Multi-Source Domain Adaptation Challenge

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Abstract

- In this work, we tried many unsupervised domain adaptation (UDA) models for multi-source dataset - DomainNet (PENG et al., 2018). We mainly used Adversarial Discriminative Domain Adaptation (ADDA) (TZENG et al., 2017) and Maximum Classifier Discrepancy (MCD) (SAITO et al., 2018) for Unsupervised Domain Adaptation in this work. We also slightly adjusted ADDA training process to make it most suitable for multi-source challenge, which will be described below.
- We also tried M^{3}SDA (PENG et al., 2018), which is designed for multi-source domain. However, the training accuracy is stuck and cannot beat single-source based methods in our experiments.

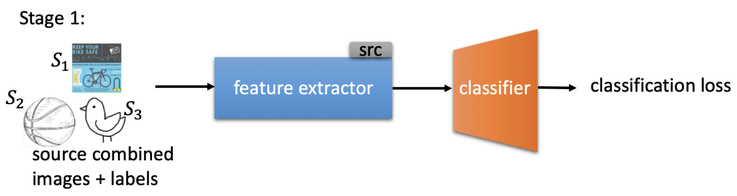
Fuzzy Adversarial Discriminative Domain Adaptation

Method

We got the idea from ADDA (TZENG et al., 2017) and do slight modification on training process. We named this method as FADDA:

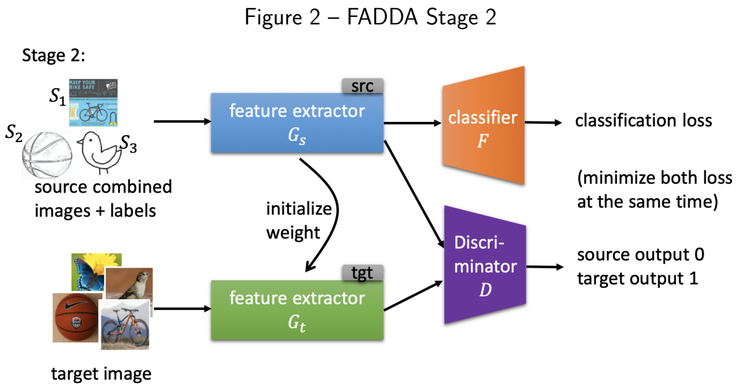
- In **Stage 1**, we pretrain the feature extractor and classifier on source data using standard cross-entropy loss, until the model converges.

Figure 1 – FADDA Stage 1



- In **Stage 2**, the full model is shown in Figure 2. We initialize both the source feature extractor, G_s, target feature extractor, G_t, and classifier F with the pretrained model in the first stage .

Figure 2 – FADDA Stage 2



Training Steps in Stage 2

Note that G_s and G_t are initialized with the same model. With regard to the discriminator D, we use a two-layer fully connected neural network. Then we train the whole model jointly, with the following order, which is slightly different from the original ADDA model:

(For simplicity, we denote the three source domain training set as S_1, S_2, S_3 respectively, and the batches as $b_i^{S_1}$, $b_i^{S_2}$, $b_i^{S_3}$. The target domain training set and the batches are denoted as T and b_i^T).

Step 1. Train three batches $b_i^{S_1} \in S_1$, $b_i^{S_2} \in S_2$, and $b_i^{S_3} \in S_3$ consecutively. In each minibatch, we compute loss $\mathcal{L}_{adv,src}$ and $\mathcal{L}_{class}$, where $\mathcal{L}_{adv,src}$ stands for the adversarial loss for D and $\mathcal{L}_{class}$ for the cross-entropy loss for F:

$$\mathcal{L}_{class} = \sum_{i,j} \sum_{k \in K, \mathbf{x}_s \in b_i^{S_j}} \mathbf{1}_{[k=y_s]} \log F(G_s(\mathbf{x}_s))$$

$$\mathcal{L}_{adv,src} = \sum_{i,j} \sum_{\mathbf{x}_s \in b_i^{S_j}} -\log D(G_s(\mathbf{x}_s))$$

Step 2. Train three minibatches b_{3i}^T, b_{3i+1}^T, $b_{3i+2}^T \in T$ and compute $\mathcal{L}_{adv,tgt}$ for D, with all the other modules fixed, and only consider the gradient of D. We train three minibatches in this step to balance the amount of data seen in step 1.

$$\mathcal{L}_{adv,tgt} = \sum_{j} \sum_{\mathbf{x}_t \in b_j^T} -\log(1 - D(G_t(\mathbf{x}_t)))$$

Step 3. Then we optimize G_s, F and D simultaneously after first and second step.

$$\min_{G_s,F,D} \mathcal{L}_{class} + \mathcal{L}_{adv,src} + \mathcal{L}_{adv,tgt}$$

Step 4. Lastly, optimize G_t (acting like generator in standard adversarial training) using b_{3i}^T, b_{3i+1}^T, $b_{3i+2}^T \in T$ in order to fool D, with both D and F fixed.

$$\min_{G_t} -\mathcal{L}_{adv,tgt}$$

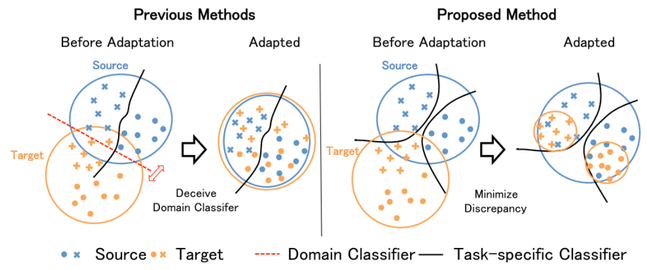
Maximum Classifier Discrepancy (MCD)

Motivation

Distribution matching based UDA algorithms (e.g. ADDA...) have some problems:

- They just align the latent vector distributions without knowing whether the decision boundary trained on source domain is still appropriate for target domain. (Figure 3)
- The generator often tends to generate ambiguous features near the boundary because this makes the two distributions similar.

Figure 3 – Comparison between distribution matching methods and MCD

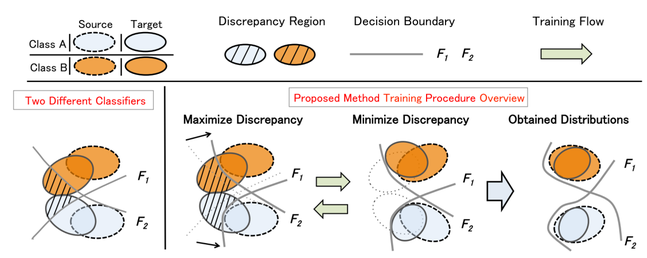


Method

To consider the relationship between class, MCD method (SAITO et al., 2018) aligns source and target features by utilizing the task-specific classifiers as a discriminator boundaries and target samples. See example in Figure 4.

- First, we pick out samples which are likely to be mis-classified by the classifier learned from source samples.
- Second, by minimizing the disagreement of the two classifiers on the target prediction with only generator updated, the generator will avoid generating target features outside the support of the source.

Figure 4 – Example to explain how MCD works.



Training Steps

Step1. Train both classifiers and generator to classify the source samples correctly.

$$\min_{G,F_1,F_2} \mathcal{L}_{class}(X_s,Y_s)$$

Step2. Fix the generator and train two classifiers (F1 and F2) to maximize the discrepancy given target features. At the same time, we still train F1, F2 to minimize classification loss, in order to keep the performance on source data.

$$\min_{F_1,F_2} \mathcal{L}(X_s,Y_s) - \mathcal{L}_{\text{adv}}(X_t)$$

$$\mathcal{L}_{\text{adv}}(X_t) = \mathbb{E}_{\mathbf{x_t} \sim X_t}[d(p_1(\mathbf{y}|\mathbf{x_t}),p_2(\mathbf{y}|\mathbf{x_t}))]$$

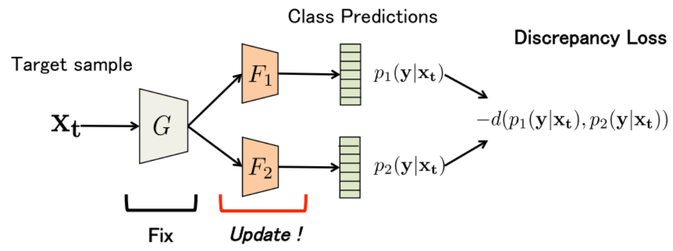


Figure 5 – MCD Step 2

Step3. Fix the classifiers and train the generator to minimize discrepancy between two classifiers. Step 3 is repeated for 4 times in our experiment.

$$\min_{G} \mathcal{L}_{\text{adv}}(X_t)$$

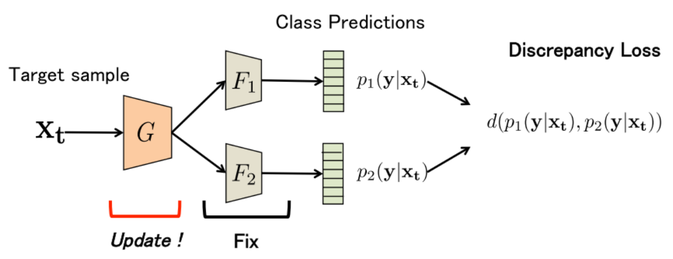


Figure 6 – MCD Step 3

Model Details & Training Settings

- **Feature extractor**: We choose ResNet-50, ResNet-152, Inception-ResNet-v2 (SZEGEDY; IOFFE; VANHOUCKE, 2016) as feature extractor G in our experiments.
- **Classifier**: In all experiments(FADDA and MCD), we use a simple one-layer fully-connected network as classifier F, which projects from feature dimension (e.g. 2048, 1536, ...) to class number (e.g. 345).
- **Discriminator**: In FADDA, we use a simple three-layer fully-connected network as discriminator. The input size is feature dimension, hidden size is 512 in hidden layers.
- **Optimizer**: We use SGD with learning rate 10^{-4}, momentum 0.9, weight decay 10^{-4} in all modules in our experiments.

Experiment Results

Before applying our methods, we also train a baseline model with source data combined and no perform any adaptation, which called "naive" method in Table 1.

Table 1 – Main Experiment Results.

Method	inf, qdr, rel → skt	inf, skt, rel → qdr	qdr, skt, rel → inf	inf, qdr, skt → rel
weak baseline	23.1	11.8	8.2	41.8
strong baseline	33.7	13.3	13.0	53.1
naive - ResNet-50	37.1	9.9	16.7	55.0
naive - ResNet-152	42.7	12.6	18.8	56.2
naive - Incep-ResNet-v2	47.4	13.5	21.5	60.6
FADDA - ResNet-152	44.1	**16.3**	20.0	59.4
FADDA - Incep-ResNet-v2	47.1	15.2	19.8	63.6
MCD - Incep-ResNet-v2	**48.8**	14.9	**22.8**	**64.7**

Table 2 – Comparison between ADDA and FADDA.

Method	inf, qdr, rel → skt	inf, skt, rel → qdr	qdr, skt, rel → inf	inf, qdr, skt → rel
ADDA - Incep-ResNet-v2	46.4	12.8	18.6	62.3
FADDA - Incep-ResNet-v2	**47.1**	**15.2**	**19.8**	**63.6**

we have also tried to use multiple pairs of classifier for different source domain in our MCD method, similar to M^{3}SDA (but without moment matching). However, the effect is not as expected and even can not be compared with source combined MCD method.

Table 3 – Comparison between single-source MCD, and multi-source MCD and M^{3}SDA.

Method	inf, qdr, rel → skt	inf, skt, rel → qdr	qdr, skt, rel → inf	inf, qdr, skt → rel
single-MCD - ResNet-50	**43.2**	**11.7**	**19.5**	**57.1**
multi-MCD - ResNet-50	33.9	9.3	11.5	44.6
M^{3}SDA - ResNet-50	-	-	-	43.7

Conclusion

- Naive method performs not bad. It is strong enough to pass all strong baseline.
- In most of cases, Inception-ResNet-v2 can outperform ResNet-50 and ResNet-152.
- We proposed FADDA, which can perform slightly better than original ADDA.
- Single-MCD is more stable and powerful than multi-MCD and M^{3}SDA to train in our experiments. This indicates that multi-source based methods are still challenging to design. In our cases, it can not leverage the difference between each source domain to get improvement on accuracy.
- We think that the images from quickdraw dataset (composed only by white background and black lines) are so different from normal images, so the single best model is not Incep-ResNet-v2(MCD), but ResNet-152(FADDA).

Reference

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SAITO, K. et al. Maximum Classifier Discrepancy for Unsupervised Domain Adaptation. In: **PROCEEDINGS of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition**. [S.l.]: IEEE Computer Society, Dec. 2018. p. 3723–3732. DOI: 10.1109/CVPR.2018.00392.

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