Discriminative Active Learning for Domain Adaptation

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Abstract

Domain Adaptation aiming to learn a transferable feature between different but related domains has been well investigated and has shown excellent empirical performances. Previous works mainly focused on matching the marginal feature distributions using the adversarial training methods while assuming the conditional relations between the source and target domain remained unchanged, \textit{i.e.}, ignoring the conditional shift problem. However, recent works have shown that such a conditional shift problem exists and can hinder the adaptation process. To address this issue, we have to leverage labeled data from the target domain, but collecting labeled data can be quite expensive and time-consuming. To this end, we introduce a discriminative active learning approach for domain adaptation to reduce the efforts of data annotation. Specifically, we propose three-stage active adversarial training of neural networks: invariant feature space learning (first stage), uncertainty and diversity criteria and their trade-off for query strategy (second stage) and re-training with queried target labels (third stage). Empirical comparisons with existing domain adaptation methods using four benchmark datasets demonstrate the effectiveness of the proposed approach.

1 Introduction

In general machine learning tasks, we usually assume the datasets, where the hypothesis was trained and tested, are from the same distribution. However, this assumption, in general, is not realistic in many practical scenarios. For example, appearance shifts caused by illumination, seasonal, or weather changes are significant challenges for computer vision-based systems. A vision system trained on one dataset but deployed on another may suffer from rapid performance drop. More severely, to train a high-performance vision system requires a large amount of labeled data, and getting such labels may be expensive. One approach to deal with this issue is Domain Adaptation (DA), which aims to improve the learning performance of a target domain by leveraging the unlabeled data in the target domain as well as the labeled data from a different but related domain (source domain). Previous works have theoretically analyzed the learning guarantees of DA [Ben-David et al., 2010; Redko et al., 2017] and have reported some empirical applications in natural language processing [Glorot et al., 2011] and computer vision [Wang et al., 2018].

Most recent DA advancements are mostly based on the basic Covariate Shift assumption that the marginal distributions of source and target domain change ($P_S(x) \neq P_T(x)$) while the conditional distribution (predictive relation) is preserved ($P_S(y|x) = P_T(y|x)$) during the adaptation process. However, some recent works have revealed that this assumption may not hold, and in this case, one may still need some labeled data from the target domain in order to successfully transfer information from one domain to another. Specifically, [Zhao et al., 2019] discussed the conditional shift problem showing that such a problem exists and can hinder the adaptation process. They proved that the risk on target domain is controlled by the source risk, the marginal distribution divergence, and disagreement between the two labeling distributions:

$$
\epsilon_T(h) \leq \epsilon_S(h) + d_R(D_S, D_T) + \min \{\mathbb{E}_{D_S}[\|f_S - f_T\|], \mathbb{E}_{D_T}[\|f_S - f_T\|]\}
$$

Impossible to measure in unsupervised DA

Here $\epsilon_T(h)$, $\epsilon_S(h)$ and $f$ refer to target risk, source risk and labeling function, respectively. In a typical unsupervised DA setting, it is not possible to measure the third term in Eq. 1. One possible way to measure this term is to query some data labels from target domain so that the learner can learn the conditional relations in the target domain. However, the label annotations usually is expensive. Notice that the convergence rate at the disagreement term would generally be $O(1/\sqrt{N_t})$ [Mohri et al., 2018] with slow convergence behaviour if the label is i.i.d. sampled from the target set with size $N_t$, which is far sufficient to minimize the last term.

To alleviate such difficulties, one can use Active Learning (AL) technique for DA so that the learner can reduce the cost of acquiring labels by requesting labeling from the oracle. AL only tries to query the labels of the most informative examples, and has been shown, in some optimal cases,
to achieve exponentially-lower label-complexity (number of queried labels) than passive learning [Cohn et al., 1994]. From this perspective, we tried to break the general i.i.d. sampling with limited information in the target domain (a.k.a semi-supervised domain adaptation approach). Most previous active learning approaches were rooted in uncertainty-based approaches. [Dasgupta, 2011] pointed out that only focusing on the uncertainty might lead to sample bias. To overcome such bias problems, we also need to consider the diversity in the query process. Recently, [Sinha et al., 2019; Shui et al., 2019] proposed adversarial training techniques to query the most informative features via a critic function, which could overcome the sample bias problems.

Aiming to address all the aforementioned issues, we proposed a three-stage discriminative active domain adaptation algorithm, which aims to actively query the most informative instances in the target domain to minimize the labeling disagreement term, under the same and small querying label budget.

In the first stage, we adopted the Wasserstein Distance-based adversarial training technique for unsupervised DA through training a critic function for learning the domain invariant feature. The critic could also be used to discriminate the target domain features for active querying. In the second stage, we derived a sample-efficient and straightforward active query strategy based on the network structure, for sampling the most informative samples in the target domain by controlling uncertainty and diversity for selecting the target instances. Finally in the third stage, we deployed a re-weighting technique based on the prediction uncertainty for determining the importance of queried samples to retrain the network.

We then implemented extensive experiments on four benchmark datasets. The empirical results showed that our proposed algorithm could improve the classification accuracy with a small query budget. When the query budget is small, the proposed approach can have better performance than its i.i.d. (random) selection counterparts (reported in Table 5), which confirms the effectiveness of our algorithm.

2 Related Works

Domain Adaptation A large number of efforts have been addressed toward DA [Wang and Deng, 2018]. As stated before, many of the previous advancements [Ben-David et al., 2010; Ganin et al., 2016; Tzeng et al., 2017; Shen et al., 2018] were based on the assumption that the conditional relations remain unchanged during the adaptation process. Some recent works proposed to tackle the conditional shifts problem. [Long et al., 2018] adopted the Conditional Generative Adversarial Nets (CoGANs) to extract the cross-covariance between the source and target feature representations, and also measure the conditional entropy as an uncertainty measure to control the transferability. [Wen et al., 2019] proposed the Bayesian Neural Network with entropy and variable uncertainty measures to jointly match the marginal distribution (P(x)) and conditional distribution (P(y|x)).

Active Learning AL has been widely investigated by academia in the context of theory or applications. Recently, [Sinha et al., 2019] proposed a variational autoencoder based adversarial approach to query the informative unlabeled feature from the labeled ones and [Gissin and Shalev-Shwartz, 2019] proposed discriminative active learning. [Shui et al., 2019] extended and adopted a critic network for querying the diverse features. Those above usually assumes that labeled and unlabeled data are from same distribution. Few works were proposed to implement active learning for enhancing domain adaptation i.e., two or more distributions.

Active Learning for Domain Adaptation [Persello and Bruzzone, 2012] proposed a two-direction AL algorithm for DA: query the most informative from the target domain and remove the most strange features out of the source domain. [Wang et al., 2014] proposed the active transfer technique for the model shift problem while assuming the shifts are smooth and implemented conditional distribution matching algorithm and off-set algorithm to modelling the source and target tasks via comparing the Gaussian Distributions. [Zhang et al., 2013] proposed a distribution correction algorithm over kernel embeddings to handle the target shift. The last two methods held on the assumption that there existed an affine transformation of conditional distribution from the source to target. [Su et al., 2019] proposed an active learning method using H divergence and the importance sampling technique to query the target instances. However, the importance sampling, query strategy they adopted, assumed that supp(T) ⊆ supp(S), may not hold in many DA settings.

3 Problem Setup

Notations and Basic Definitions We consider a classification task, denote X and Y as the input and output space. A learning algorithm is then provided with a labeled source dataset S = {(x_i, y_i)}_{i=1}^{m_s} consisting of m_s examples drawn i.i.d. from S_{x,y} ∼ D_s and an unlabeled target sample T = {x_j} j=1^{m_t} consisting of m_t examples drawn i.i.d. from T_x, where S_{x,y} is the joint distribution on x × y and T_x is the marginal target distribution on x, respectively. The expected source and target risk of h ∈ H over S (respectively, T), are the probabilities that h errs on the entire distribution D_S (respectively, D_T): e_S(h) = E_{(x,y) ∼ S} L(h(x, y)) and e_T(h) = E_{(x,y) ∼ T} L(h(x, y)), where L(·) is the loss function. The goal of DA is to build a classifier h ∈ H : X → Y training on source domain with a low target risk e_T(h).

3.1 Optimal Transport and Wasserstein Distance

Optimal Transport (OT) theory and Wasserstein Distance were recently widely investigated in machine learning [Arjovsky et al., 2017] especially in the domain adaptation area [Courty et al., 2016]. We follow [Redko et al., 2017] and define c : X × X → R+ as the cost function for transporting one unit of mass x to x’, then Wasserstein Distance could be computed by

\[ W_p^p(D_{x}, D_{x'}) = \inf_{\gamma \in \Pi(D_{x}, D_{x'})} \int_{x \times x'} c(x, x')^p d\gamma(x, x') \]

where \( \Pi(D_{x}, D_{x'}) \) is joint probability measures on \( X \times X \) with marginals \( D_{x} \) and \( D_{x'} \) referring to all the possible coupling functions. Throughout this paper, we shall use Wasserstein-1
distance only \((p = 1)\). According to Kantorovich-Rubinstein theorem, let \(f\) be a Lipschitz-continuous function \(\|f\|_L < 1\), we have
\[
W_1(D_i, D_j) = \sup_{\|f\|_L < 1} \mathbb{E}_{x \in D_i} f(x) - \mathbb{E}_{x' \in D_j} f(x')
\]
(2)

### 3.2 Conditional Shift and Error Bound

From a probabilistic perspective, the general learning process of most previous DA approaches is to learn the joint distribution of the target domain \(P_T(x, y)\) through source domain joint distribution \(P_S(x, y)\). Note that \(P_T(x, y) = P_T(x|y)P_T(x)\), to guarantee a successful transfer from source domain \(S\) to target domain \(T\), the underlying assumption is \(P_S(y|x) \approx P_T(y|x)\). Recently, [Wen et al., 2019] showed that such condition is not sufficiently hold.

For the conditional shift situation, \(P_S(y|x) \neq P_T(y|x)\), [Zhao et al., 2018] theoretically showed that such a conditional shift problem exists in many situations and that typically if we only try to minimize the source error together with the domain distances, the target error might increase, which shall hinder the adaptation process. Their analysis was based on \(\hat{H}\) divergence, which is somehow hard to compute in deep learning based methods.

**Theorem 1.** Let \(\langle D_S, f_s \rangle\) and \(\langle D_T, f_T \rangle\) be the source and target distributions and corresponding labeling function, if the hypothesis \(h\) is 1-Lipschitz and the loss function is 0 – 1 loss, then we have
\[
e_T(h) \leq \epsilon_S(h) + 2W_1(D_S, D_i) + \mathbb{E}_{D_S} \|f_S - f_T\|
\]
(3)

The proof is based on Lemma 1 of [Shen et al., 2018] and is symmetric to the proof of Theorem 3 of [Zhao et al., 2019].

Due to space limit, we show the sketch idea of proof.

**Proof.** Based on Lemma 1 of [Shen et al., 2018], let \(h' = f_T\), we have
\[
e_i(h, f_T) \leq \epsilon_s(h, f_T) + 2W_1(D_s, D_i)
\]
We noticed that
\[
\epsilon_s(h, f_T) = \mathbb{E}_{x \sim D_s} |h(x) - f_T(x)| \\
\leq \mathbb{E}_{x \sim D_s} |h(x) - h_S(x)| + \mathbb{E}_{x \sim D_s} |h_S(x) - f_T(x)| \\
= \epsilon_s(h) + \mathbb{E}_{x \sim D_s} |h_S(x) - f_T(x)|
\]
Plugging in we have the result.

Besides, the Wasserstein distance between the source and target distribution (second term in Eq. 3), is measured by total transportation cost between the source domain. Denote \(D_U\) and \(D_L\) by the corresponding distributions of unlabeled and labeled datasets, then the Wasserstein distance is denoted by:
\[
W_1(D_U, D_L) = \inf_{\gamma \in \Pi(D_U, D_L)} \int_{x \times x} c(x_t, x_u) d\gamma(x_t, x_u)
\]

Intuitively, if we can query some instances in the target domain \(T\) (\(D_U\)) and move them from target into the source domain \(S\) (\(D_L\)), we can reduce the total transportation cost between the two domains, i.e., the Wasserstein distance between the two domains.

Based on this, to minimize the RHS of Eq. 3 is equivalent to train a learner \(h \in \mathcal{H}\) that: 1) minimize the source error; 2) train a critic to estimate the empirical Wasserstein Distance between the source and target domain and approximately find a feature extractor that can minimize the total transportation cost between the source and target domain in an adversarial way with the critic; 3) can query the labeling information in the target domain so that to minimize the disagreement of labeling function between the source and target domain i.e., the third term of Eq. 3.

To this end, we argue that if the learner can actively query labeling information in the target domain, then, it can partially get the conditional information in the target domain. With the minority of labeled target instances in hand, it can learn to jointly minimize the error both on the source and target domain. Furthermore, to \(i.i.d\). query the label is somehow slow. In order to reduce the annotation expense, we may expect the learner to query some informative instances using an active learning strategy. Also, if the queried instances in the target domain are informative enough, they will have a better representative property on the target domain. Then, the learner can have better generalization performance on the target domain. Take those above into consideration, we can formally propose the discriminative active domain adaptation method.

### 4 Active Discriminative Domain Adaptation

Our learning process mainly consists of three main stages. We will introduce them in details.

#### 4.1 Stage 1: Domain Adversarial Training via Optimal Transport

For the first stage, we adopt Wasserstein Distance Guided Representation Learning [Shen et al., 2018] method for adversarial training. The network receives a pair of instances from the source and target domain. Denoted by \(F\) and \(C\) the feature extractor and classifier, parameterized by \(\theta_f\) and by \(\theta_c\) respectively. The feature extractor is trained to learn invariant features, and the classifier is expected to learn the conditional prediction relations \(P(Y|X)\) for predicting the instances from both source and target domain correctly. For the classification loss, we employ the traditional cross-entropy loss:
\[
L_{cls} = - \sum_{i=1}^m y_i \log(P(C(F(x_i))))
\]

Then, there follows the domain critic network \(D\), parameterized by \(\theta_d\). It estimates the empirical Wasserstein Distance between the source and target domain through a pair of
Figure 1: Ac-DA workflow: feature extractor are trained to learn a domain invariant feature space together with the critic. The learner selects the informative instances by measuring uncertainty and diversity based on critic and classifier outputs.

4.2 Stage 2: Active Query with Wasserstein Critic

For the second stage, we hope the active learner can find out the most informative features among the unlabeled target so that it could leverage from the labeling information of the target domain. The informative features, intuitively, are the ones most different from what the learner has already known. Intuitively, the hardest instances to adapt are those with least confidence, i.e., the most uncertain ones, to predict based on current classifier. As pointed out as previous work [Dasgupta, 2011], only focus on the uncertainty shall lead to the sampling bias. In order to reduce the sampling bias, the active learner shall also search diversity some target samples. We therefore find the most informative target samples holding both uncertainty and diversity properties.

Prediction Uncertainty The conditional prediction $P_T(Y|X)$ is learned by the classification network. To measure the uncertainty, we can borrow from ideas by [Long et al., 2018] to adopt entropy measure to quantify the uncertain of the classifier. The uncertainty entropy measure over an instance $x_i$ is denoted by

$$U(y_i|x_i) = H(\hat{P}(y_i|x_i))$$

where $H(\cdot)$ is the information entropy measure, $\hat{P}(y_i|x_i)$ is the output of classification network $\hat{P}(y_i|x_i) = C(F(x_i))$.

Diversity by Critic Function If some instances, in terms of distribution distance measures, are very far from the unknown labeled ones, then they should contain most informative and diverse features from the known labeled ones. Recall that in the first stage, we match the marginal distribution between the source and target domain to achieve a domain invariant feature space with Wasserstein Distance. Then, for the target domain instances, the one with highest critic score is the one that have the highest transportation cost.

[Sinha et al., 2019; Shui et al., 2019] showed that such critic term $D(F(\cdot)) : X \rightarrow [0, 1]$ indicates the diversity in the query process. Then, we can leverage from the trained Wasserstein Critic network to evaluate and find out the most informative (diverse) target features on the invariant feature space. That is, measuring the diversity of target instances via critic score. Consider the critic output of a target instance $x_i$, if $D(F(x_i)) \rightarrow 1$, then $x_i$ is far, w.r.t. Wasserstein Distance, from the source domain images and if $D(F(x_i)) \rightarrow 0$, then $x_i$ is near to the source images.

Based on those above, if we hope to find out the most informative (uncertain and diverse) instances in the target domain, then we should query by controlling two terms:

- uncertainty score $U = H(\hat{P}(y_i|x_i))$ defined by Eq. 6, which is indicates the uncertainty of the classifier to predict a label $y_i$ given the instance $x_i$ in the target domain
- critic score $D(F(x_i))$ by the the Wasserstein critic function, which indicates the diversity of the unlabeled target instance compared with the source labeled ones.

Then, we shall have the following objective

$$\arg\max_{x_i \in X_T} U(y_i|x_i) - \lambda_{div} D(F(x_i))$$

where $\lambda_{div}$ is a coefficient to regularize the Wasserstein critic term. So, for a query budget $\beta$ and $m_t$ of target set instances, the query process could be described as: looking for $m_t = \beta m_s$ instances by solving Eq. 7 and query the labels of those $m_t$ instance from the oracle. Denote the queried set by $Q = \{[x_{1}^{q}, y_{1}^{q}], \ldots, [x_{m_t}^{q}, y_{m_t}^{q}]\}$. Then, uniting such small batch instances with the source domain and removing them from the target domain. The source and target datasets shall be updated as: $S' = S \cup Q$, $T' = T/Q$. We illustrate a general query workflow in Fig. 1.

4.3 Stage 3: DA training with new dataset

The goal of our proposed method is to leverage the most informative instances in the target domain to reinforce the adaptation process. General adversarial training methods for domain adaptation usually assign each instance with the same importance weight. In order to enforce the uncertainty information to the classifier, we hope to give higher weights to the instances with higher uncertainty scores during the supervised classification process.

Denote by a set of $m_q$ queried instances $\{x^{(i)}, y^{(i)}\}_{i=1}^{m_q}$, we shall re-weight the importance of each instance classes based on their uncertainty score. Denote by uncertainty vector $\alpha = [\alpha_1, \ldots, \alpha_j, \ldots, \alpha_C]^{C \times 1}$ over all $C$ classes. For each class $j$, the weight is computed by,

$$\alpha_j = \frac{N_j \cdot U(y_j|x)}{\sum_{i=1}^{N_j} U(y^{(i)}|x)}$$
Algorithm 1 The Active Discriminative Domain Adaptation

Input: Source and target domain input $S, T$; Query budget $\beta$

Parameter: Feature extractor $\theta_f$; Classifier $\theta_c$; Critic $\theta_d$

Output: Optimized $\theta_f^*, \theta_c^*, \theta_d^*$

1: while Domain level adaptation not finish do
2: Sample batches $(x_s, y_s) \sim S, x_t \sim T$
3: Train the network based on Eq. 5 until converge
4: end while
5: if Query budget is not empty then
6: Select the target instances $\{x^q_1, \ldots, x^q_{m_q}\}$ according to Eq. 7 and query the label $\{y^q_1, \ldots, y^q_{m_q}\}$ from oracle.
7: else
8: Update the dataset $Q = \{(x^q_1, y^q_1), \ldots, (x^q_{m_q}, y^q_{m_q})\}$
9: end if
10: Compute the uncertainty vector $\alpha = [\alpha_1, \ldots, \alpha_C]_{j=1}^C$ with Eq. 8
11: Train the network on new labeled and unlabeled dataset via domain adaptation techniques with Eq. 9.
12: return solution

where $N_j$ is the number of instances with label $y_j$, $U(\cdot)$ is the uncertainty score defined in Eq.6.

For a batch of queried instances, the weighted crossentropy loss could be computed by

$$L^w = \alpha_j (-y_j \log \sum_{j=1}^C \exp(P(y_j|x)))$$

Then, objective function for the third stage is,

$$\min_{\theta_f, \theta_c, \theta_d} \max \mathcal{L}^w + \mathcal{L}_{cls} + \lambda_w(W_1(V'_S, V'_T) - \mathcal{L}_{grad})$$

(9)

where $V'_S$ and $V'_T$ are sampled from the updated source and target datasets, $\mathcal{L}_{cls}$ is the classification loss on the original source set and $\mathcal{L}^w$ is the weighted loss for the query set. Finally, we illustrate our Active Discriminative Domain Adaptation (Ac-DA) algorithm in Algorithm 1

5 Experiments and Results

We evaluate the performance of the proposed algorithm on four benchmark datasets and compared with some other approaches: Wasserstein Guided Domain Adaptation (W-GRL [Shen et al., 2018]), Domain Adversarial Neural Networks (DANN [Ganin et al., 2016]), Adversarial Discriminative Domain Adaptation (ADDA [Tzeng et al., 2017]) and Conditional Adversarial Domain Adaptation (CDAN [Long et al., 2018]). In order to show the benefits of active query method, we also compare the results with random selection process when the query budget is the same. All experiments are programmed by Pytorch.

5.1 Datasets and Implementations

We test our proposed algorithm on four benchmark datasets.

| Method | M \rightarrow MM | M \rightarrow U | U \rightarrow M | avg. |
|--------|-----------------|----------------|----------------|-----|
| LeNet5 | 56.1            | 67.4           | 65.3           | 60.3|
| DANN   | 74.2            | 77.1           | 73.2           | 74.6|
| WDGRL  | 80.3            | 81.1           | 74.2           | 78.5|
| ADDA   | 78.9            | 83.5           | 82.3           | 81.5|
| Rand.  | 92.4            | 95.7           | 95.8           | 94.7|
| Ac-DA  | 95.4            | 95.5           | 96.5           | 95.6|

Table 1: Classification accuracy (%) on digits datasets with different adaptation tasks. The last two line are our method, Random refers to randomly query some instance while Ac-DA is the proposed approach. Both two methods are restrict to 10% query budget.

| Method | A \rightarrow W | A \rightarrow D | D \rightarrow A | W \rightarrow A | avg. |
|--------|-----------------|-----------------|-----------------|-----------------|-----|
| ResNet50 | 68.6            | 69.3           | 61.1           | 60.7           | 64.9|
| DAN    | 80.5            | 78.6           | 63.6           | 60.7           | 62.7|
| DANN   | 81.3            | 79.2           | 68.2           | 67.4           | 74.0|
| WDGRL  | 79.2            | 80.2           | 69.3           | 69.1           | 74.5|
| Rand.  | 86.1            | 85.6           | 76.3           | 78.1           | 81.6|
| Ac-DA  | 86.6            | 87.7           | 78.5           | 80.2           | 83.3|

Table 2: Classification accuracy (%) on Office-31 dataset with different adaptation settings with 10% query budget.

**Digits Datasets** We test our algorithm on digits datasets with the experiments setting : USPS (U)\rightarrow MNIST (M) and MNIST \rightarrow MNIST-M (MM). For USPS we resize the images to size 28 × 28. We train the network using training sets with size: MNIST/MNIST-M (60k), USPS(7, 291) and testing sets with size: MNIST/MNIST-M (10k), USPS(2, 007).

**Office-31 dataset** is a standard benchmark for domain adaptation evaluations. It contains three different domains: Amazon (A), Dslr (D) and WebCam (W), with 31 categories in each domain. We report the average results in Table 2.

**Office Home dataset** is more challenging than Office-31, contains four different domains: Art (Ar), Clipart (Cl), Product (Pr) and Real World (Rw), with 65 categories in each domain. We report the average results in Table 3.

**Image-CLEF 2014 dataset** contains three domains, which are Caltech-256(C), ILSVRC-2012(I), and PascalVOC-2012(P), with 12 common shared categories. We report the average results in Table 4.

For digits datasets, we do not apply any data-augmentation. For Office-31, Office-Home and Image-CLEF datasets, we apply the following pre-processing pipeline: 1) for training set, firstly resize the image to 256 x 256 then, apply RandomCrop downgrade the size to 224 x 224, after that, apply the same random flipping strategy of [You et al., 2019]; 2) for testing set, resize the images to 256 x 256 then use CenterCrop to size 224 x 224.

**CNN Architecture and Implementations** For digits experiments, we adopt LeNet-5 as feature extractor and trained from scratch. For the rest three real-world datasets, we implement ImageNet pretrained ResNet-50 as feature extractor. For the digits experiments, we train the network with mini-batch size 64 and for the rest three datasets with mini-batch size 16. We adopt Adam optimizer for training the network. For stable
training, we set $\lambda_{wu} = \frac{2}{1 - \exp(-\delta p)} - 1$, where $\delta = 10$ and $p$ is the training progress. Also, we empirically set $\lambda_{dy} = 10$. To avoid over-training, we also adopt early-stopping technique.

5.2 Results and Analysis
We illustrate the T-SNE visualization comparison of non-adaptation setting and our proposed approach Ac-DA. We can observe that our proposed method has a good alignment performance. We report the average results of our proposed algorithm and baselines using our data pre-processing pipeline on Digits, Office-31, Office-Home and Image-CLEF datasets in Table 1, 2, 3 and 4, respectively. In order to show the effectiveness of active query strategy, for a given budget, we also implemented random (i.i.d.) selection method to query the labels for comparison. The name of such implementations are denoted by rand. and Ac-DA in each table. In Table 5, we also compared the performances under different budget.

Value of Target Labels From the tests results on the four benchmark datasets, we could observe that the to randomly select some instances in the target domain could benefit the classification performance on the target domain. Our method is rooted in WDGRIL, comparing accuracy performance between the random selection with WDGRIL we could observe improvements with +8.5% on Digits, +7.6% on Office-31, +11.5% on Office-Home and +4.7% on Image-CLEF dataset which confirm the usefulness of label information for adaptation. Also, for each adaptation task on every dataset, we can observe that the proposed Ac-DA algorithm outperforms the random selection method in almost all the tasks. This also confirms that active query can outperform i.i.d. selection.

**Effectiveness of Active Query** We compared the performance with active query and random random selection. We also implement the experiments with different query budgets (5%, 10% and 15%), the average on different dataset is reported in Table 5. we can observe that the accuracy will increase as the query budget increases. Also, for same query budget, we compare the accuracy of active query and random selection. We can observe that active query method can outperform the random query method with query budget 5% and 10%. That is, with smaller query budget, the active query strategy can have better performance than random selection. This confirms the effectiveness of active query strategy. When the query budget goes to 15%, we don’t observe distinguishable differences. One interpolation is that as the query budget increase, the more instances in the target domain will be labeled and those most informative ones will be covered with high probability. When the query budget is relatively small, the active strategy can exactly look for the most informative instances rather than uniformly (random) selecting some instances.

### Table 3: Classification accuracy (%) on Office Home dataset with different adaptation settings with query budget 10%.

| Method  | C → I | C → P | I → P | I → C | P → C | P → I | avg. |
|---------|------|------|------|------|------|------|-----|
| ResNet50 | 76.4  | 82.3 | 90.7  | 91.3  | 92.8 | 87.2 | 85.5 |
| DANN    | 84.8  | 82.8 | 91.5  | 81.9  | 82.9 |     |     |
| WDGRIL | 82.3  | 73.4 | 93.1  | 87.2  | 82.4 |     |     |
| CDAN   | 87.5  | 73.4 | 75.3  | 93.1  |     |     |     |
| Rand.  | 89.8  | 75.0 | 78.2  | 94.4  | 94.9 | 89.9 | 87.1 |
| Ac-DA  | 91.1  | 76.3 | 80.8  | 96.7  | 94.7 | 94.2 | 88.9 |

### Table 4: Classification accuracy (%) on Image-CLEF dataset with different adaptation tasks under 10% query budget.

![Non-Adapted](image1.png) ![Ac-DA](image2.png)

![figure2.png](image3.png)

Figure 2: T-SNE visualization between our proposed Active Discriminative Domain Adaptation (right, with 5% query budget) and non-adapted setting (left) for MNIST → MNIST-M adaptation task.

### Table 5: Comparison of different query budgets (5%, 10%, 15%) on three datasets. For each query budget, we report the improvements by applying the active query strategy comparing with the random query strategy in the parentheses.

| Dataset       | 5%      | 10%     | 15%     |
|---------------|---------|---------|---------|
| Digits        | Rand.   | Ac-DA   | Rand.   | Ac-DA   |
| Office-Home   | Rand.   | Ac-DA   | Rand.   | Ac-DA   |
| Image-CLEF    | Rand.   | Ac-DA   | Rand.   | Ac-DA   |
| 5%            | 91.6 (+3.3) | 92.9 (+3.3) | 62.4 (+3.3) | 65.6 (+3.3) |
| 15%           | 94.7 (+4.9) | 95.6 (+4.9) | 68.6 (+5.0) | 70.7 (+5.1) |

6. Conclusion
We proposed a three-stage discriminative active algorithm to improve the domain adaptation performance. The first stage adopted general domain adversarial training. In the second stage, we proposed an end-to-end query strategy combining uncertainty and diversity criteria to find out the most informative features in the target domain. Finally, in the third stage, we deployed a re-weighting technique based on the prediction uncertainty for determining the importance of the queried samples to retrain the network. The empirical results confirmed the effectiveness of our active domain adaptation algorithm especially when the query budget is small.
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