Transfer Learning: 10 Concerns

—Annual Progress Review

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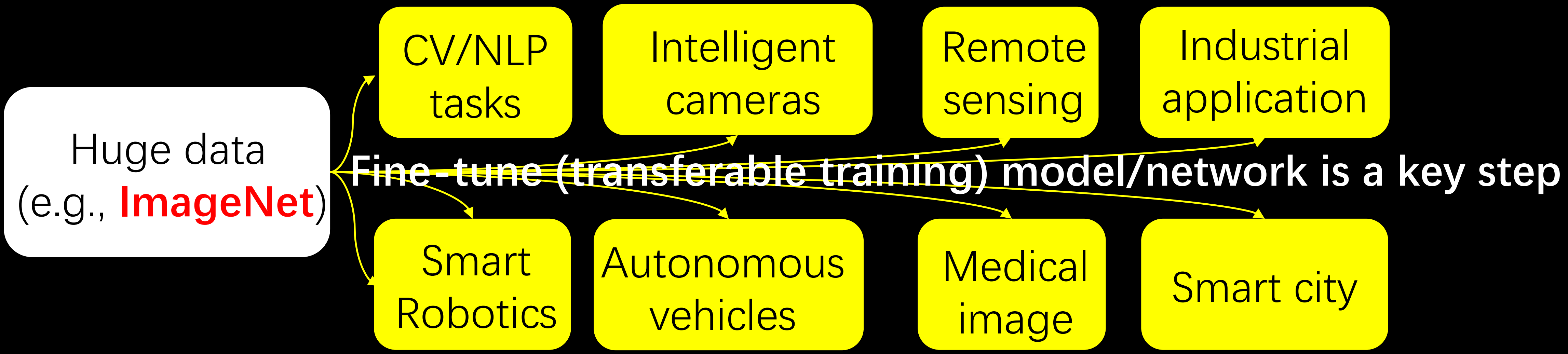
Fine-tune is all you need

- Transfer learning has been a widely used technique in a wide spread of applications.
- In deep learning era, you must hear from about the “fine-tune” technique for various down-stream tasks.



Label dilemma

- For learning a **target** classifier/predictor based on **(X, y)**, you should first have **label** y.

$$R[\Pr, \theta, l(x, y, \theta)] = \mathbf{E}_{(x,y)\sim \Pr}\left[l(x, y, \theta)\right]$$

- Actually, data collection is sometimes expensive, but label is more expensive. **Label scarcity is daily sight**.
- An idea is to “**borrow**” the sufficiently labeled data from another domain (**source**).
- Chinese idioms :“他山之石，可以攻玉”--《诗经》

The devil of distribution discrepancy (non iid)

Pan S.J. and **Yang Q.** (Survey on Transfer learning)
Saenko et al. (Visual domain adaptation)

Pratt L.
(Neural network)

Ben-David et al.
(Domain adaptation theory)

Budding period | Boom period | Explosion period

1991
(bud)

2006
(milestone)

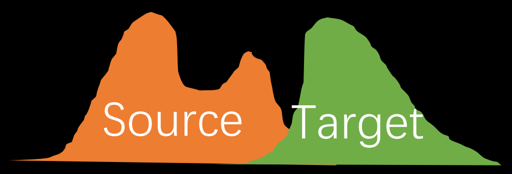
2010
(milestone)

2015
(milestone)

2020s
(mature?)

Trustworthy AI
(generalization, extrapolation)

$$\epsilon_T(h) \leq \hat{\epsilon}_S(h) + \sqrt{\frac{4}{m}\left(d\log\frac{2em}{d} + \log\frac{4}{\delta}\right)} + d_{\mathcal{H}}(\tilde{\mathcal{D}}_S, \tilde{\mathcal{D}}_T) + \lambda$$



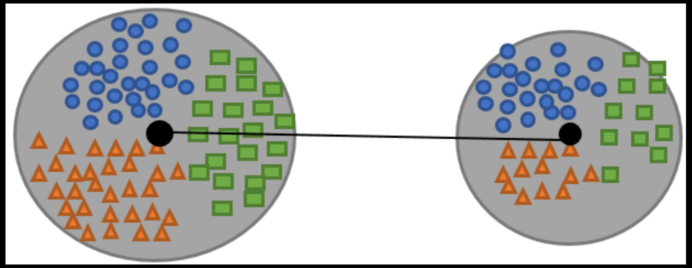
Long et al. (Deep network adaptation)
Ganin et al. (Adversarial domain adaptation)
Tzeng et al. (Deep adversarial transfer)

10 concerns in today’s transfer learning

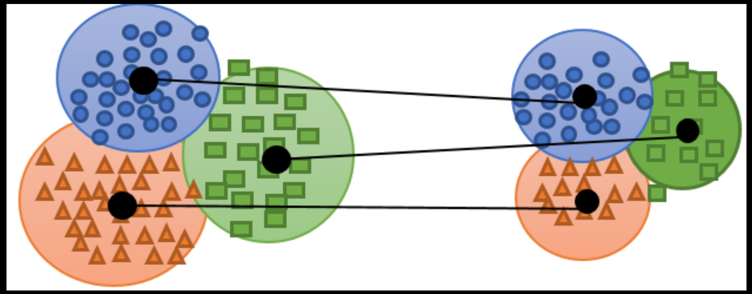
- 1. Local alignment with conditional shift (条件偏移问题)
- 2. Pseudo-labeling for self-training (伪标注质量问题)
- 3. Universal adaptation with category shift (通用迁移问题)
- 4. Multi-source domain adaptation (多源迁移问题)
- 5. Source-free domain adaptation due to privacy (数据隐私问题)
- 6. Balancing alignment and discrimination (任务偏见问题)
- 7. Replacement of entropy minimization (预测偏见问题)
- 8. Domain generalization (未知域泛化、OOD外推问题)
- 9. Transferable robustness and trustworthiness (迁移鲁棒和可信问题)
- 10. Transfer learning + X (迁移学习的应用)

1. Local alignment with conditional shift

- MMD, adversarial alignment and kernel optimal transport can only reflect marginal distribution instead of conditional distribution.



Source Target



Source Target

- **Ideas:** Re-weighting, class-wise alignment, sample-level alignment, conditional metrics based on MMD and OT, pseudo-labels

Examples:

[1] Unsupervised Domain Adaptation with Hierarchical Gradient Synchronization, CVPR 2020.

[2] Self-adaptive Re-weighted Adversarial Domain Adaptation, IJCAI 2020.

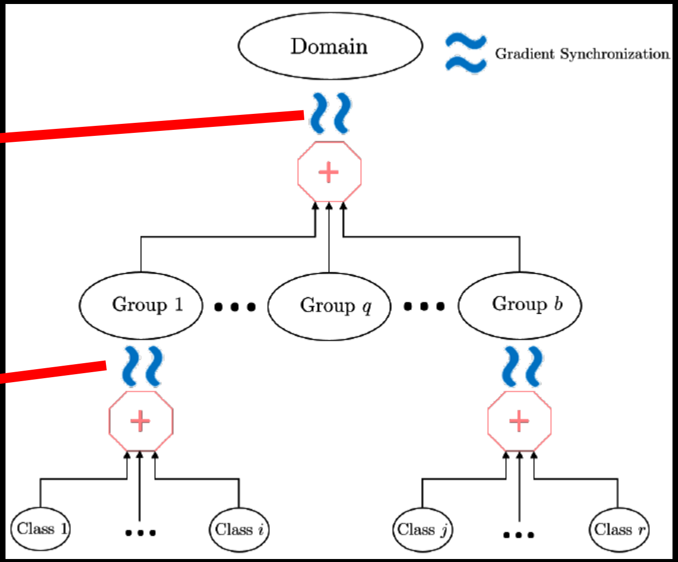
[3] Conditional Bures Metric for Domain Adaptation, CVPR 2021.

1. Local alignment with conditional shift

- [1] gives a perspective that local alignment should be consistent with global alignment, and a gradient synchronization idea is done.

$$L^{syn}_{dom\sim grp} = \left| \sum_{\substack{x_i\in \\ X^s\cup X^t}} \left\| \frac{\partial L^g}{\partial \mathcal{E}(x_i)} \right\|_2 - \sum_{q=1}^{b} \sum_{\substack{x_i\in \\ X^s\cup X^t}} \left\| \frac{\partial L_q^{grp}}{\partial \mathcal{E}(x_i)} \right\|_2 \right|$$

$$L^{syn}_{grp\sim cls} = \left| \sum_{\substack{x_i\in \\ X^s\cup X^t}} \left\| \frac{\partial L_q^{grp}}{\partial \mathcal{E}(x_i)} \right\|_2 - \sum_{k\in grp_q} \sum_{\substack{x_i\in \\ X^s\cup X^t}} \left\| \frac{\partial L_k^{cls}}{\partial \mathcal{E}(x_i)} \right\|_2 \right|$$



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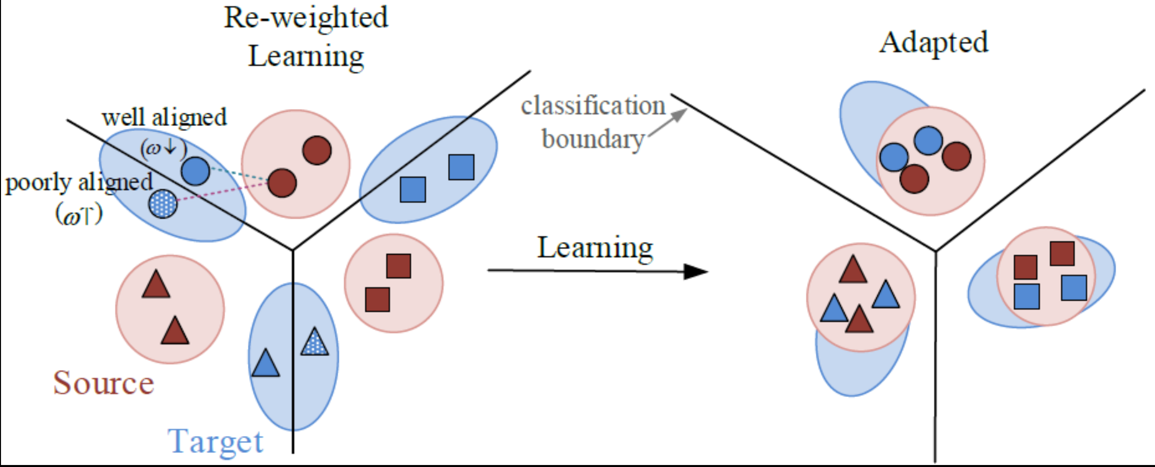
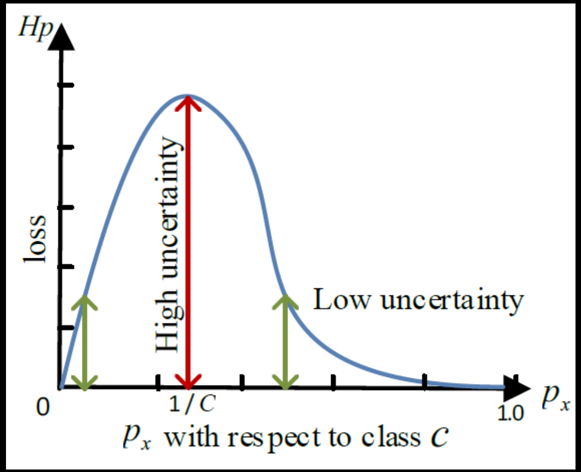
1. Local alignment with conditional shift

- [2] holds that poorly aligned samples may have higher probability to be local misaligned category. Reweighting with entropy criteria.





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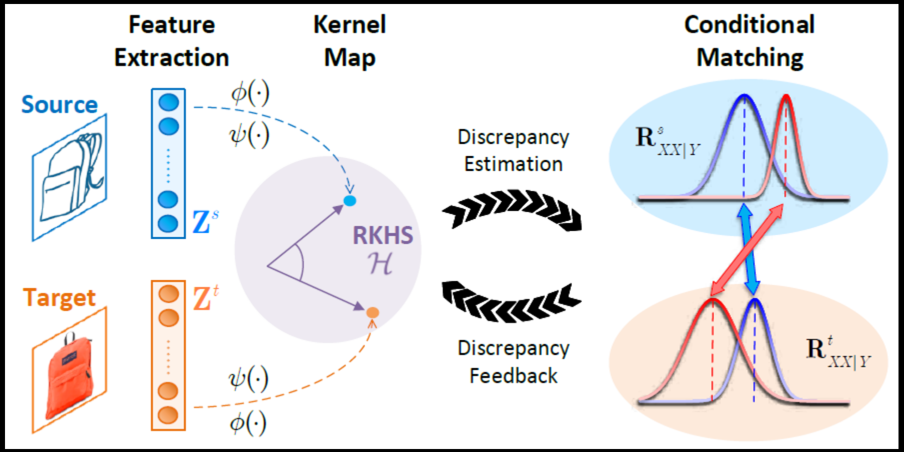
1. Local alignment with conditional shift

- [3] constructs a conditional kernel Bures (CKB) metric based on the kernel optimal transport theory, a lower bound of KOT.
- Conditional Covariance Operator

Theorem 2 *The empirical estimation of the CKB metric is computed as*

$$
\begin{aligned}
&\hat{d}^2_{\mathrm{CKB}}(\hat{\mathbf{R}}^s_{XX|Y}, \hat{\mathbf{R}}^t_{XX|Y}) \\
=&\varepsilon \mathrm{tr}\left[\mathbf{G}^s_X\left(\varepsilon n \mathbf{I}_n + \mathbf{G}^s_Y\right)^{-1}\right] + \varepsilon \mathrm{tr}\left[\mathbf{G}^t_X\left(\varepsilon m \mathbf{I}_m + \mathbf{G}^t_Y\right)^{-1}\right] \\
&- \frac{2}{\sqrt{nm}}\left\|\left(\mathbf{H}_m \mathbf{C}_t\right)^T \mathbf{K}^{ts}_{XX}\left(\mathbf{H}_n \mathbf{C}_s\right)\right\|_*, \qquad (5)
\end{aligned}
$$



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2. Pseudo-labeling for self-training

- Due to domain shift, error accumulation of Pseudo labeling is a big problem.
- High prediction confidence is often threshold as pseudo labels for self-training, but easily gives rise to sparse pseudo labels.
- **Ideas**: class prototype/centroid constraints, progressive updating (easy to hard), pseudo-label denoising/densification

Examples:

[1] Progressive Feature Alignment for Unsupervised Domain Adaptation, CVPR 2019.

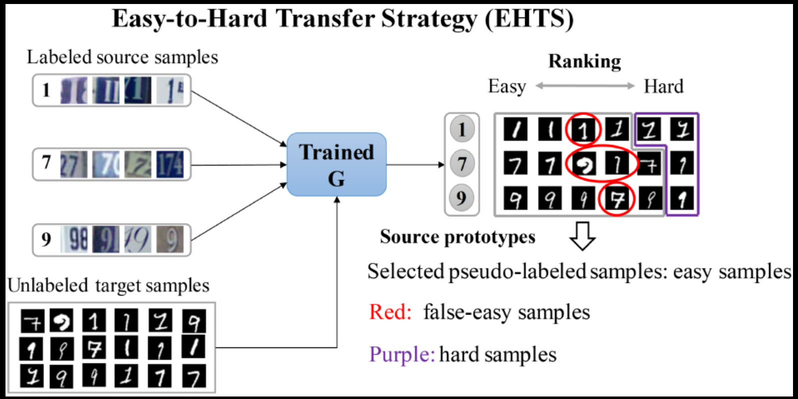
[2] Domain adaptation with Auxiliary Target domain-oriented classifier, CVPR 2021.

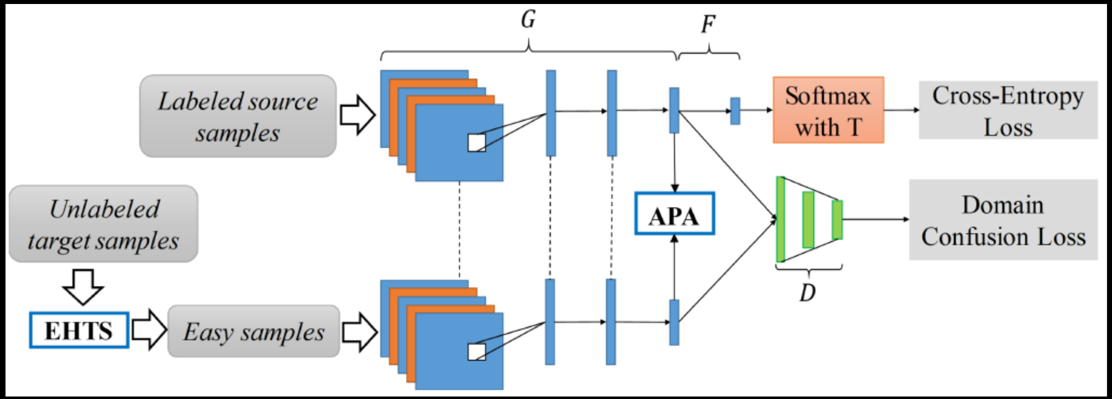
[3] Implicit class-conditional domain alignment for unsupervised domain adaptation, ICML 2020.

[4] Two-phase pseudo label densification for self-training based domain adaptation, ECCV 2020.

2. Pseudo-labeling for self-training

- [1] adopts a progressive training strategy and holds that easy samples have better pseudo labels than hard samples. Adaptive prototype alignment (class centroid alignment) is used.





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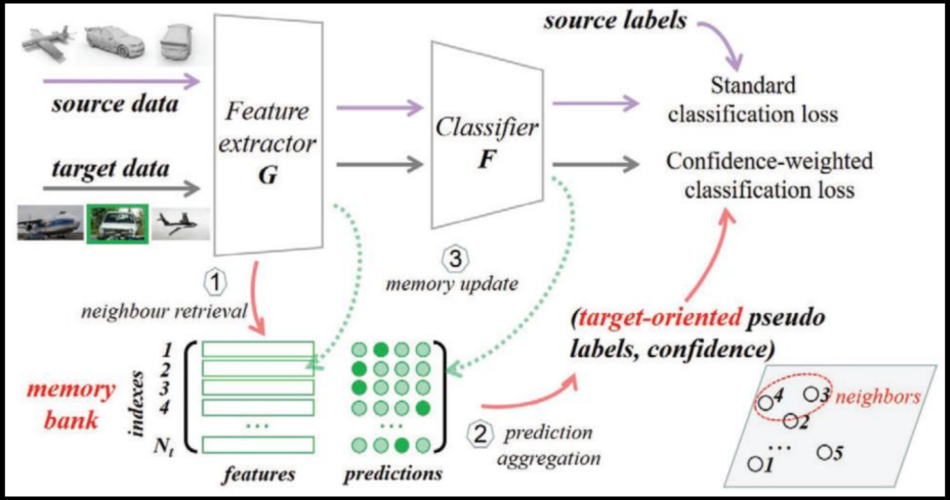
2. Pseudo-labeling for self-training

- [2] adopts an auxiliary target classifier with nearest centroid to get pseudo labels. Confidence weighted cross-entropy loss is used.



$$\mathcal{L}_{na} = -\frac{\lambda}{N_{tu}} \sum_{i=1}^{N_{tu}} \hat{q}_{i,\hat{y}_i} \log p_{i,\hat{y}_i}.$$

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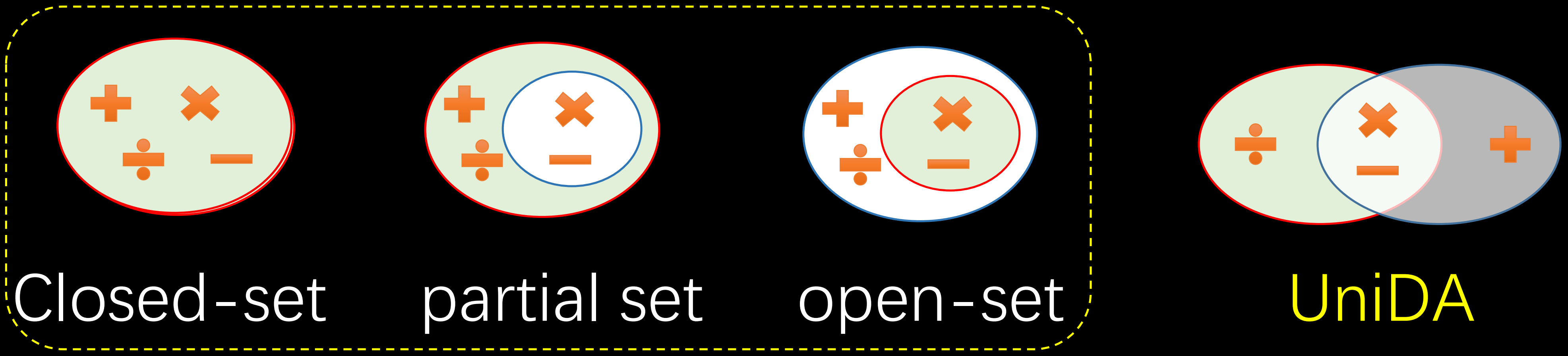
3. Universal DA with category shift

- UniDA solves a mixture of closed-set, partial set and open-set DA.



Examples:

[1] Universal Domain Adaptation, CVPR 2019.

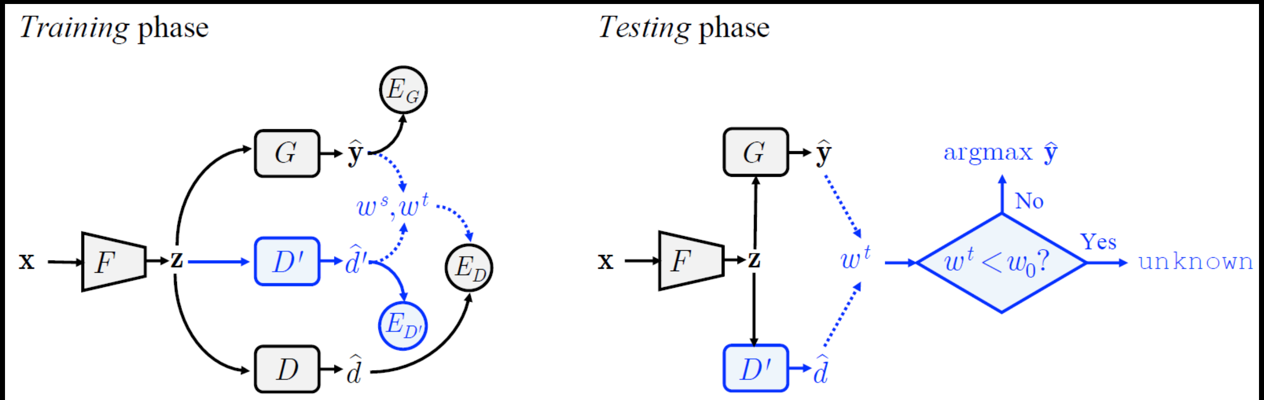
[2] Universal domain adaptation through self-supervision, NeurIPS 2020.

[3] Divergence optimization for noisy universal domain adaptation, CVPR 2021.

[4] Domain Consensus Clustering for Universal Domain Adaptation, CVPR 2021.

3. Universal DA with category shift

- [1] firstly defines the new problem UniDA and proposes intuitive prior assumption for weighting the common and private classes. The weight is based on domain similarity vs. entropy based uncertainty (two assumptions).



$$\mathbb{E}_{\mathbf{x}\sim p_{\overline{\mathcal{C}}_s}} \hat{d}' > \mathbb{E}_{\mathbf{x}\sim p_{\mathcal{C}}} \hat{d}' > \mathbb{E}_{\mathbf{x}\sim q_{\mathcal{C}}} \hat{d}' > \mathbb{E}_{\mathbf{x}\sim q_{\overline{\mathcal{C}}_t}} \hat{d}'$$

$$\mathbb{E}_{\mathbf{x}\sim q_{\overline{\mathcal{C}}_t}} H(\hat{\mathbf{y}}), \mathbb{E}_{\mathbf{x}\sim q_{\mathcal{C}}} H(\hat{\mathbf{y}}) > \mathbb{E}_{\mathbf{x}\sim p_{\mathcal{C}}} H(\hat{\mathbf{y}}), \mathbb{E}_{\mathbf{x}\sim p_{\overline{\mathcal{C}}_s}} H(\hat{\mathbf{y}})$$

$$w^s(\mathbf{x}) = \frac{H(\hat{\mathbf{y}})}{\log |\mathcal{C}_s|} - \hat{d}'(\mathbf{x})$$

$$w^t(\mathbf{x}) = \hat{d}'(\mathbf{x}) - \frac{H(\hat{\mathbf{y}})}{\log |\mathcal{C}_s|}$$

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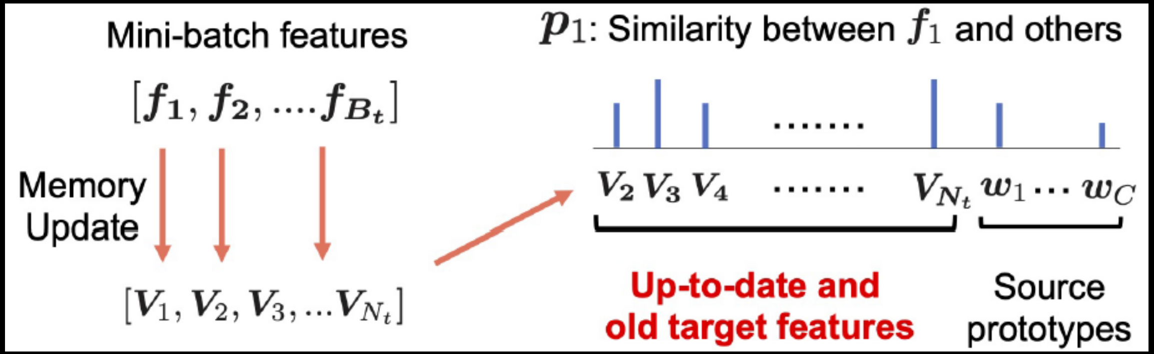
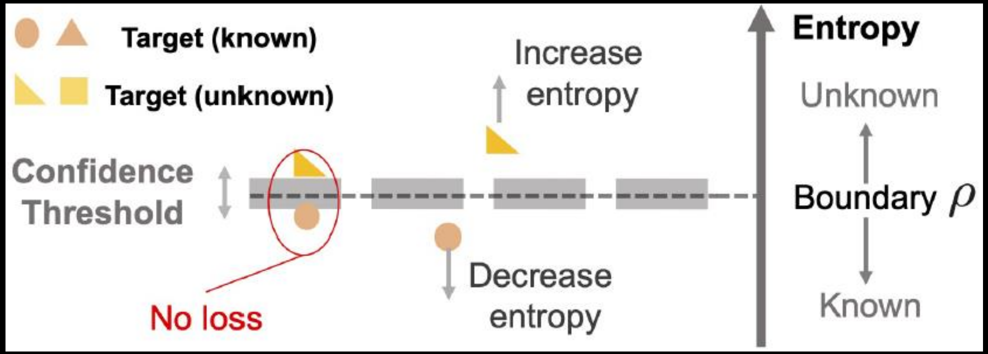
3. Universal DA with category shift

- [2] is different from [1] that explicit weighting mechanism is not used. Neighborhood clustering loss and Entropy separation loss.





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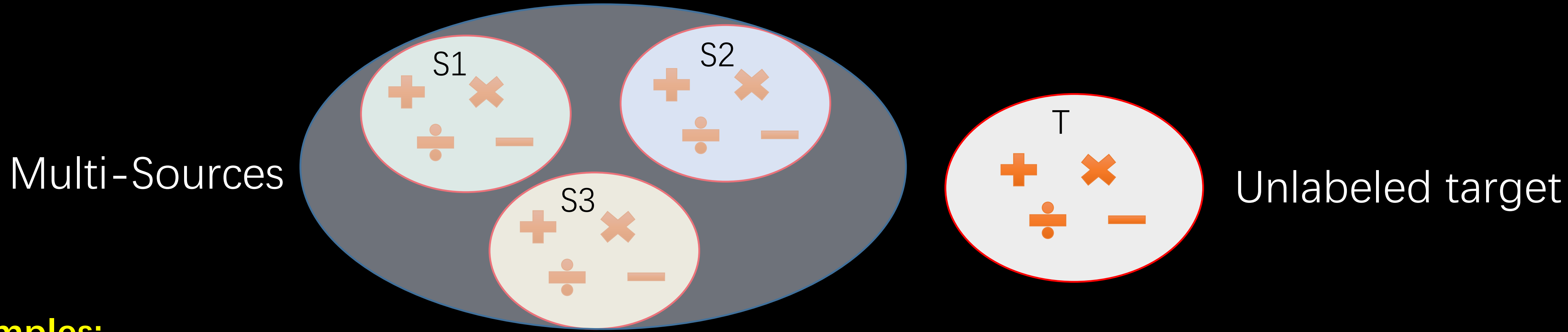
4. Multi-source domain adaptation

- Multi-source DA is more realistic than single-source DA. How to explore the positive effect of less confident source is a challenge.



Examples:

[1] Multi-source distilling domain adaptation, AAAI 2020.

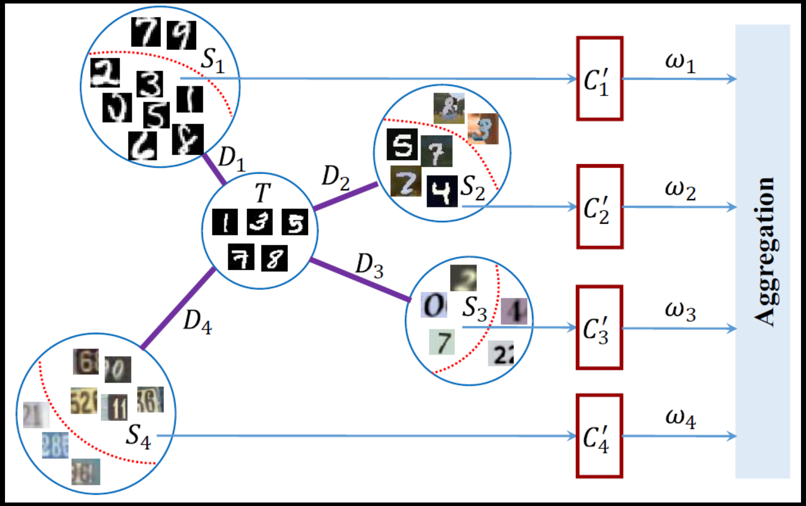
[2] Your Classifier can Secretly Suffice Multi-source domain adaptation, NeurIPS 2020.

[3] Curriculum Manager for Source Selection in Multi-source domain adaptation, ECCV 2020.

[4] Partial Feature Selection and Alignment for Multi-source domain adaptation, CVPR 2021.

4. Multi-source domain adaptation

- [1] proposes to progressively fine-tune source classifiers with selected target-like source samples through Wasserstein distance.



Weighted aggregation for inference

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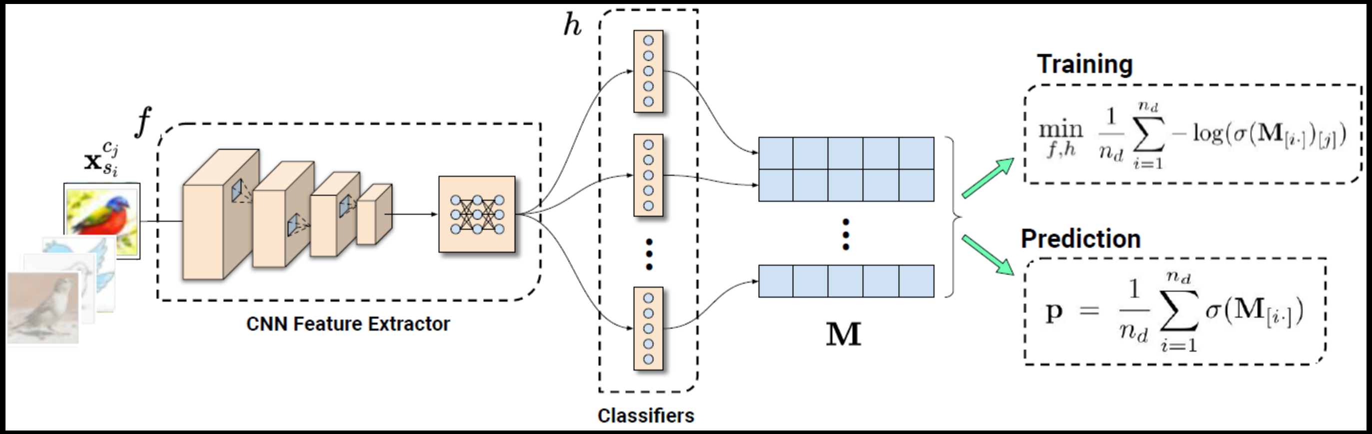
4. Multi-source domain adaptation

- [2] proposes implicit adaptation without explicit alignment via weighting. Source classifiers prediction agreement is used for target pseudo-labels and self-training on target.



Source cls. losses

Target cls. loss

Average probability

Examples:

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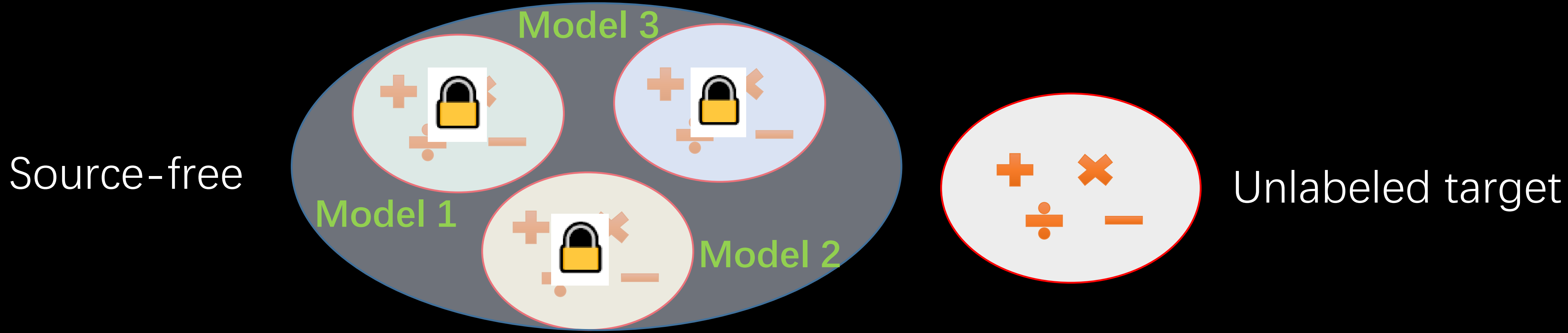
5. Source-free domain adaptation

- Source-free DA is for data privacy critical applications, without access to source data. Its essence is hypothesis transfer and decentralization.



Problem: the essence of DA to bridge the distribution gap may be overlooked!

Examples:

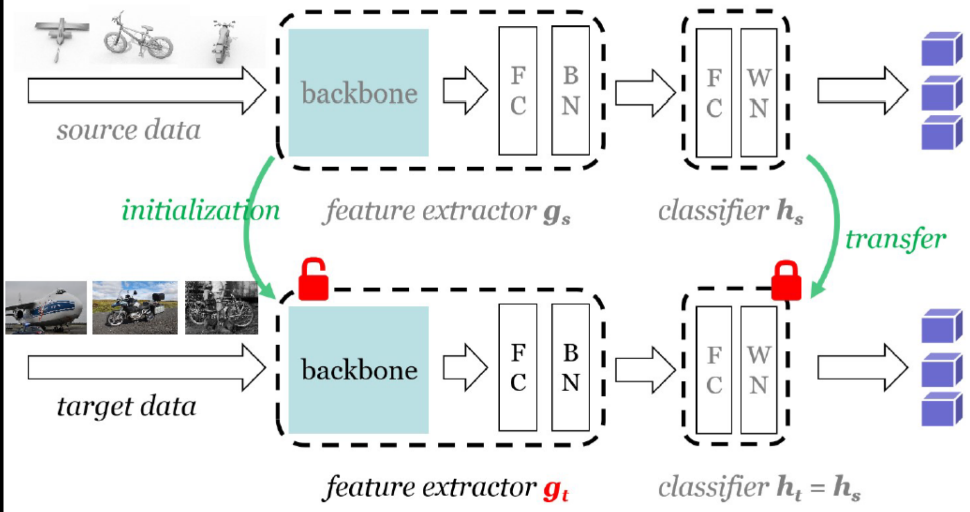
[1] Do We Really Need to Access the Source Data? Source Hypothesis Transfer for Unsupervised Domain Adaptation, ICML 2020.

[2] Unsupervised Multi-source domain adaptation without access to source data, CVPR 2021.

[3] KD3A: Unsupervised Multi-source decentralized Domain adaptation via knowledge distillation, ICML 2021.

5. Source-free domain adaptation

- [1] proposes to optimize the target feature encoder by sharing the source hypothesis classifier, which implies the distribution consistency. Information maximization and pseudo-labeling for local align are given.



Off-line training

Online training

Examples:

[1] Do We Really Need to Access the Source Data? Source Hypothesis Transfer for Unsupervised Domain Adaptation, ICML 2020.

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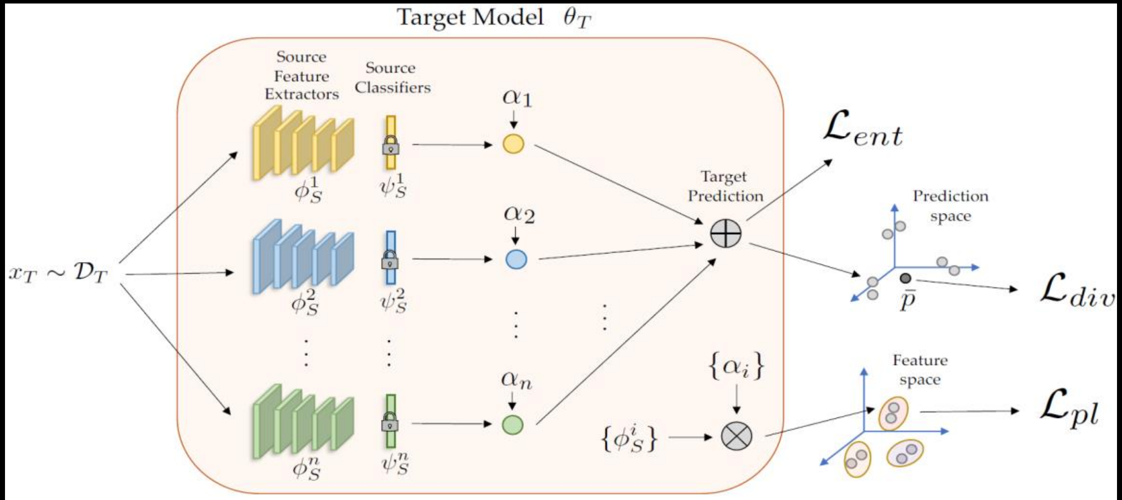
5. Source-free domain adaptation

- [2] proposes to weight multi-source hypothesis and get weighted target pseudo labels for self-training, by optimizing source encoders and weights with classifiers frozen.



→ Entropy loss

→ Class diversity maximize

→ Cls. self-training

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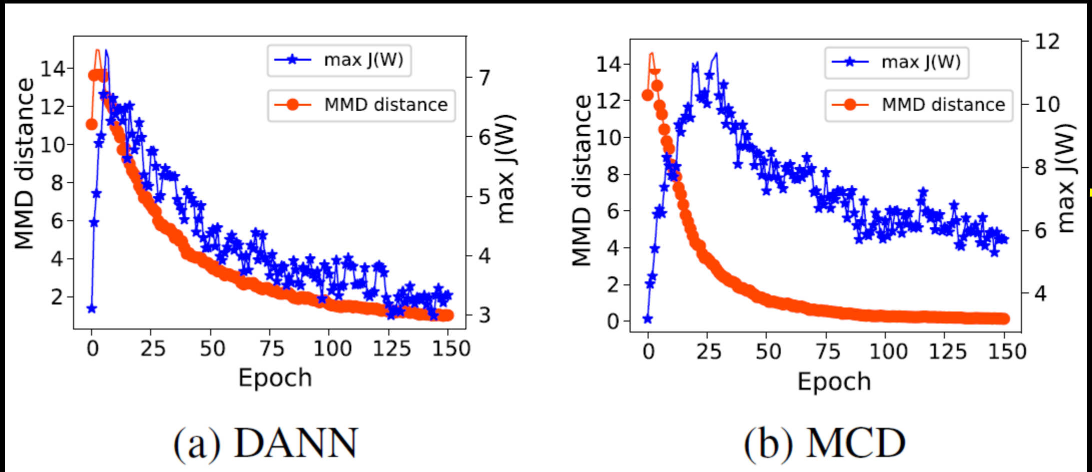
6. Balancing alignment and discrimination

- DA is generally a multi-task co-training between domain alignment and class discrimination, and inevitably meets imbalance in optimization.

Transferability is increasing



Discrimination is decreasing

Optimization inconsistency

Examples:

[1] MetaAlign: Coordinating Domain Alignment and Classification for Unsupervised Domain Adaptation, CVPR 2021.

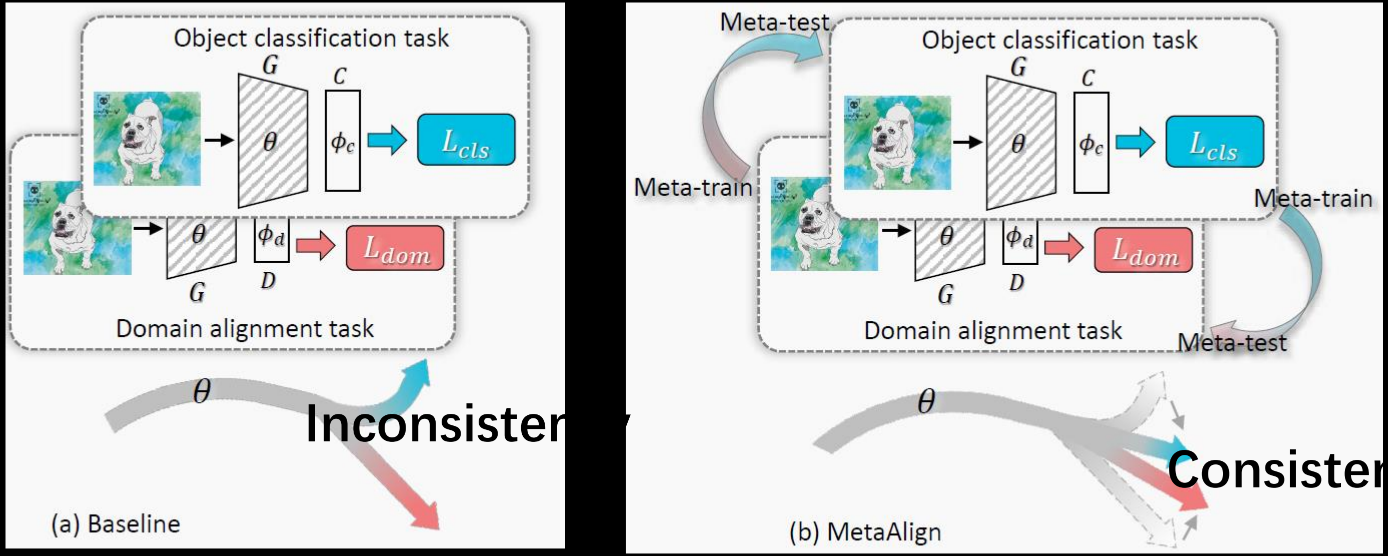
[2] Dynamic Weighted Learning for Unsupervised Domain Adaptation, CVPR 2021.

[3] Transferability vs. Discriminability: Batch Spectral Penalization for Adversarial Domain Adaptation, ICML 2019.

[4] Harmonizing transferability and discriminability for adapting object detectors, CVPR 2020.

6. Balancing alignment and discrimination

- [1] proposes to improve the consistency by using meta learning strategy (meta-train vs. meta-test), such that between-task gradient correlation (similarity) is maximized.



Essence: Loss Alignment.

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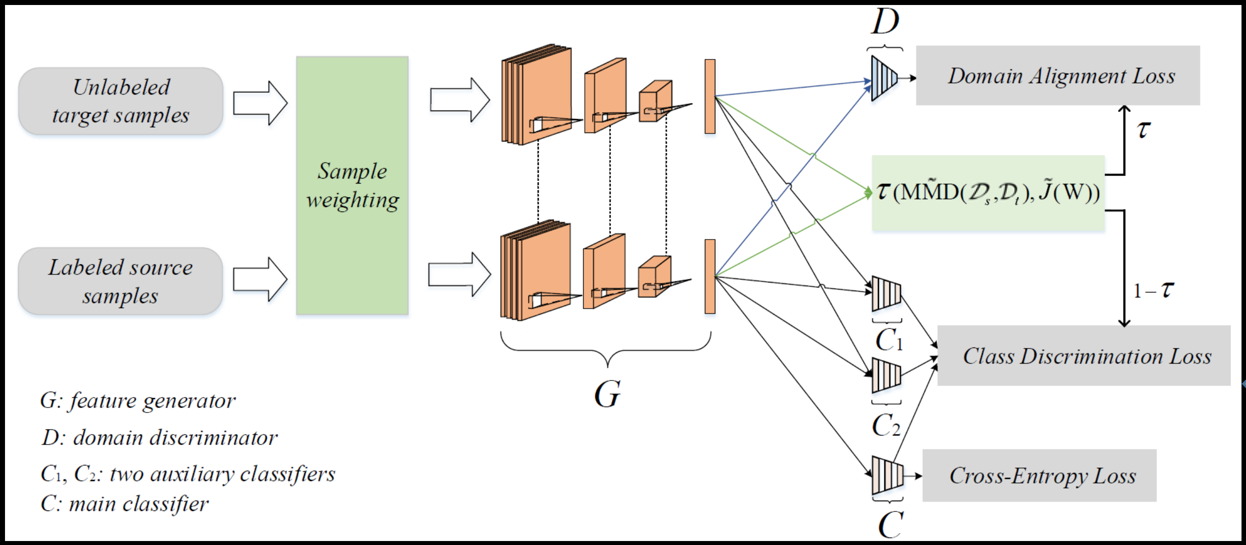
6. Balancing alignment and discrimination

- [2] proposes to dynamically weight the two tasks (losses) by designing dynamic comprehensive weight w.r.t. discrimination and transferability.



$$\tau = \frac{\mathrm{M\tilde{M}D}\left(\mathcal{D}_s, \mathcal{D}_t\right)}{\mathrm{M\tilde{M}D}\left(\mathcal{D}_s, \mathcal{D}_t\right) + (1 - \tilde{J}(\mathbf{W}))}$$

$$\min_{\theta_g,\theta_c} \max_{\theta_d,\theta_{c_1},\theta_{c_2}} \tau \cdot \mathcal{L}_{da}\left(\theta_g, \theta_d\right) + (1-\tau) \cdot \mathcal{L}_{cd}\left(\theta_g, \theta_c, \theta_{c_1}, \theta_{c_2}\right)$$

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7. Replacement of Entropy minimization

- Due to the target label dilemma, with only entropy regularization, target prediction bias tends to have low class-diversity and high class-confusion.

✓With **entropy minimization**, minority classes of target may be mis-classified as majority classes (common case in a batch).

✓With **entropy minimization**, class prediction confusion between correct and ambiguous classes is serious.

Examples:

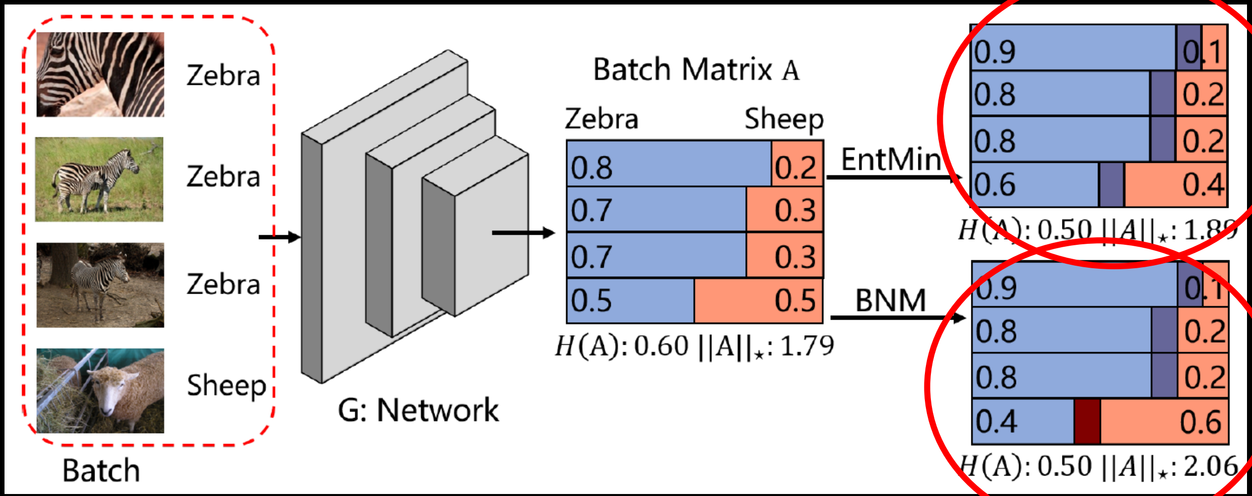
[1] Towards Discriminability and Diversity: Batch Nuclear-norm Maximization under Label Insufficient Situations, CVPR 2020.

[2] Minimum Class Confusion for Versatile Domain Adaptation, ECCV 2020.

[3] Dual Mixup Regularized Learning for Adversarial Domain Adaptation, ECCV 2020.

7. Replacement of Entropy minimization

- [1] proposes an interesting observation, i.e., Shannon entropy minimization loss is equal to **rank (nuclear-norm) maximization** loss, but improves the **class-diversity** of pred. probability matrix (in a batch).



Minority class (shape) is misclassified as majority class

$$\mathcal{L}_{all} = \frac{1}{B_L}\left\|Y^L log(G(X^L))\right\|_1 - \frac{\lambda}{B_U}\left\|G(X^U)\right\|_\star$$

Nuclear-norm maximization improves prediction diversity

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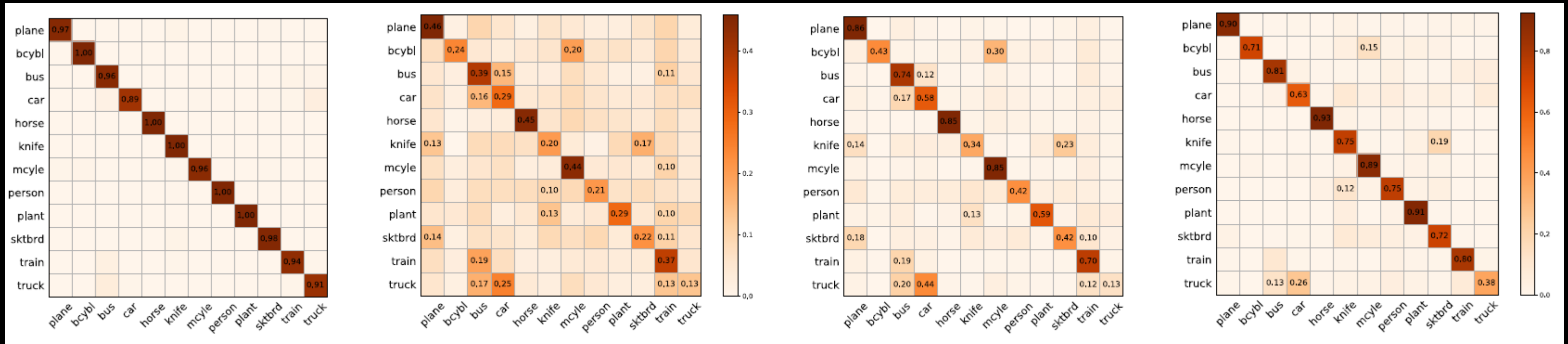
7. Replacement of Entropy minimization

- [2] unveils that a **minimum class confusion** (MCC) indicates high class discriminability and implies high transferability, without explicit DA. **Entropy minimization is replaced with MCC**.



(a) Source (b) Target (c) Target by MinEnt [12] (d) Target by MCC

$$L_{\mathrm{MCC}}(\widehat{\mathbf{Y}}_t) = \sum_{j=1}^{|\mathcal{C}|} \sum_{j' \neq j}^{|\mathcal{C}|} \left| \widetilde{\mathbf{C}}_{jj'} \right|.$$

$$\min_{F,G} \mathbb{E}_{(\mathbf{x}_s,\mathbf{y}_s)\in\mathcal{S}} L_{\mathrm{CE}}\left(\widehat{\mathbf{y}}_s, \mathbf{y}_s\right) + \mu\, \mathbb{E}_{\mathbf{X}_t\subset\mathcal{T}} L_{\mathrm{MCC}}(\widehat{\mathbf{Y}}_t)$$

No DA

Examples:

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[2] Minimum Class Confusion for Versatile Domain Adaptation, ECCV 2020.

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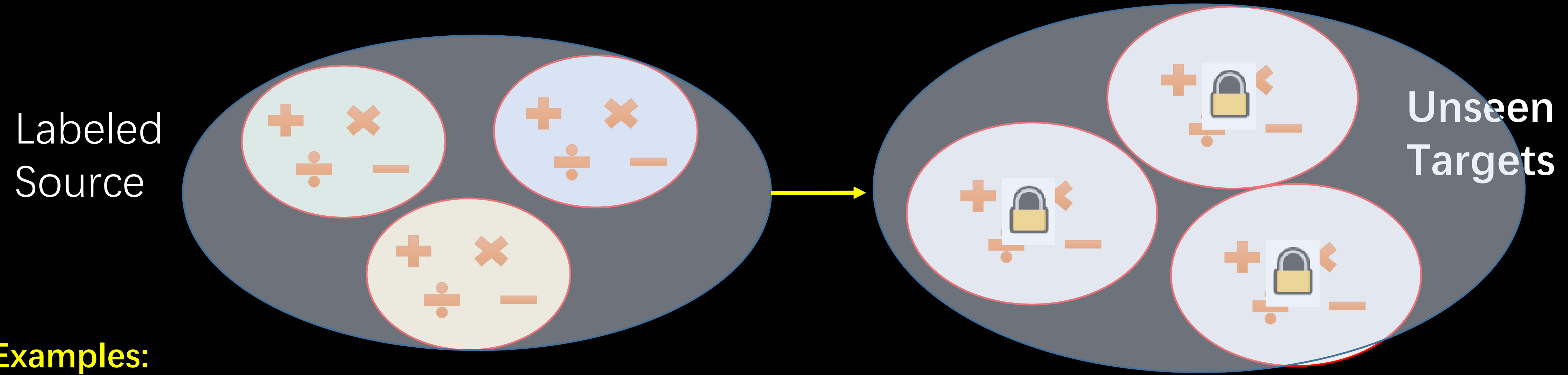
8. Domain generalization (OOD)

- Domain generalization (DG) is more realistic than DA. Generalization to **unseen** target domains with **source diversity and training strategy**.



Examples:

[1] Learning to Generate Novel Domains for Domain Generalization, ECCV 2020.

[2] Open Domain Generalization with Domain-Augmented Meta-Learning, CVPR 2021.

[3] FSDR: Frequency Space Domain Randomization for Domain Generalization, CVPR 2021.

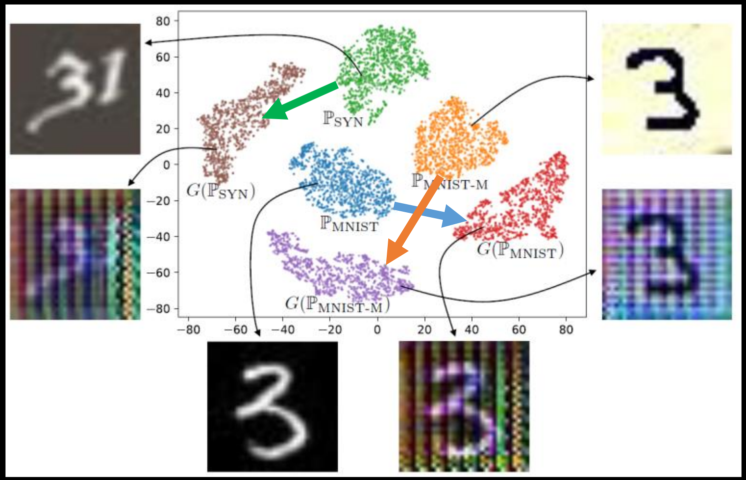
[4] Generalization on Unseen Domains via Inference-time Label-Preserving Target Projections, CVPR 2021.

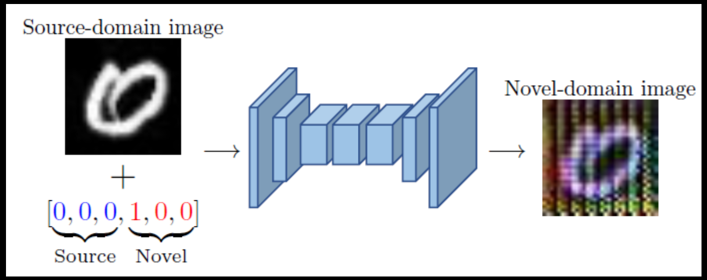
[5] Progressive Domain Expansion Network for Single Domain Generalization, CVPR 2021.

[6] Test-time training with self-supervision for generalization under distribution shifts, ICML 2020.

8. Domain generalization (OOD)

- [1] utilizes GAN to generate novel domains for DG with **similar semantics** (CycleGAN) but **different distribution** (maximum domain divergence).





Examples:

[1] Learning to Generate Novel Domains for Domain Generalization, ECCV 2020.

[2] Open Domain Generalization with Domain-Augmented Meta-Learning, CVPR 2021.

[3] FSDR: Frequency Space Domain Randomization for Domain Generalization, CVPR 2021.

[4] Generalization on Unseen Domains via Inference-time Label-Preserving Target Projections, CVPR 2021.

[5] Progressive Domain Expansion Network for Single Domain Generalization, CVPR 2021.

[6] Test-time training with self-supervision for generalization under distribution shifts, ICML 2020.

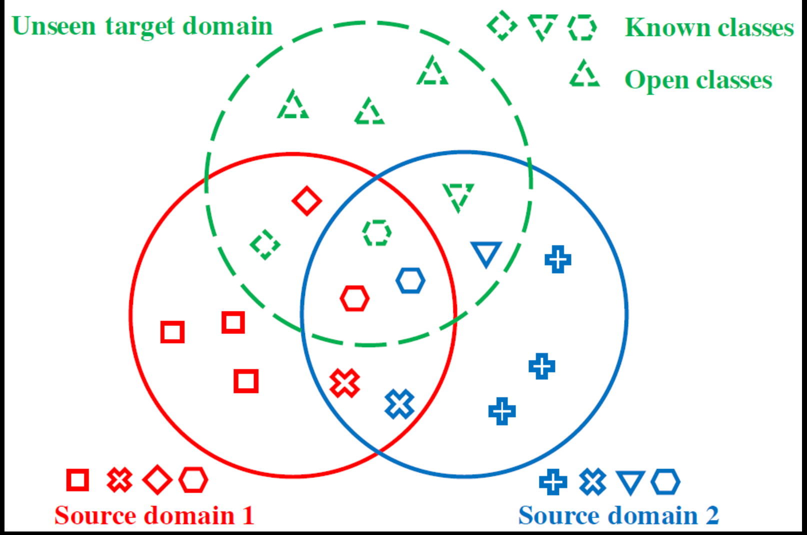
8. Domain generalization (OOD)

- [2] defines an OpenDG problem by supposing the category shift in image classification, via domain augmentation (mixup) and meta-learning strategy.

✓Feature-level augmentation (Dirichlet mixup)

✓Label-level augmentation (soft label distillation)

✓Meta-learning with raw data and domain augmented data



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9. Transferable robustness and trustworthiness

- With the explosive increase of transfer learning and domain adaptation in models and algorithms, how about their robustness and trustworthiness?

✓Theoretical limitations (large domain gap)

✓Transferable robustness vs. accuracy

✓Adversarial robustness vs. trustworthiness

Examples:

[1] Understanding Self-Training for Gradual Domain Adaptation, ICML 2020

[2] CARTL: Cooperative Adversarially-Robust Transfer Learning, ICML 2021.

[3] On the robustness of domain adaption to adversarial attacks, arXiv 2021.

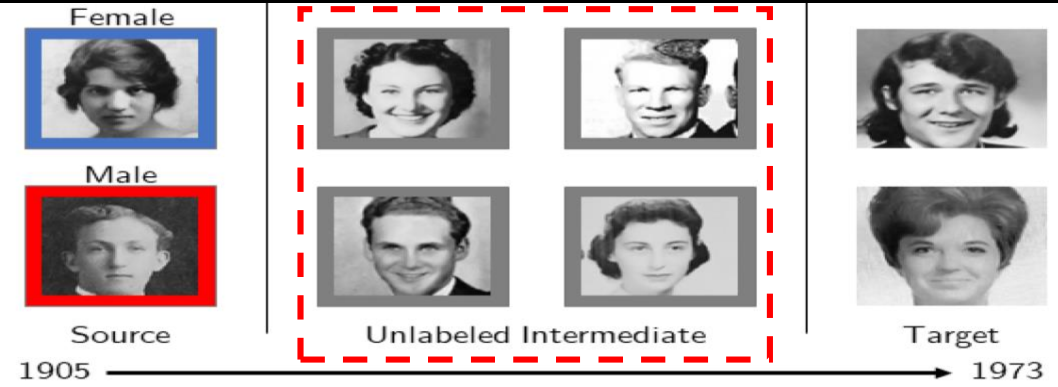
[4] Exploring Robustness of Unsupervised Domain Adaptation in Semantic Segmentation, ICCV 2021.

9. Transferable robustness and trustworthiness

- Theoretical limitations (large domain gap)

[1] proposes to gradually domain adaptation for alleviating the large domain gap by self-training on pseudo-labels of intermediate domains.

✓Theory proves that self-training is better when the domain gap is small, because of high-quality of pseudo-labels.



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9. Transferable robustness and trustworthiness

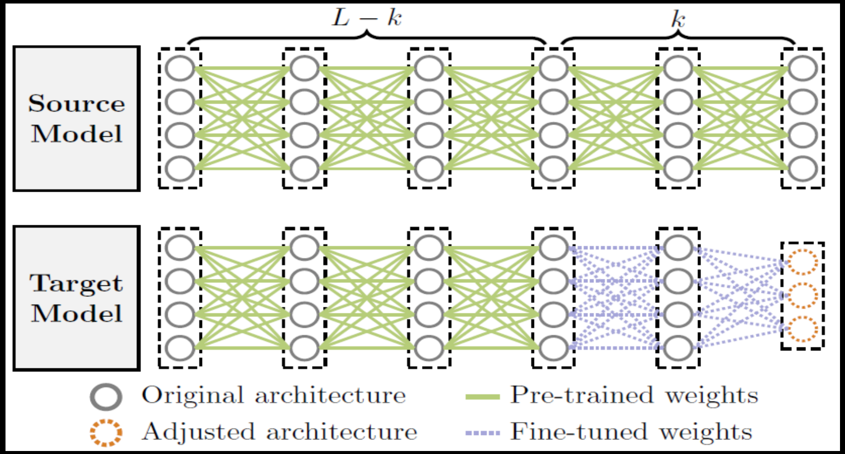
- Transferable robustness vs. accuracy

[2] finds that fine-tuning different number of layers has different impacts on the transferable robustness and accuracy.

✓Fine-tune more layers may result in good accuracy, but low robustness.

✓Fine-tune few layers may lose accuracy, but improve robustness.

✓Strategy that achieves both increment is necessary.



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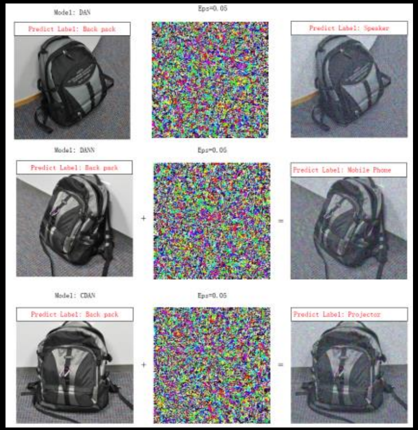
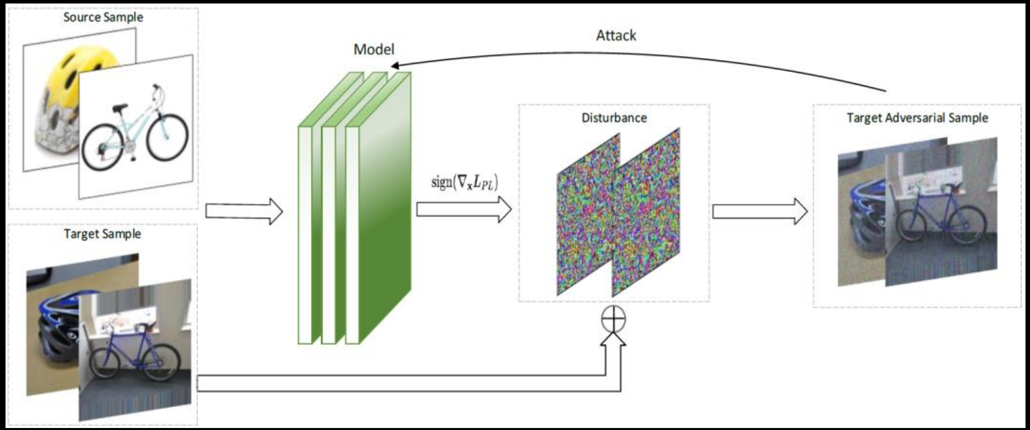
9. Transferable robustness and trustworthiness

- Adversarial robustness vs. trustworthiness

[3,4] firstly studies the vulnerability of domain adaption models, and find it is easily attacked by adversarial (人眼不可察觉) perturbation.





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10. Transfer learning + X

- Transfer learning + Object detection
- Transfer learning + Semantic segmentation
- Transfer learning + Person re-identification
- Transfer learning + Image retrieval
- Transfer learning + Pose estimation/recognition

....

Transfer learning + Images/Videos/Texts (Medical, Hyperspectral, Remote sensing, Multi-Media, ...)

Examples:

[1] Domain Adaptive Object Detection via Asymmetric Tri-way Faster-RCNN, ECCV 2020.

[2] Probability Weighted Compact Feature for Domain Adaptive Retrieval, CVPR 2020.

[3] Group-aware Label Transfer for Domain Adaptive Person Re-identification, CVPR 2021.

[4] From Synthetic to Real: Unsupervised Domain Adaptation for Animal Pose Estimation , CVPR 2021.

[5] Unsupervised Multi-Source Domain Adaptation for Person Re-Identification, CVPR 2021.

A Brief Summary

- Transfer learning has become a tool that all you need.
- No matter what kind of learning techniques, **robustness vs. generalization** should be the final objective, upon the *interpretability*, *adaptability*, *fairness (de-bias)*, *security*, *trustworthiness*, *etc*.
- **待突破的方向：Include but not limited to transfer learning, domain generalization, out of distribution (OOD) extrapolation, life-long/continual learning, etc.**
- **解决思路：1）Causality invariance and essential representation may be a solution; 2）Super-big pre-trained model.**

Thank you

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VALSE 2021 Hangzhou