Supplementary to Domain Generalization and Adaptation using Low Rank Exemplar SVMs

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1 Experiments on the Office Dataset

In this section, we further evaluate our proposed LRE-LSSVMs-DA method for the domain adaptation task on the benchmark Office dataset [1].

We compare our LRE-LSSVMs-DA method with the recently proposed deep transfer learning methods DDC [2], DAN [3], and ReverseGrad [4], which have shown promising results on this dataset. We employ the standard unsupervised domain adaptation protocol by treating one domain as the source domain, and another one as the target domain, which leads to six cases. In each case, all the target domain samples are used as unlabeled training samples in the training stage.

We strictly follow the experimental setup in [3], [4]. We first fine-tune the pretrained AlexNet model base on the ImageNet dataset using labeled samples in the source domain, and then use the fine-tuned CNN model to extract $fc7$ features for the images in both source and target domains. The parameters for fine-tuning the CNN model are suggested in [3], [4]. The images are resized to 256×256, and a single crop with size of 227×227 at the center of the resized image is used to extract features.

The results on the Office dataset are shown in Table 1, in which the results of baseline methods CNN, DCC, DAN are taken from their papers. For ReverseGrad, the results of the upper row are taken from their paper, which contains only three cases. The lower row are the reproduced results by using their released codes. It can be observed that our proposed method achieves comparable results with those CNN based methods. Although we do not mix multiple datasets as one source domain in this scenario, the results show that it is still beneficial to exploit the locality property to reduce the domain distribution mismatch by using our proposed method. This is because there are many factors (*e.g.*, pose and illumination) overlap and interact in images and videos in complex ways [5].

TABLE 1
Recognition accuracies (%) of different methods for domain adaptation on the Office dataset. The results of the baseline methods CNN, DDC, DAN, and ReverseGrad are taken from their papers. The best results are denoted in bold.

Source	A	D	W	A	D	W
Target	W	W	D	D	A	A
CNN [6]	61.6	95.4	99.0	63.8	51.1	49.8
DDC [2]	61.8	95.0	98.5	64.4	52.1	52.2
DAN [3]	68.5	96.0	99.0	67.0	54.0	53.1
ReverseGrad [4]	73.0	96.4	99.2	–	–	–
ReverseGrad (Reprod)	74.6	95.6	99.0	71.5	52.4	54.5
LRE-LSSVMs-DA	68.3	95.6	**99.3**	70.7	**55.4**	53.7
LRE-LSSVMs (ReverseGrad)	**75.6**	**96.5**	99.1	**74.7**	53.4	**55.4**

Moreover, the deep transfer learning methods are proposed to learn domain-invariant features, while our proposed LRE-SVMs and LRE-LSSVMs methods aim to improve the cross-domain generalization ability by learning robust exemplar classifiers. So our methods are complementary to those deep transfer learning based methods in methodology. Observing that the ReverseGrad method gives better results than DDC and DAN, we additionally report the results of our LRE-LSSVMs method using the features extracted from the ReverseGrad method, which is denoted as *LRE-LSSVMs (ReverseGrad)*. It can be observed that our LRE-LSSVMs (ReverseGrad) method consistently improved the results of ReverseGrad, which demonstrates that it is beneficial to learn exemplar classifiers by using our LRE-LSSVMs method for improving the cross-domain generalization ability.

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