Unsupervised Visual Domain Adaptation Using Subspace Alignment-Supplementary material

1. Overview of supplementary material

In section 1.1, we present the experimental protocol we used for Office+Caltech10 datasets. Next in section 1.2, we present results for full Office dataset. Afterwards, in section 1.3 we present the pseudo code for our method. Then in section 1.4 we give details about the domain divergence experiments. Finally, in section 1.5 we report results for semi-supervised DA using SVM on Office+Caltech10 dataset.

1.1. Experimental protocol details for Office + Caltech10 dataset

The original Office dataset introduced in [8] consists of 31 object classes from three domains DSLR, Webcam and Amazon. In [4] Gong et al. add another domain, the Caltech-256 dataset. They used 10 common classes from all four domains for evaluation. This results in 2500+ images from all four domains. In our paper we follow the experimental protocol introduced in [4]. The 10 object classes are BACKPACK, TOURING-BIKE, CALCULATOR, HEAD PHONES, COMPUTER-KEYBOARD, LAPTOP-101, COMPUTER-MONITOR, COMPUTER-MOUSE, COFFEEMUG, and VIDEO-PROJECTOR. For the unsupervised DA setting we use 8 images from each class for training when the source domain is DSLR or Webcam. When source domain is Amazon or Caltech-10, we use 20 images for training (as in [4]). We randomly select training images and evaluate on the target images using either SVM (LibSVM) or a nearest neighbour classifier. For each domain adaptation problem we repeat the experiment 20 times and report only the mean classification accuracy. The standard deviation for 12 domain adaptation problems varies between 0.1 and 3.5. For semi-supervised setting we use three images with labels for each class from the target domain as in [4].

Note that we use the features provided by the authors of [4].For GFK, we use the codes provided by the authors [4].

Additionally, We also evaluate our method using the experimental protocol used in [3] which is different from the experimental protocol in [4]. In this setting we use all source samples for training and evaluate on the target domain. This alternative evaluation protocol allows us to compare against several other DA methods that we mentioned in the related work – See Table 1.

Method	**D→W**	**W→D**	**A→W**
GFS [5]	43.1	47.1	14.6
GFK [4]	42.7	47.2	14.8
OUR	**50.1**	**56.9**	**15.3**

Table 2. Unsupervised DA on Office full dataset using NN classifier.

Method	**D→W**	**W→D**	**A→W**
LRR [2]	36.8	32.9	**50.7**
Metric [8]	31.0	27.0	44.0
Metric [6]	36.1	25.3	50.4
GFS [5]	61.4	63.4	45.1
GFK [4]	61.1	63.8	46.0
OUR	**63.8**	**69.9**	45.0

Table 3. Semi-supervised DA on Office full dataset.

1.2. Experimental results for full Office dataset

Following the standard experimental protocol in [4, 5, 8], we also evaluate our subspace alignment DA method using the full Office dataset. Results are reported in Table 2 for unsupervised DA and in Table 3 for semi-supervised DA. In Table 3, for our method we use a NN classifier and for other methods we report the best results reported in respective papers.

1.3. Pseudo-code of our algorithm

The pseudo-code of our algorithm is presented in Algorithm 1. Note that the simplicity of this algorithm: it only requires two PCAs and some matrix multiplications.

1.4. Evaluating DA with divergence measures - details

Here we present experimental details on how to compute $H\Delta H$ and $TDAS$.

To compute $H\Delta H$ using a SVM we use the following protocol. For each baseline method and GFK we apply DA using both source and target data. Afterwards, we give label $+1$ for the source samples and label -1 for the target samples. Then we randomly divide the source samples into

Method	A→C	A→D	A→W	C→A	C→D	C→W	W→A	W→C	W→D	AVG
NA	41.7	41.4	34.2	51.8	54.1	46.8	31.1	31.5	70.7	44.8
TCA [7]	35.0	36.3	27.8	41.4	45.2	32.5	24.2	22.5	80.2	38.3
GFS [5]	39.2	36.3	33.6	43.6	40.8	36.3	33.5	30.9	75.7	41.1
SCL [1]	42.3	36.9	34.9	49.3	42.0	39.3	34.7	32.5	83.4	43.9
GFK [4]	42.2	42.7	40.7	44.5	43.3	44.7	31.8	30.8	75.6	44.0
Landmark [3]	45.5	**47.1**	46.1	56.7	**57.3**	49.5	**40.2**	**35.4**	75.2	50.3
OUR	**46.7**	44.2	**50.7**	**57.9**	50.4	**50.1**	38.7	34.3	**89.8**	**51.4**

Table 1. Unsupervised DA on Office dataset + Caltech10 dataset using the experimental protocol in [3].

Data: Source data S, Target data T, Source labels L_S, Subspace dimension d
Result: Predicted target labels L_T
$X_S \leftarrow PCA(S,d)$;
$X_T \leftarrow PCA(T,d)$;
$X_a \leftarrow X_S X_S' X_T$;
$S_a = S X_a$;
$T_T = T X_T$;
$L_T \leftarrow Classifier(S_a, T_T, L_S)$;
Algorithm 1: Subspace alignment DA algorithm

two sets of equal size. The source train set (S_{train}) and source test set (S_{test}). We do the same thing for the target samples and obtain target train set (T_{train}) and target test set (T_{test}). Finally, we train a SVM classifier using (S_{train}) and (T_{train}) as the training data and evaluate on the test set consisting of (S_{test}) and (T_{test}). The final classification rate obtained by this approach is an empirical estimate of $H\Delta H$.

To compute $TDAS$ we use similar approach. $TDAS$ is always associated with a metric as we need to compute the similarity $Sim(\mathbf{y_S}, \mathbf{y_T}) = \mathbf{y_S} A \mathbf{y_T}'$. For $baseline1$, the metric is $XsXs'$. For $baseline2$, the metric is $XtXt'$. For GFK we obtain the metric as explained in [4]. We set ϵ to the mean similarity between the source sample and the nearest target sample.

1.5. NN and SVM semi-supervised DA Office dataset

Here we report the classification accuracy for semi-supervised domain adaptation with a NN classifier on Office+Caltech10 dataset,– see Table 4 and with a SVM classifier in Table 5.

1.6. Classifying PASCAL-VOC-2007 images using classifiers built on ImageNet semi-supervised DA

In this experiment, we compare the average precision obtained on PASCAL-VOC-2007 by a SVM classifier in a semi-supervised DA settings. We use ImageNet as the source domain and PASCAL-VOC-2007 as the target domain. The results are shown in Figure 1 for the semi-supervised one.

Method	C→A	D→A	W→A	A→C	D→C	W→C
NA	23.1	31.3	30.8	24.0	22.4	20.8
Baseline 1	37.6	29.5	34.6	31.6	27.2	31.7
Baseline 2	44.3	44.9	44.1	36.3	34.2	33.8
GFS [5]	42.0	44.9	43.0	37.5	32.9	32.9
GFK [4]	42.0	45.0	42.8	37.7	32.7	32.8
OUR	**45.3**	**45.8**	**44.8**	**38.4**	**35.8**	**34.1**
Method	A→D	C→D	W→D	A→W	C→W	D→W
NA	28.1	26.5	44.3	31.6	25.2	55.5
Baseline 1	33.3	38.6	70.8	35.1	33.8	71.3
Baseline 2	54.7	54.7	70.3	**61.2**	**60.6**	76.8
GFS [5]	46.9	50.2	75.2	54.2	54.2	78.6
GFK [4]	47.0	49.5	75.0	53.7	54.2	78.7
OUR	**55.1**	**56.6**	**82.3**	60.3	**60.7**	**84.8**

Table 4. Recognition accuracy with semi-supervised DA with NN classifier(Office dataset + Caltech10).

Method	C→A	D→A	W→A	A→C	D→C	W→C
NA	45.1	32.8	28.2	37.8	28.4	23.8
Baseline1	**46.2**	37.7	35.6	37.1	31.6	29.3
Baseline2	43.6	38.5	34.3	36.6	31.6	27.8
GFK	45.4	36.3	32.1	38.8	28.5	26.3
OUR	44.7	**41.6**	**39.3**	**40.6**	**34.8**	**32.6**
Method	A→D	C→D	W→D	A→W	C→W	D→W
NA	38.6	39.3	71.8	38.7	64.6	83.1
Baseline1	39.1	33.7	66.8	36.1	76.6	83.1
Baseline2	39.1	34.1	64.2	36.8	67.9	83.1
GFK	39.5	39.1	70.3	**41.1**	77.7	83.1
OUR	**40.9**	**41.1**	**77.6**	38.2	**82.2**	**87.1**

Table 5. Recognition accuracy with semi-supervised DA with SVM classifier(Office dataset + Caltech10).

References

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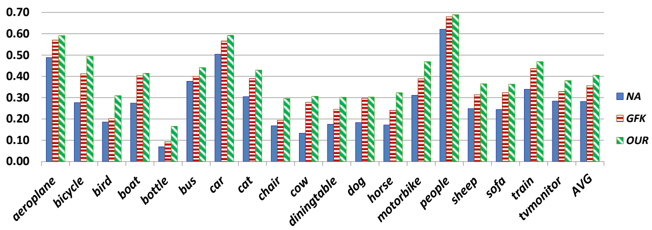

Figure 1. ImageNet as the source and classifying PASCAL-VOC-2007 images using semi-supervised DA with SVM.

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