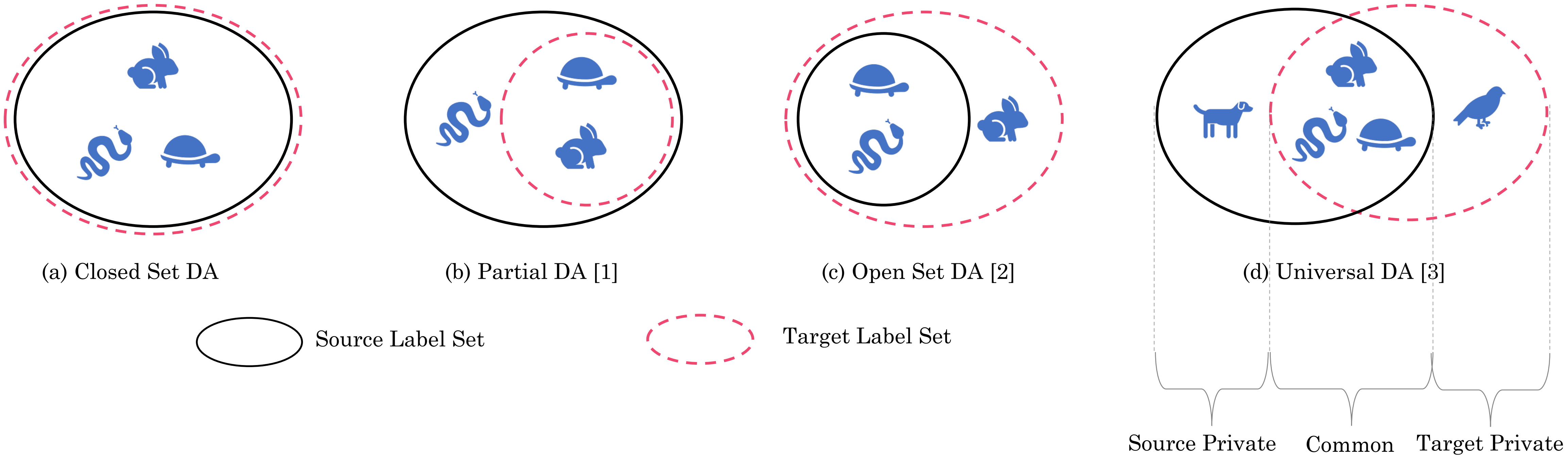


Background: Universal Domain Adaptation (UniDA)



[1] Saito et.al. Open set domain adaptation by backpropagation. ECCV2018
[2] Cao et.al. Partial transfer learning with selective adversarial networks. CVPR2018.
[3] You et.al. Universal Domain Adaptation. CVPR2019.

Challenges and Solutions in Universal DA

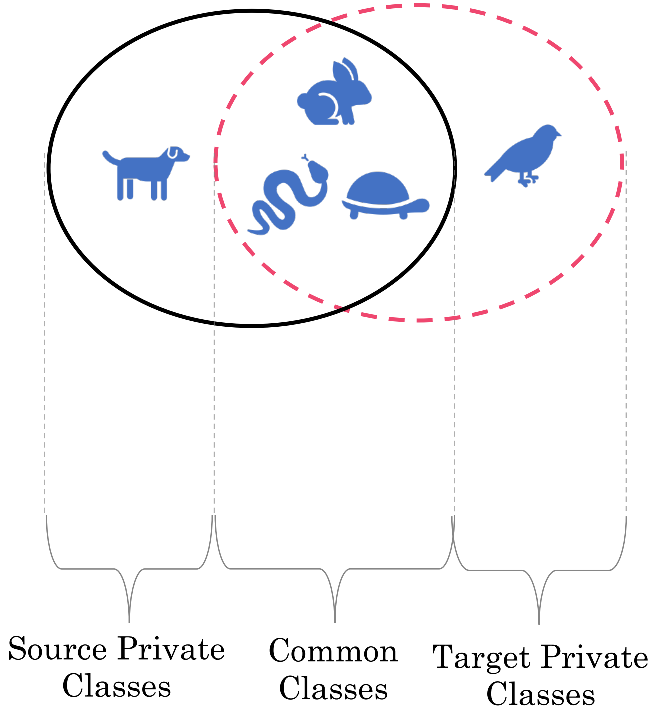
How to separate common classes from private classes?

Previous researches could be categorized into two streams:

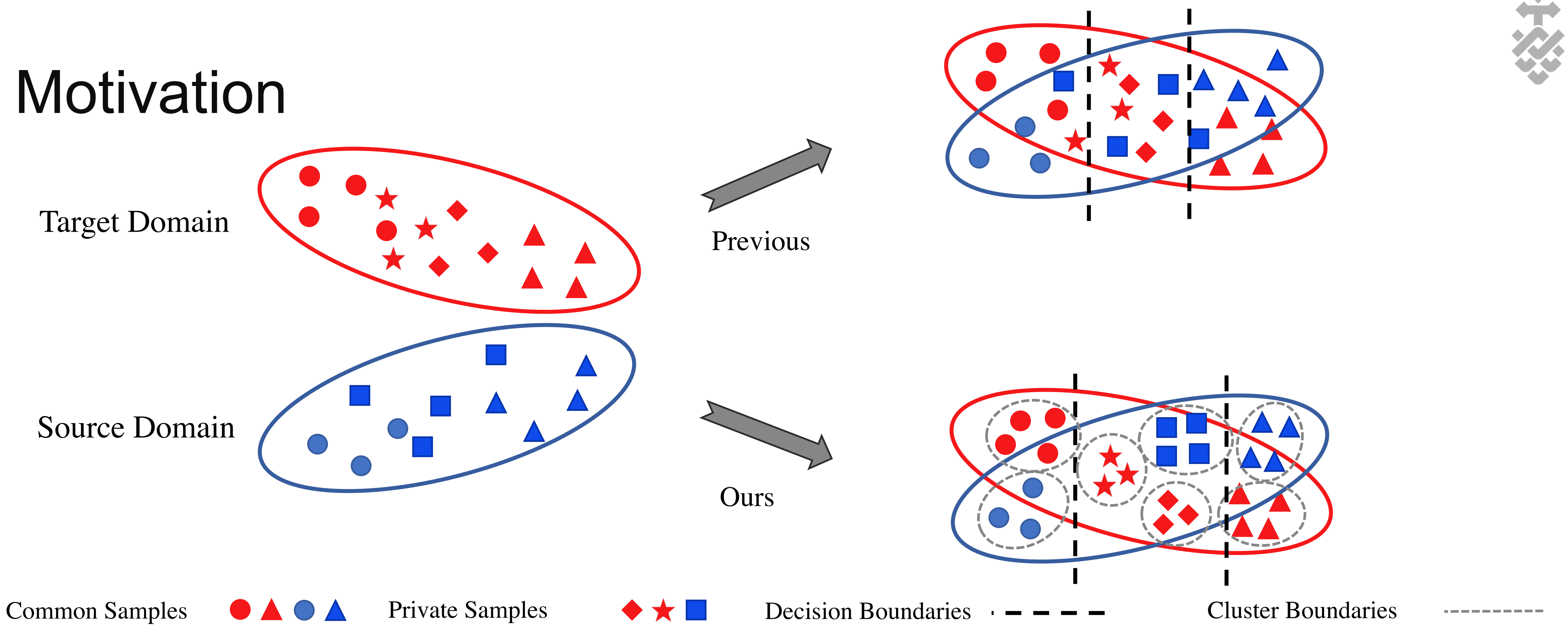
- Designing **new criteria** based on domain-conditional distribution, entropy, etc.
- Introducing **extra discriminators** to achieve the common-private separation.

Flaws:

- They both treat private samples from **multiple semantic classes** as **one generic class**, while ignores its intrinsic structure.
- The resulted representations are not compact enough, hence leads to the confusion with common samples.



Motivation



Aim:

- Discover discriminative clusters on both common samples and private ones
- Achieve a better common-private separation

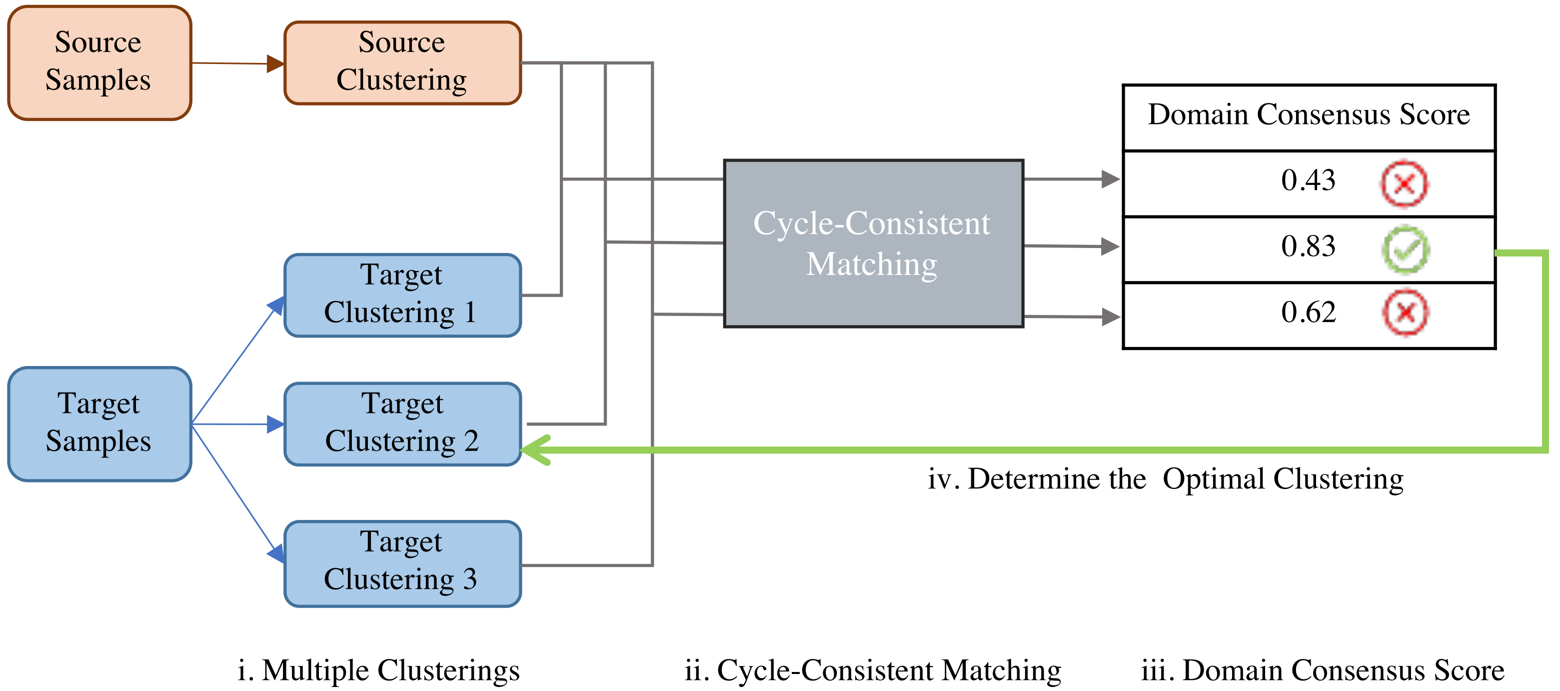
Domain Consensus Clustering

i. Multiple Clusterings

ii. Cycle-Consistent Matching

iii. Domain Consensus Score

iv. Determine the Optimal Clustering



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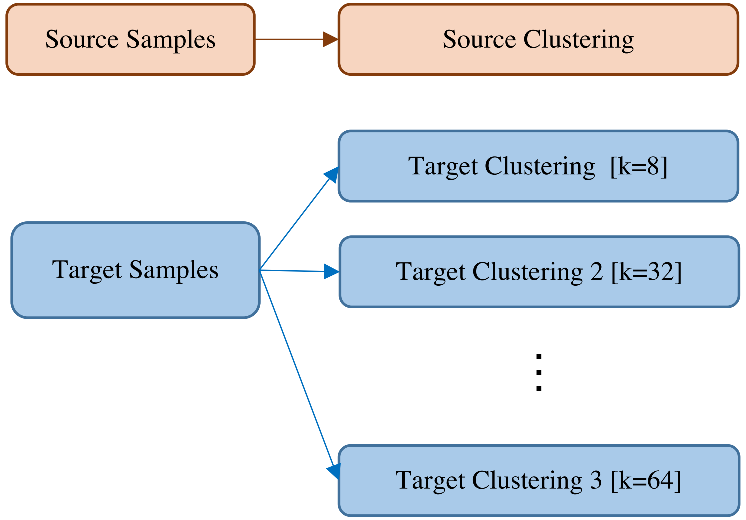

The number of target classes is unknown →

- we perform multiple clusterings with varying **K** (i.e. number of clusters)
- then determine the optimal one with the proposed metric, domain consensus score.

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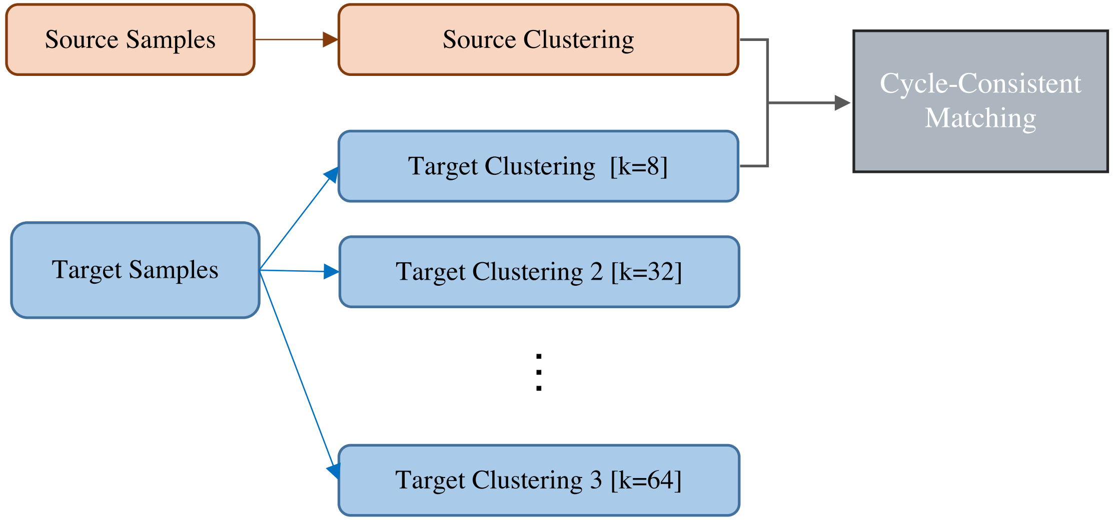

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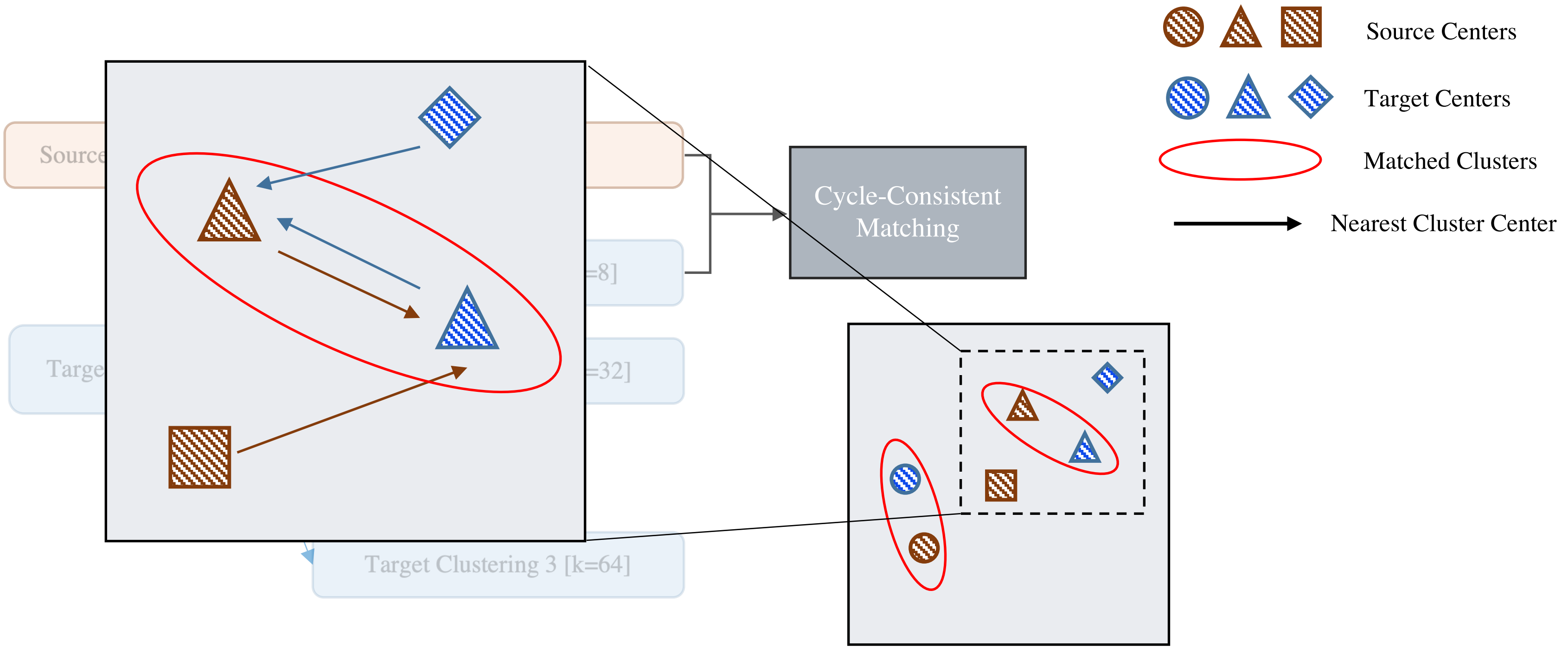

If two centers both act as the other's **nearest center** simultaneously, these two clusters are recognized **common clusters** that hold the same semantic label

Domain Consensus Clustering

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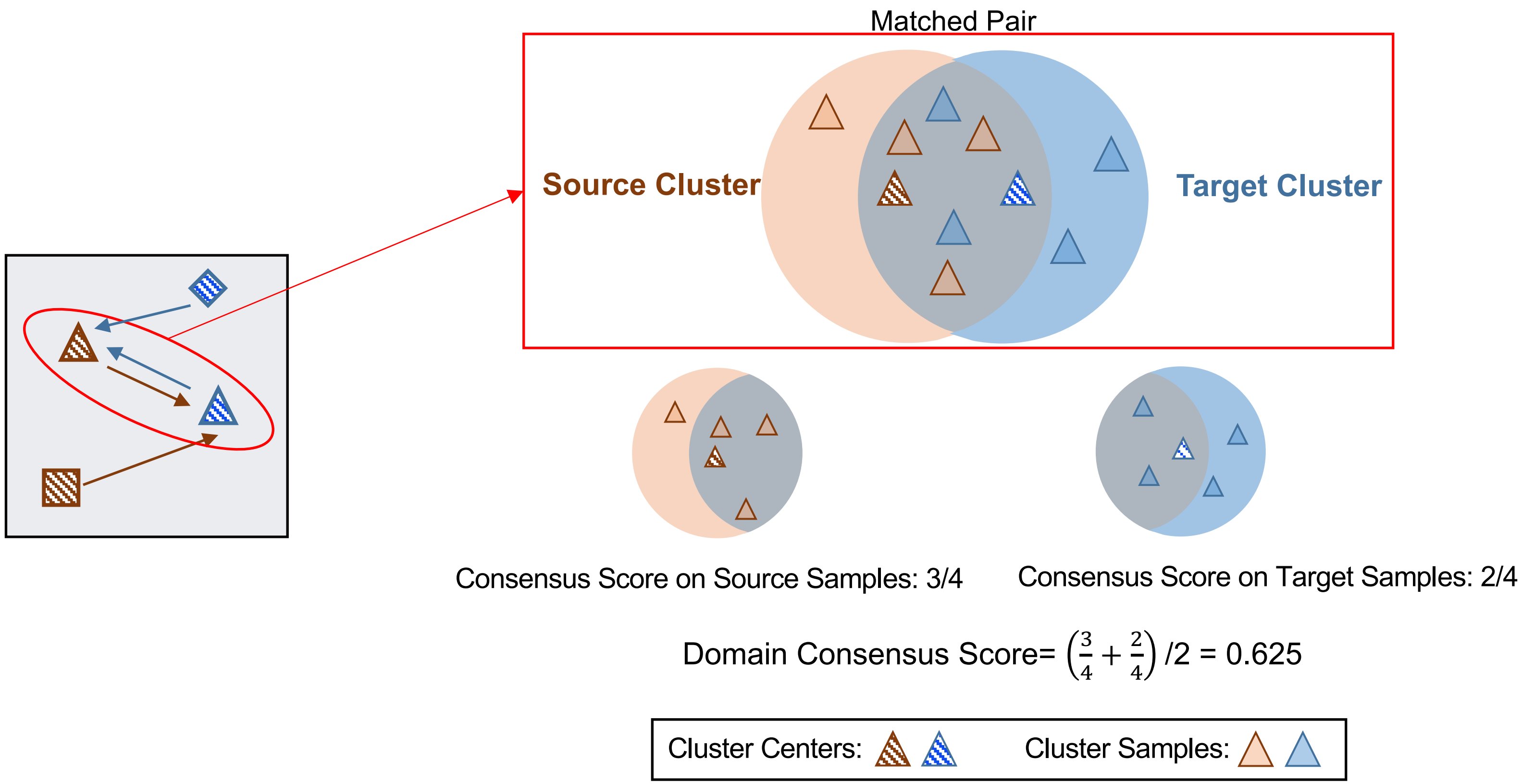

For identified pairs of clusters, we employ domain consensus score to estimate its matchiness

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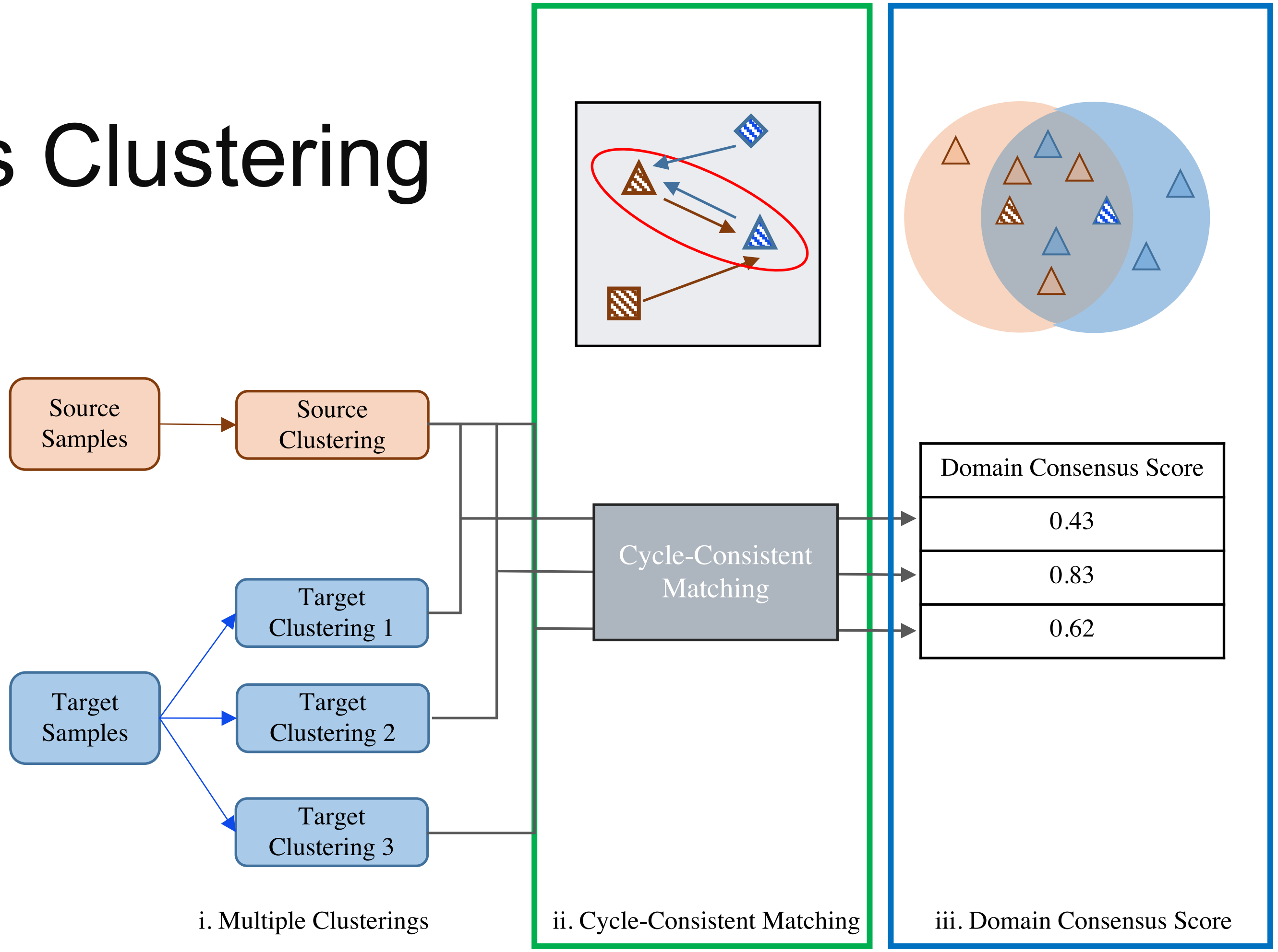

Finally, based on domain consensus score, we could determine the optimal clustering.

Domain Consensus Clustering

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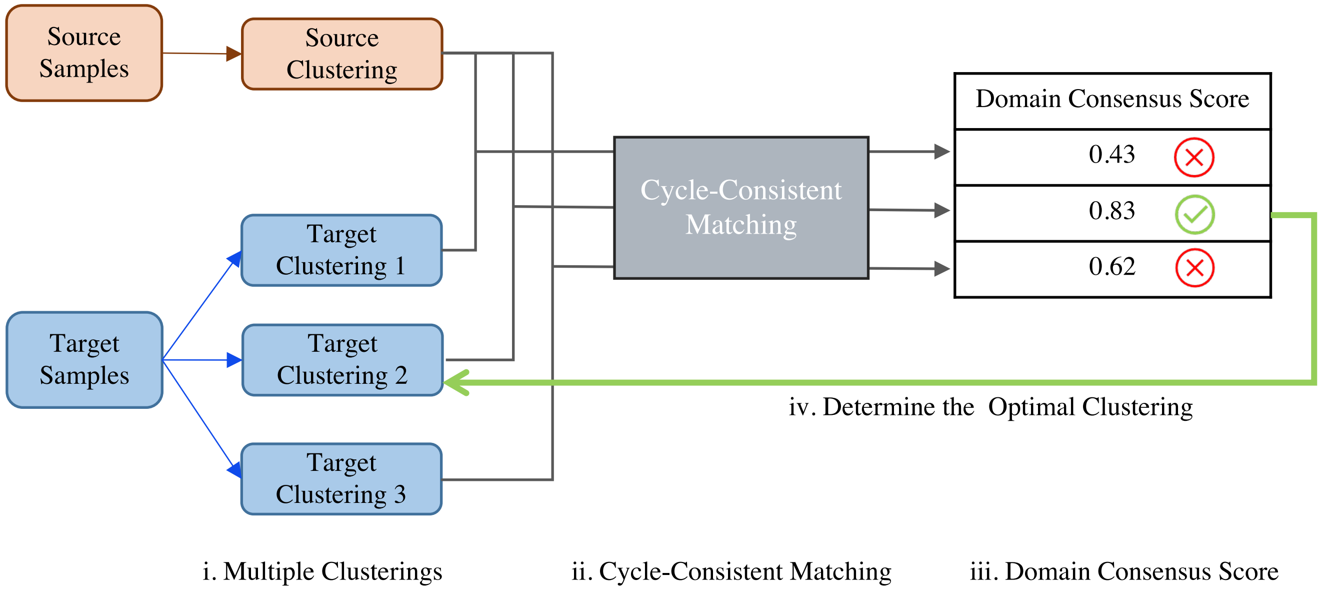


Finally, based on domain consensus score, we could determine the optimal clustering.

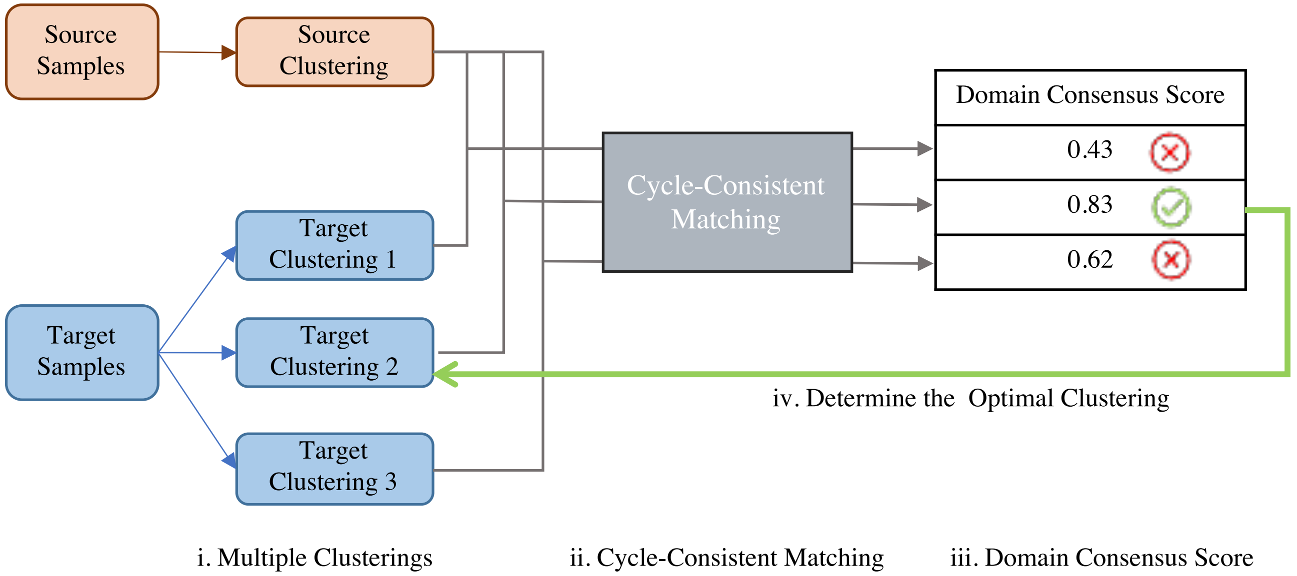
Domain Consensus Clustering

Main challenge:

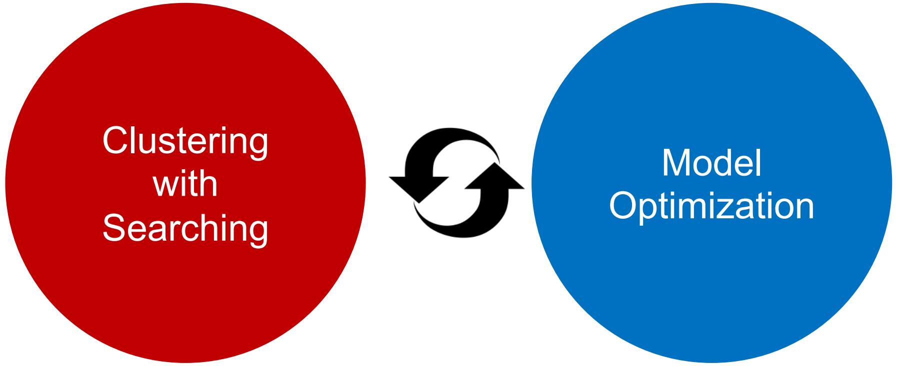
- How to associate common clusters across domains? →
- How to determine the number of target clusters? →

Domain Consensus Knowledge:

- Semantic-level: Cycle-Consistent Matching
- Sample-level: Domain Consensus Score

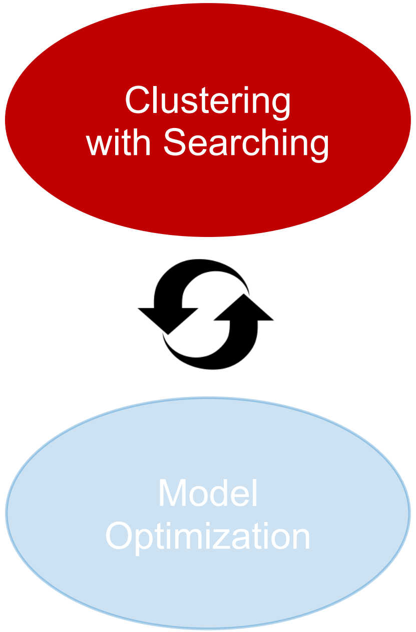


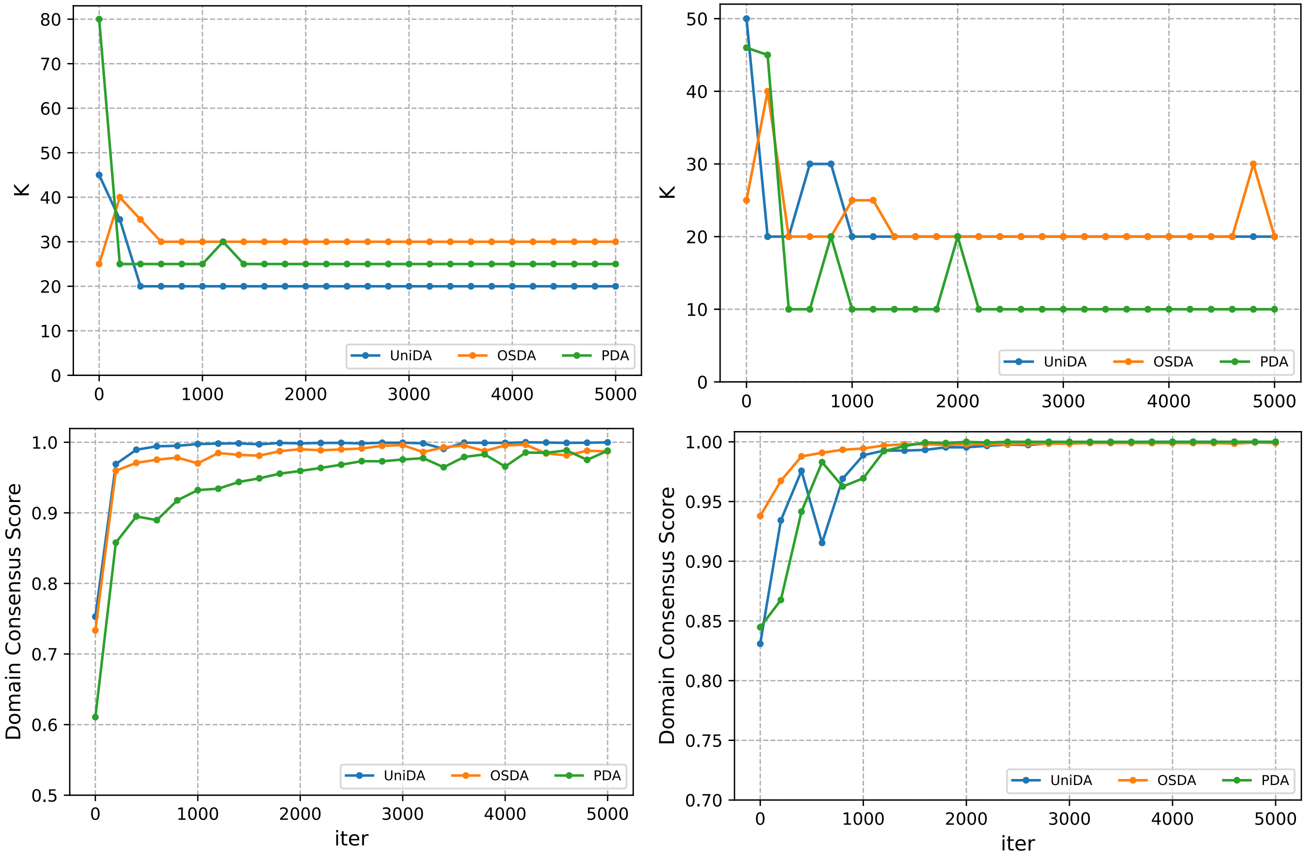
Cluster Optimization and Objectives



We update the model optimization and clustering alternatively, to avoid the error accumulation.

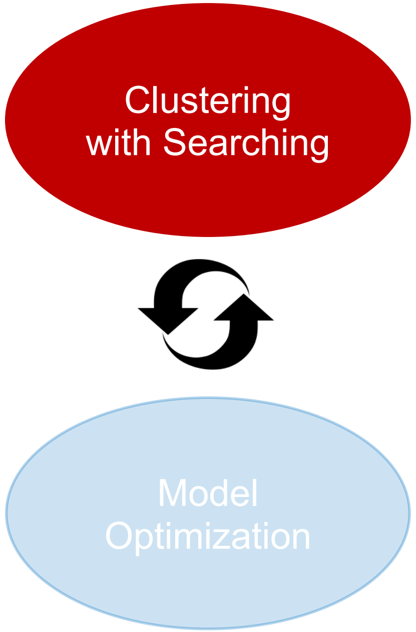
Simplify the Clustering

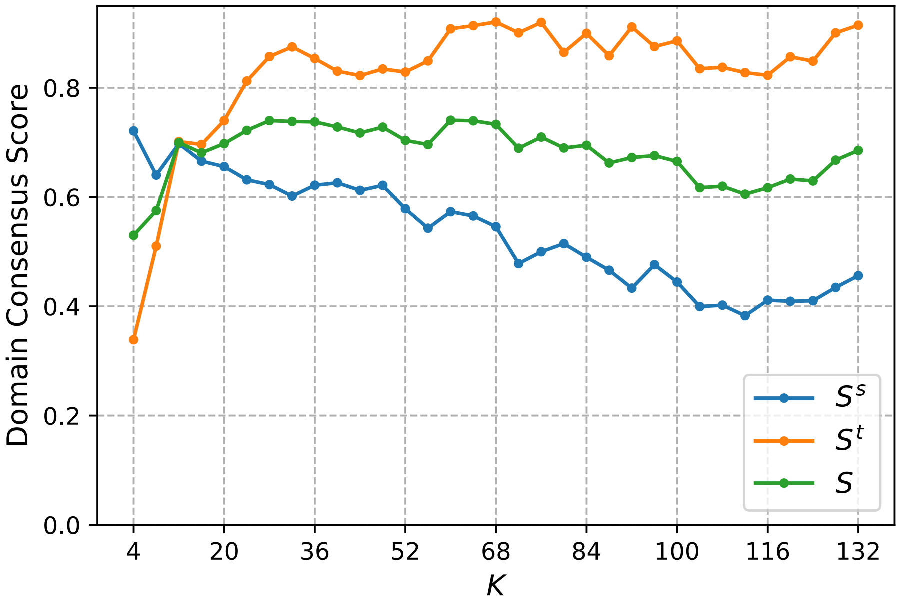




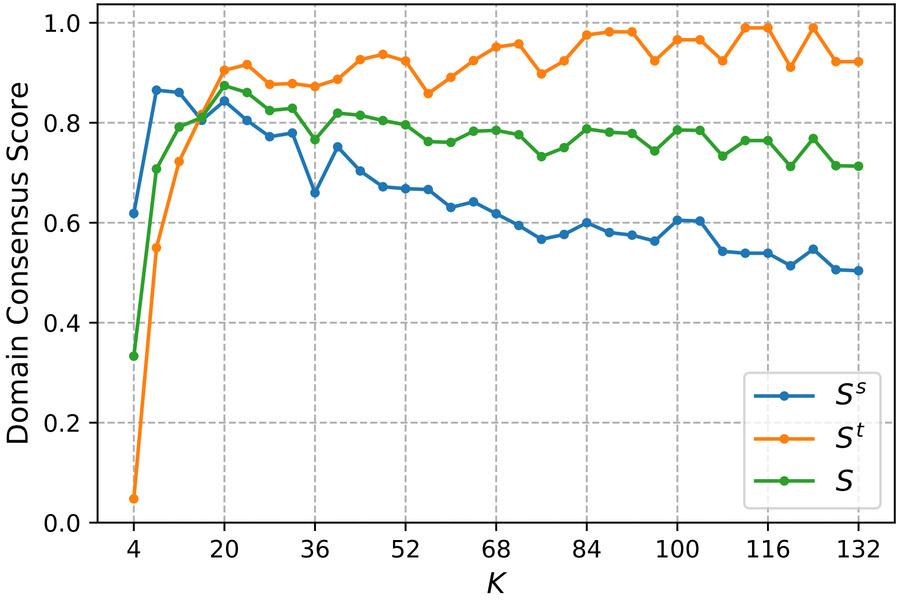
The searching is only necessary as the initial stages.
Stopping Criterion: fix the K if it holds a certain value for a certain number of rounds.

Simplify the Clustering





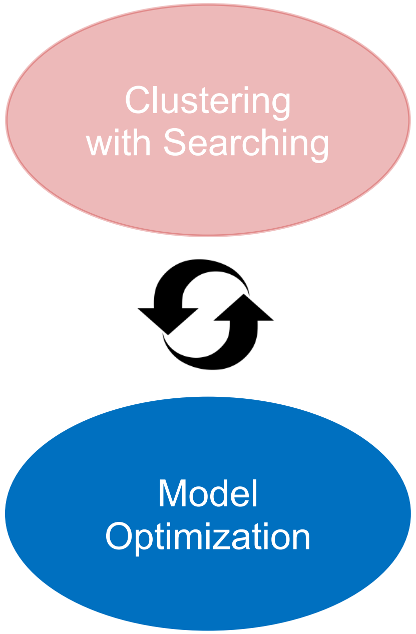
Office-31

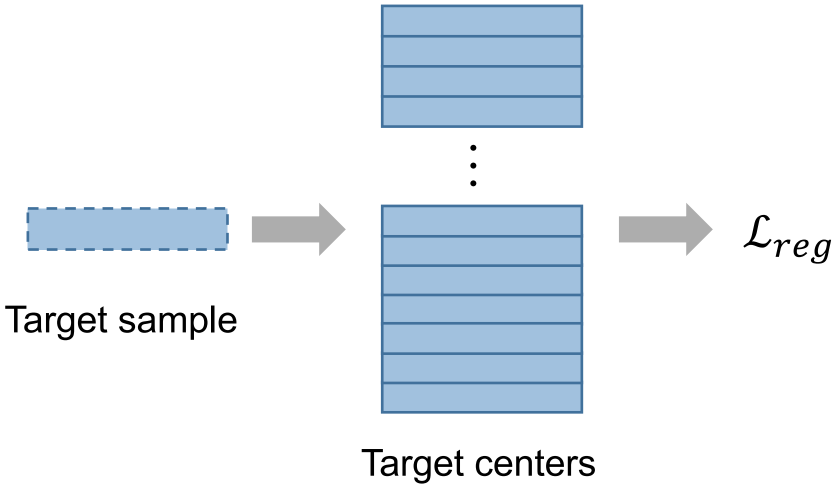


OfficeHome

Stopping Criterion: stop the searching once the consensus score drops a certain number of times continuously

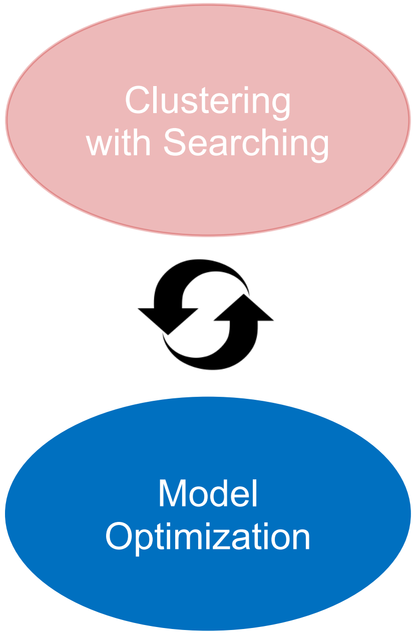
Prototypical Regularizer

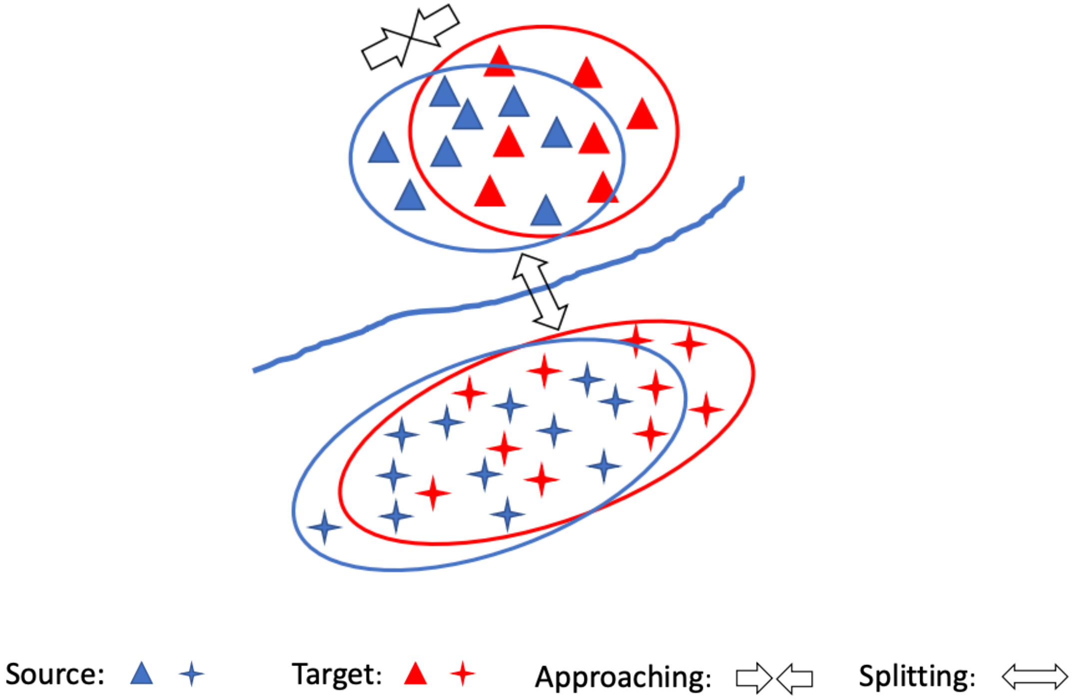




$$\mathcal{L}_{reg} = -\sum_{i=1}^{n_t}\sum_{k=1}^{K} \hat{y}_{i,k}^{t} \log \hat{p}_{(i,k)}$$

Contrastive Domain Discrepancy[1]





UTS [1] Kang et.al. Contrastive Adaptation Network for Unsupervised Domain Adaptation. CVPR 2019

Overall Objective

$$\mathcal{L} = \mathcal{L}_{ce} + \lambda\mathcal{L}_{cdd} + \gamma\mathcal{L}_{reg}$$

Cross-entropy loss

Learning source distribution with the ground truth

Contrastive Domain Discrepancy

Mitigate the distribution shift on identified common samples

Regularizer

Sustain the cluster structure in the target domain

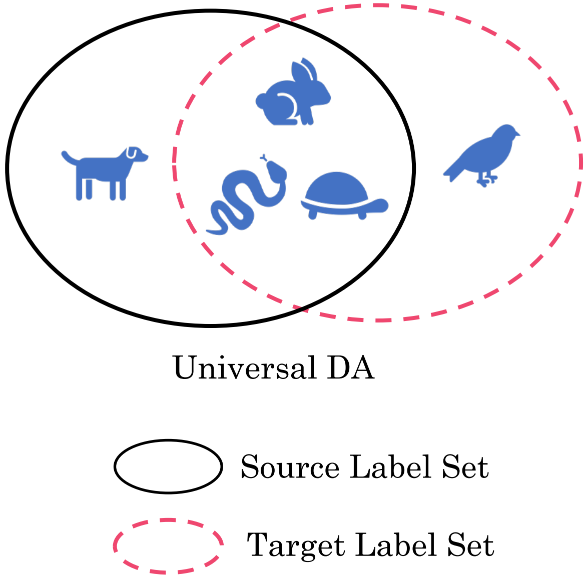
Results under the UniDA setting

Table 1. Results (%) on **Office-31** for UniDA (ResNet-50).

UniDA	A→W		D→W		W→D		A→D		D→A		W→A		Avg	
	Acc.	HM	Acc.	HM	Acc.	HM	Acc.	HM	Acc.	HM	Acc.	HM	Acc.	HM
DANN [17]	80.65	48.82	80.94	52.73	88.07	54.87	82.67	50.18	74.82	47.69	83.54	49.33	81.78	50.60
RTN [38]	85.70	50.21	87.80	54.68	88.91	55.24	82.69	50.18	74.64	47.65	83.26	49.28	83.83	51.21
IWAN [58]	85.25	50.13	90.09	54.06	90.00	55.44	84.27	50.64	84.22	49.65	86.25	49.79	86.68	51.62
PADA [4]	85.37	49.65	79.26	52.62	90.91	55.60	81.68	50.00	55.32	42.87	82.61	49.17	79.19	49.98
ATI [43]	79.38	48.58	92.60	55.01	90.08	55.45	84.40	50.48	78.85	48.48	81.57	48.98	84.48	51.16
OSBP [49]	66.13	50.23	73.57	55.53	85.62	57.20	72.92	51.14	47.35	49.75	60.48	50.16	67.68	52.34
UAN [57]	85.62	58.61	94.77	70.62	97.99	71.42	86.50	59.68	85.45	60.11	85.12	60.34	89.24	63.46
CMU [15]	86.86	67.33	**95.72**	**79.32**	**98.01**	80.42	89.11	68.11	88.35	**71.42**	88.61	72.23	91.11	73.14
Ours	**91.66**	**78.54**	94.52	79.29	96.20	**88.58**	**93.70**	**88.50**	**90.43**	70.18	**91.97**	**75.87**	**93.08**	**80.16**

Table 2. HM (%) on **Office-Home** for UniDA (ResNet-50).

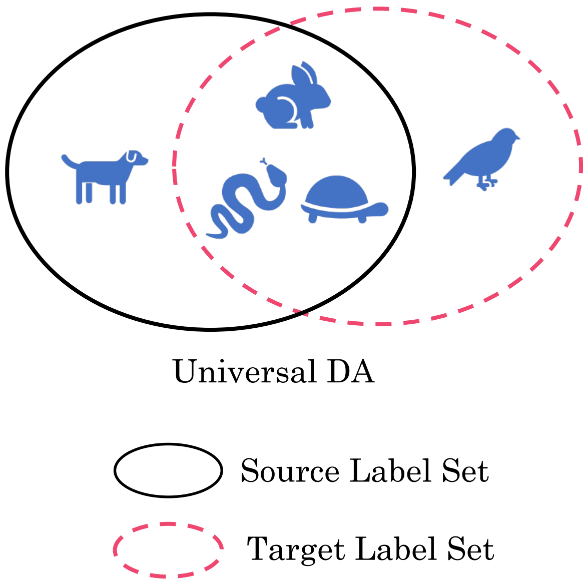
UniDA	Ar→Cl	Ar→Pr	Ar→Rw	Cl→Ar	Cl→Pr	Cl→Rw	Pr→Ar	Pr→Cl	Pr→Rw	Rw→Ar	Rw→Cl	Rw→Pr	Avg
DANN [17]	42.36	48.02	48.87	45.48	46.47	48.37	45.75	42.55	48.70	47.61	42.67	47.40	46.19
RTN [38]	38.41	44.65	45.70	42.64	44.06	45.48	42.56	36.79	45.50	44.56	39.79	44.53	42.89
IWAN [58]	40.54	46.96	47.78	44.97	45.06	47.59	45.81	41.43	47.55	46.29	42.49	46.54	45.25
PADA [4]	34.13	41.89	44.08	40.56	41.52	43.96	37.04	32.64	44.17	43.06	35.84	43.35	40.19
ATI [43]	39.88	45.77	46.63	44.13	44.39	46.63	44.73	41.20	46.59	45.05	41.78	45.45	44.35
OSBP [49]	39.59	45.09	46.17	45.70	45.24	46.75	45.26	40.54	45.75	45.08	41.64	46.90	44.48
UAN [57]	51.64	51.70	54.30	61.74	57.63	61.86	50.38	47.62	61.46	62.87	52.61	65.19	56.58
CMU [15]	56.02	**56.93**	**59.15**	66.95	64.27	67.82	54.72	51.09	66.39	68.24	57.89	69.73	61.60
Ours	**57.97**	54.05	58.01	**74.64**	**70.62**	**77.52**	**64.34**	**73.60**	**74.94**	**80.96**	**75.12**	**80.38**	**70.18**



Results under the UniDA setting

Table 7. HM (%) on **DomainNet** for UniDA (ResNet-50).

Method	P→R	R→P	P→S	S→P	R→S	S→R	Avg
DANN [19]	31.18	29.33	27.84	27.84	27.77	30.84	29.13
RTN [41]	32.27	30.29	28.71	28.71	28.63	31.90	30.08
IWAN [62]	35.38	33.02	31.15	31.15	31.06	34.94	32.78
PADA [4]	28.92	27.32	26.03	26.03	25.97	28.62	27.15
ATI [46]	32.59	30.57	28.96	28.96	28.89	32.21	30.36
OSBP [53]	33.60	33.03	30.55	30.53	30.61	33.65	32.00
UAN [61]	41.85	43.59	39.06	38.95	38.73	43.69	40.98
CMU [17]	50.78	**52.16**	**45.12**	44.82	**45.64**	50.97	48.25
Ours	**56.90**	50.25	43.66	**44.92**	43.31	**56.15**	**49.20**



Results under PDA and OSDA settings

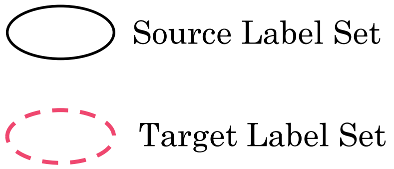


Table 5. HM (%) on **Office** and **Office-Home** under the OSDA scenario (ResNet-50). The reported numbers for previous OSDA methods are cited from [1]. We use 'U' and 'O' to denote methods designed for UniDA setting and OSDA setting, respectively.

Method	Type	Office							Office-Home												
		A2W	A2D	D2W	W2D	D2A	W2A	Avg	Ar2Cl	Ar2Pr	Ar2Rw	Cl2Ar	Cl2Pr	Cl2Rw	Pr2Ar	Pr2Cl	Pr2Rw	Rw2Ar	Rw2Cl	Rw2Pr	Avg
STA_{sum} [38]	O	75.9	75.0	69.8	75.2	73.2	66.1	72.5	55.8	54.0	68.3	57.4	60.4	66.8	61.9	53.2	69.5	67.1	54.5	64.5	61.1
OSBP [53]	O	82.7	82.4	**97.2**	91.1	75.1	73.7	83.7	55.1	65.2	72.9	**64.3**	64.7	**70.6**	**63.2**	53.2	73.9	66.7	54.5	72.3	64.7
ROS [1]	O	82.1	82.4	96.0	**99.7**	77.9	77.2	85.9	**60.1**	**69.3**	76.5	58.9	65.2	68.6	60.6	56.3	**74.4**	**68.8**	60.4	**75.7**	**66.2**
Ours	O	**87.1**	**85.5**	91.2	87.1	**85.5**	**84.4**	**86.8**	52.9	67.4	**80.6**	49.8	**66.6**	67.0	59.5	52.8	64.0	56.0	**76.9**	62.7	64.2
UAN [61]	U	46.8	38.9	68.8	53.0	**68.0**	54.9	55.1	0.0	0.0	0.2	0.0	0.2	0.2	0.0	0.0	0.2	0.2	0.0	0.1	0.1
Ours	U	**54.8**	**58.3**	**89.4**	**80.9**	67.2	**85.3**	**72.6**	**56.1**	**67.5**	**66.7**	**49.6**	**66.5**	**64.0**	**55.8**	**53.0**	**70.5**	**61.6**	**57.2**	**71.9**	**61.7**

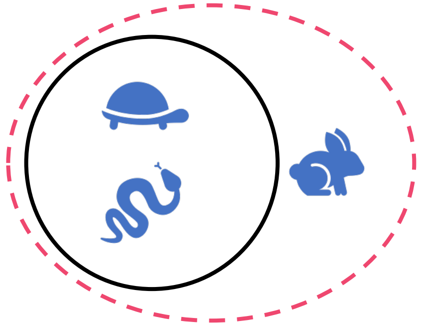
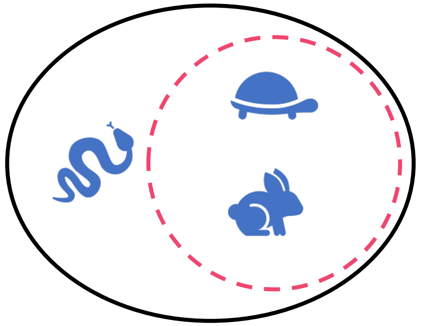
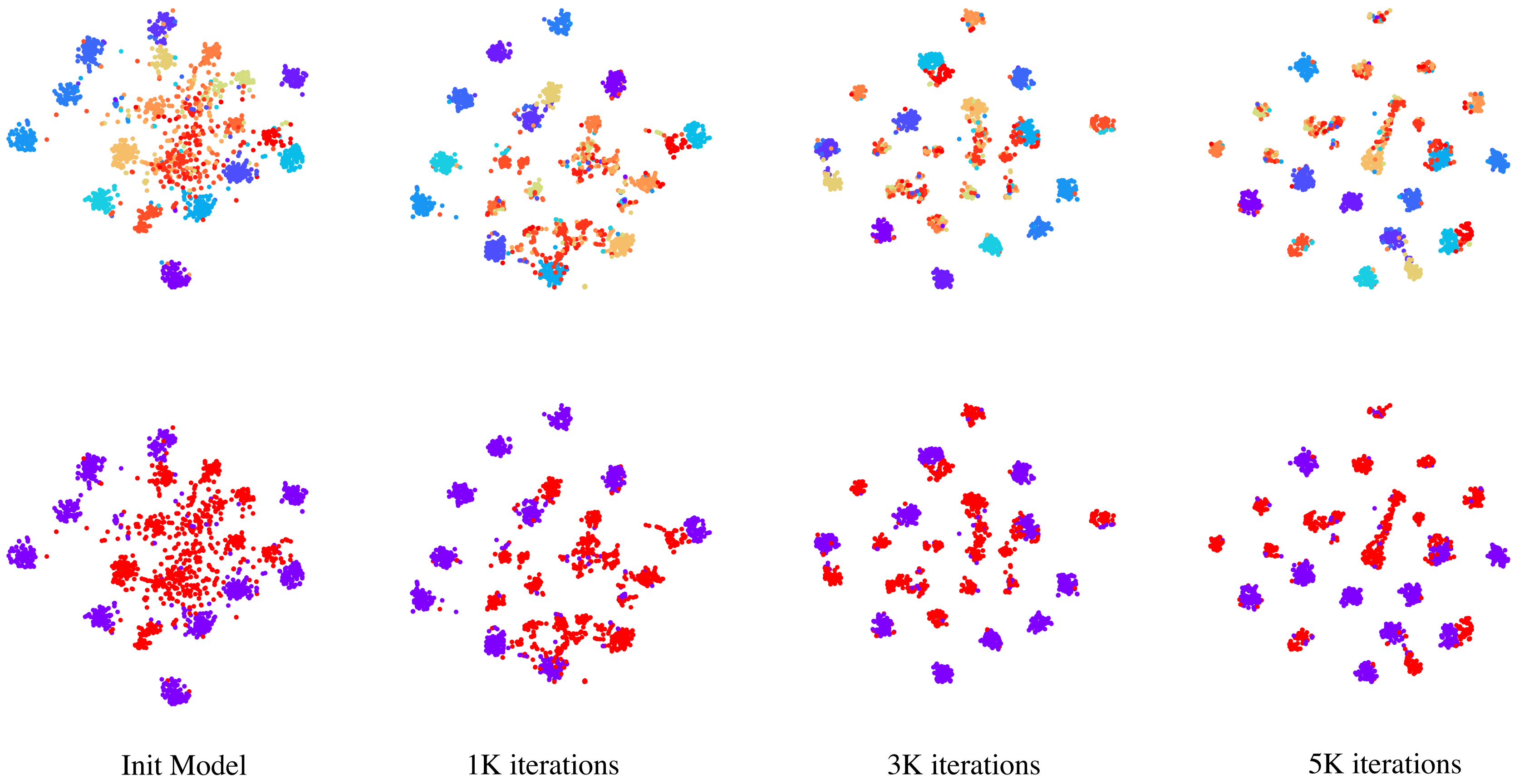


Table 6. Accuracy (%) on **Office** and **Office-Home** under the PDA scenario (ResNet-50). We use 'U' and 'P' to denote methods designed for UniDA setting and PDA setting, respectively.

Method	Type	Office							Office-Home												
		A2W	A2D	D2W	W2D	D2A	W2A	Avg	Ar2Cl	Ar2Pr	Ar2Rw	Cl2Ar	Cl2Pr	Cl2Rw	Pr2Ar	Pr2Cl	Pr2Rw	Rw2Ar	Rw2Cl	Rw2Pr	Avg
IWAN [62]	P	90.5	89.2	95.6	99.3	94.3	99.4	94.7	53.9	54.5	78.1	61.3	48.0	63.3	54.2	52.0	81.3	76.5	56.8	82.9	63.6
SAN [3]	P	94.3	93.9	94.2	99.3	88.7	99.4	95.0	44.4	68.7	74.6	67.5	65.0	77.8	59.8	44.7	80.1	72.1	50.2	78.7	65.3
PADA [4]	P	82.2	86.5	92.7	99.3	95.4	**100.0**	92.7	52.0	67.00	78.7	52.2	53.8	59.1	52.6	43.2	78.8	73.7	56.6	77.1	62.1
ETN [5]	P	94.5	95.0	100.0	100.0	**96.2**	94.6	96.7	**59.2**	77.0	79.5	62.9	65.7	75.0	68.3	**55.4**	84.4	75.7	57.7	84.5	70.5
RTNet [9]	P	96.2	**97.6**	100.0	100.0	92.3	95.4	96.9	63.2	80.1	80.7	66.7	69.3	77.2	71.6	53.9	**84.6**	**77.4**	57.9	85.5	72.3
Ours	P	**99.7**	96.1	**100.0**	**100.0**	95.3	96.3	**97.9**	59.0	**84.4**	**83.4**	**67.8**	**72.7**	**79.8**	**68.4**	53.2	83.7	75.8	**59.0**	**88.3**	**73.0**
UAN [61]	U	76.8	79.7	93.4	98.3	82.7	83.7	85.8	35.0	41.5	34.7	32.3	32.7	32.7	21.1	43.0	39.7	26.6	46.0	34.2	39.7
Ours	U	**97.6**	**87.3**	**100.0**	**100.0**	**96.6**	**96.3**	**96.3**	**54.2**	**47.5**	**57.5**	**83.8**	**71.6**	**86.2**	**63.7**	**65.0**	**75.2**	**85.5**	**78.2**	**82.6**	**70.9**



Visualization



→ Different colors denote different semantic classes

→ Red: private samples
→ Blue: common samples

t-SNE plot of target samples at different training stages in D→A of Office-31

Conclusion and Future Works

- This paper proposes Domain Consensus Clustering (DCC), which performs adaptation over unaligned label space via encouraging discriminative target clusters.

- Future works:
    - Universal domain adaptation in semantic segmentation;
    - Novel category discovery in one domain scenario and cross-domain scenario;

Thanks for Watching

Paper and code available at:

You can reach me with: Guangru.li@outlook.com