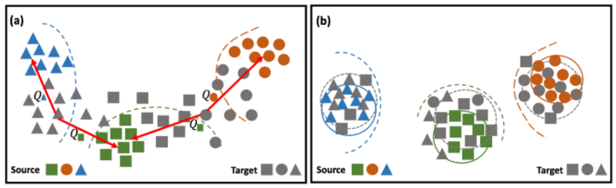
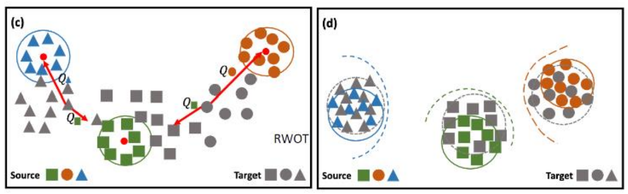
Reliable Weighted Optimal Transport for Unsupervised Domain Adaptation

This paper tackles the intra-domain alignment in domain adaptation. The paper is based on the centroid clustering method and solved the problem of hard examples lying around the decision boundary.

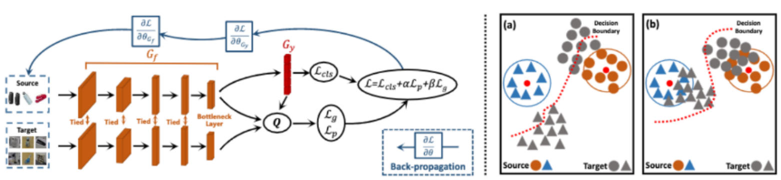


Hard-aligned target samples distributed near the decision boundary cause negative transfer.



(c) RWOT using shrinking subspace reliability, weighted optimal transport, and discriminative centroid loss, exploits spatial prototypical information and intra-domain structure.
(d) Our proposed RWOT model achieves intra-class compactness and inter-class separability in both of the source and target domains.

5. RWOT Architecture



G_f : feature generator
G_y : adaptive classifier
L_g : weighted optimal transport loss based on shrinking subspace reliability
L_p : discriminative centroid loss
L_{cls} : standard cross-entropy loss
α and β : hyper-parameters

$$\min_{G_y,G_f} \mathcal{L}_{cls} + \alpha\mathcal{L}_p + \beta\mathcal{L}_g,$$

Main idea:

1. Clustering centroid method
2. New distance metric between samples and centroids. Previous single kernel method defines the distance based the relation of samples and centroids. Multi kernel method defines the distance as the relations between samples and samples, samples and centroids, centroids and centroids.
3. Based on distance, calculate the probabilities of pseudo labels with a smoothed temperature.
4. Using these values to weight the Kantorovich problem which is about pair-wise alignment on categories of source and target domains.
5. Using metric learning method to pull close the same class and push away different classes based on the weighted distance

Experiments on resnet-50 achieves new SOTA.

Towards Discriminability and Diversity: Batch Nuclear-Norm Maximization Under Label Insufficient Situations

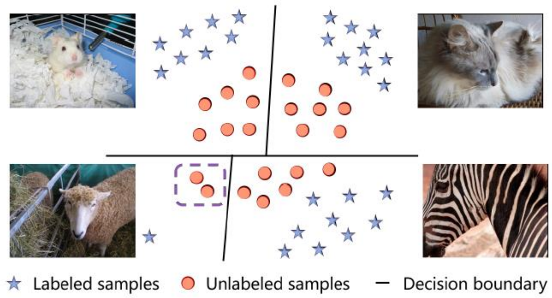


Figure 1. Illustration of problem. Beyond the discriminability, we also focus on the minority category with few samples bounded in the dotted frame at the bottom left part. The influence of minority category tends to be reduced in direct entropy minimization, resulting in the degradation of the category prediction diversity.

This paper addresses the importance of context information in scene understanding task such as object detection and semantic segmentation. Current successive CNN increase the receptive field linearly like max pooling, which is insufficient and inefficient.

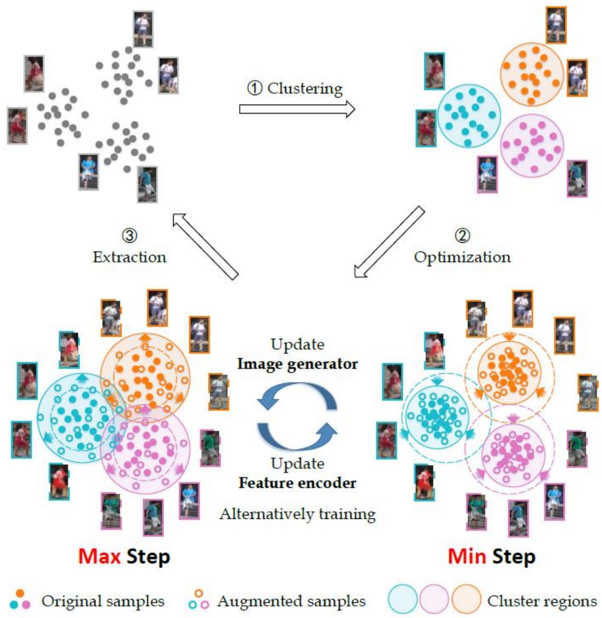
Main idea:

1. Instead of increasing the receptive field, the paper learns a scheme to dynamically sample different contexts conditioned on this image. This overcomes the issues of limited receptive field of CNN.
2. Input the features, construct a graph based on these feature observations.
3. Uniformly sampling the neighbors of each node, and then do random walk for these neighbors.
4. Use neighbors to propagate refine latent feature of this node.

Experiment results on semantic segmentation and object detection show the proposed module can be combined with different backbones and outperforms Mask-RCNN.

AD-Cluster: Augmented Discriminative Clustering for Domain Adaptive Person Re-identification

This paper presents a novel augmented discriminative clustering (AD-Cluster) technique that estimates and augments person clusters in target domains and enforces the discrimination ability of re-ID models with the augmented clusters.

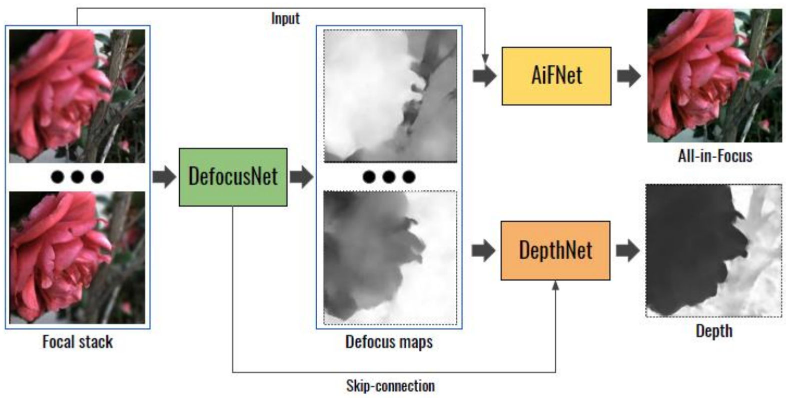


AD-Cluster is trained by iterative density-based clustering, adaptive sample augmentation, and discriminative feature learning. It learns an image generator and a feature encoder which aim to maximize the intra-cluster diversity in the sample space and minimize the intra-cluster distance in the feature space in an adversarial minmax manner.

Focus on defocus: bridging the synthetic to real domain gap for depth estimation

In this paper, we tackle this issue by using domain invariant defocus blur as direct supervision.

We leverage defocus cues by using a permutation invariant convolutional neural network that encourages the network to learn from the differences between images with a different point of focus



Light-weight calibrator: a separable component for unsupervised domain adaptation

Existing domain adaptation methods aim at learning features that can be generalized among domains. These methods commonly require to update source classifier to adapt to the target domain and do not properly handle the trade off between the source domain and the target domain.

This work use a separable component called data calibrator to help the fixed source classifier recover discrimination power in the target domain, **while preserving the source domain's performance.**

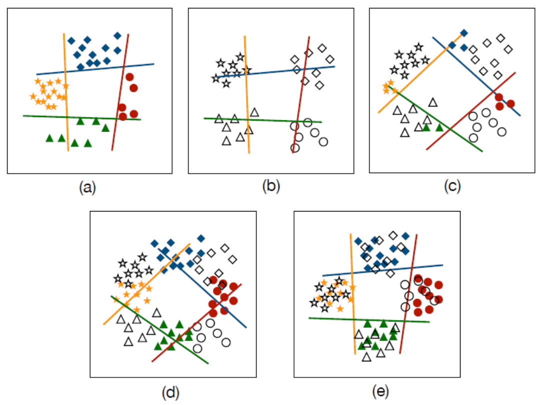


Figure 1. **Concept Illustration**. (a) The source classifier in labeled source domain. (b) The source classifier in unlabeled target domain. (c) Existing methods that are developed to learn domain-invariant features. (d) In real world, the testing set consists of both source domain images and target domain images. (e) The proposed method keeps the representation of source classifier and calibrates target images to fit the source classifier's representation.