Supplementary Materials

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***Abstract*—In the supplementary materials, the generally used benchmarks for testing transfer adaptation learning (TAL) models in visual classification are presented. Totally, 14 benchmarks including small-scale and large-scale datasets are summarized. Further, 61 TAL algorithms in total including baselines and very recent state-of-the art approaches from shallow learning to deep learning are introduced and their performances on 10 mainstream benchmarks are presented. This work shows a clear recognition of the progress in this community.**

***Index Terms*—Transfer adaptation learning, benchmarks, visual classification**

I. Benchmark Datasets of VTAL

In this section, the benchmark datasets for testing TAL models are introduced to facilitate readers' impression on how to start studies of transfer adaptation learning. Totally, 14 benchmark datasets including Office-31 (3DA) [1], Office+Caltech-10 (4DA) [1], [2], [3], [4], MNIST+USPS [5], [6], Multi-PIE [5], [6], COIL-20 [7], MSRC+VOC2007 [8], IVLSC [9], [10], AwA [11], Cross-dataset Testbed [12], Office Home [13], ImageCLEF [14], P-A-C-S [9], VisDA-2017 [15] and DomainNet [16] are summarized, each of which contains at least 2 different domains. For these benchmarks, classification accuracy of target data is commonly used for performance comparison. Due to the space limitation, the classification performances of different models are not listed, so that we can focus more on discussing the methodological advances and potential issues.

Office-31 (3DA). Office-31 is a popular benchmark for visual domain transfer, which includes 31 categories of samples drawn from three different domains, i.e., Amazon (A), DSLR (D) and Webcam (W). Amazon consists of online e-commerce pictures, DSLR contains high-resolution pictures and Webcam contains low-resolution pictures taken by a web camera. There are totally 4652 images, composed of 2817, 498 and 795 images from domain A, D and W, respectively. In feature extraction, (1) for shallow features, 800-dimensional feature vectors extracted by the Speed Up Robust Features (SURF) were used, and (2) for deep features, 4096-dimensional feature vectors extracted from pre-trained AlexNet/VGG-net/ResNet-50 were generally used. In model evaluation, six kinds of source-target domain pairs are tested, i.e., A→D, A→W, D→A, D→W , W→A, W→D.

Office+Caltech-10 (4DA). This 4DA dataset contains 4 domains, in which 3 domains (A, D, W) are from the Office-31 and another domain (C) is from Caltech-256, a benchmark containing 30,607 images of 256 classes in object recognition. The common 10 classes among the Office-31 and Caltech-256 were selected to form the 4DA, and therefore 2,533 images composed of 958, 157, 295 and 1123 images from domain A, D, W and C were collected. In evaluation, 12 tasks with different source-target domain pairs are addressed, i.e., A→D, A→C, A→W, D→A, D→C, D→W, C→A, C→D, C→W, W→A, W→C, W→D.

MNIST+USPS. MNIST and USPS are two benchmarks containing 10 categories of digit images under different distribution for handwritten digit recognition, and therefore qualified for TAL tasks. The MNIST includes 60,000 training pictures and 10,000 test pictures. The USPS includes 7291 training pictures and 2007 test pictures. For TAL tasks, 2000 pictures and 1800 pictures were randomly selected from MNIST and USPS, respectively. For feature extraction, each image was resized into 16×16 and a 256-dimensional feature vector that encode the pixel values was finally extracted. In evaluation, 2 cross-domain tasks, i.e., MNIST→USPS and USPS→MNIST are addressed.

Multi-PIE. Multi-PIE is a benchmark with poses, illuminations and expressions in face recognition, which includes 41,368 faces of 68 different identities. For TAL tasks, (1) face recognition across poses is generally evaluated on five different face orientations, including C05: left pose, C07: upward pose, C09: downward pose, C27: front pose and C29: right pose. Totally, 3332, 1629, 1632, 3329, and 1632 facial images are contained in C05, C07, C09, C27 and C29. Therefore, 20 tasks were evaluated, i.e., C05→C07, C05→C09, C05→C27, etc.; (2) face recognition across illuminations and exposure conditions is evaluated by randomly selecting two sets: PIE1 and PIE2 from front face images. Two tasks: PIE→PIE2 and PIE2→PIE1 are evaluated.

COIL-20. COIL-20 is a 3D object recognition benchmark containing 1440 images of 20 object categories. By rotating each object class horizontally of 5 degrees, 72 images per class after rotating 360 degrees were obtained. For TAL tasks, two disjoint subsets with different distribution i.e., COIL1 and COIL2 were prepared, where COIL1 contains the images in [0°, 85°] U [180°, 265°] and the images of COIL2 are in [90°, 175°] U [270°, 355°]. Therefore, two cross-domain tasks i.e., COIL1→COIL2 and COIL2→COIL1 are evaluated.

MSRC+VOC2007. The MSRC contains 4323 images of 18 categories and VOC2007 contains 5011 images of 20 categories. 1269 and 1530 images w.r.t six common categories, i.e., *aeroplane, bicycle, bird, car, cow* and *sheep*, were finally selected from MSRC and VOC2007, respectively. In feature representation, 128-dimensional DenseSIFT features were extracted for cross-domain image classification tasks, i.e., MSRC→VOC2007 and VOC2007→MSRC.

IVLSC. IVLSC is a large-scale image dataset containing five subsets, i.e., ImageNet (I), VOC2007 (V), LabelMe (L), SUN09 (S), and Caltech (C). For TAL tasks, 7341, 3376, 2656, 3282, and 1415 samples w.r.t. five common categories i.e., *bird, cat, chair, dog* and *human*, were randomly selected from I, V, L, S, and C domains, respectively. In feature representation, 4096-dimensional DeCaf6 deep features were extracted for cross-domain image classification under 20 tasks, i.e., I→V, I→L, I→S, I→C, ..., C→I, C→V, C→L, C→S.

AwA. AwA is an animal identification dataset containing 30,475 images of 50 categories, which provides a benchmark due to the inherent data distribution difference. This data set is currently less used in evaluating TAL algorithms.

Cross-dataset Testbed. This benchmark contains 10,473 images of 40 categories, collected from three domains: 3,847 images in Caltech256 (C), 4,000 images in ImageNet (I), and 2,626 images in SUN (S). In feature extraction, the 4096-dimensional DeCAF7 deep features were used for cross-domain image classification tasks, i.e., C→I, C→S, I→C, I→S, S→C, S→I.

Office Home. Office Home is a relatively new benchmark containing 15,585 images of 65 categories, collected from 4 domains, i.e., (1) Art (Ar): artistic depictions of objects in the form of sketches, paintings, ornamentation, etc.; (2) Clipart (Cl): collection of clipart images; (3) Product (Pr): images of objects without background, akin to the Amazon category in Office dataset; (4) Real-World (RW): images of objects captured with a regular camera. In detail, there contains 2421, 4379, 4428 and 4357 images in *Ar, Cl, Pr* and *RW* domains, respectively. In evaluation, 12 cross-domain tasks are tested, e.g., Ar→Cl, Ar→Pr, Ar→RW, Cl→Ar, etc.

ImageCLEF. This benchmark includes 1800 images of 12 categories, drawn from 3 domains: 600 images in Caltech 256 (C), 600 images in ImageNet ILSVRC2012 (I), and 600 images in Pascal VOC2012 (P). Therefore, 6 cross-domain tasks i.e., C→I, C→P, I→C, I→P, P→C, P→I are evaluated.

P-A-C-S. PACS is a new benchmark containing 7 common categories: *dog, elephant, giraffe, guitar, horse, house* and *person*, from 4 domains, i.e., 1670 images in Photo (P), 2048 images in Art Painting (A), 2344 images in Cartoon (C), and 3929 images in Sketch (S). 4096-dimensional VGG-M deep features were used and 12 cross-domain tasks are evaluated, e.g., P→A, P →C, P→S, A→P, A→C, etc.

VisDA-2017. VisDA-2017 is a large-scale synthetic-to-real dataset containing 152397 training images and 55388 validation images across 12 classes. we take synthetic images rendered from 3D models as the source domain and real images cropped from the Microsoft COCO dataset [17] as the target domain. Following the common protocol [18], [19] to evaluate on Synthetic → Real task.

DomainNet. DomainNet is the largest and most challenging dataset over 600,000 images with 345 categories for domain adaptation so far. It has 6 distinct domains: Clipart (clp), infograph (inf), Painting (pnt), Quickdraw (qdr), Real (rel) and Sketch (skt). On DomainNet dataset, 30 cross-domain tasks are evaluated, e.g., clp→inf, clp→pnt, clp→qdr, clp→rel, clp→skt inf→clp, inf→pnt, inf→qdr, inf→rel, etc.

II. Representative Methods and Performances

We totally overview 61 representative transfer adaptation learning methods including baselines and state-of-the-arts from shallow to deep learning ones, which are capable to represent the current progress of the TAL topic, including NN (Nearest Neighbor) [20], PCA (Principal Component Analysis) [21], GFK (Geodesic Flow Kernel) [22], TCA (Transfer Component Analysis) [23], TSL (Transfer Subspace Learning) [24], JDA (Joint Domain Adaptation) [25], DTSL (Discriminative Transfer Subspace Learning) [26], CDML (Cross-Domain Metric Learning) [27], RTML (Robust Transfer Metric Learning) [28], DICD (Domain Invariant and Class Discriminative) [29], DIPDA (Discriminative Information Preservation for Domain Adaptation) [30], GSL (Guide Subspace Learning) [31], SCA (Scatter Component Analysis) [32], VDA (Visual Domain Adaptation) [33], KOT (Kernel Optimal Transport map) [34], LDA (Label Disentangled Analysis) [35], ResNet-50 [36], DAN (Deep Adaptation Networks) [37], DANN (Domain-adversarial Neural Network) [38], MCD (Maximum Classifier Discrepancy) [39], CDAN (Conditional Domain Adversarial Networks) [18], SymNets (Domain-symmetric networks) [40], ETD (Enhanced Transport Distance) [41], BNM (Batch nuclear-norm maximization) [42], MDD (Margin Disparity Discrepancy) [43], MEDM (Minimal-entropy Diversity Maximization) [44], CADA (Certainty Attention based Domain Adaption) [45], GSDA (Domain Adaptation with Hierarchical Gradient Synchronization) [46], DCAN (Domain Conditioned Adaptation Network) [47], TCM (Transporting Causal Mechanisms) [48], MetaAlign [49],ADDA (Adversarial Discriminative Domain Adaptation) [50], JAN (Joint Adaptation Networks) [51], GTA (Generate To Adapt) [52], DWL (Dynamic Weighted Learning) [53], DADA (Discriminative Adversarial Domain Adaptation) [54], GVB (Gradually Vanishing Bridge) [19], CAN (Contrastive Adaptation Network) [55], SRDC (Structurally Regularized Deep Clustering) [56], RADA (Re-enforceable Adversarial Domain Adaptation) [57], RTN (Residual Transfer Networks) [58], MADA (Multi-adversarial Domain Adaptation) [59], HAFN ((Hard Adaptive Feature Norm)) [60], CAT (Cluster Alignment with a Teacher) [61], BCDM (Bi-classifier Determinacy Maximization) [62], A^2LP(Label Propagation with Augmented Anchors) [63], MinEnt (Minimum Entropy) [64], ADR (Adversarial Dropout Regularization) [65], JADA (Joint Adversarial Domain Adaptation) [66], TPN (Transferrable Prototypical Networks) [67], AFN (Adaptive Feature Norm) [60], GICT (Generatively Inferential Cotraining) [68], LPJT (Locality Preserving Joint Transfer) [69], BSP (Batch Spectral Penalization) [70], SWD (Sliced Wasserstein Discrepancy) [71], CGDM (Cross-domain Gradient Discrepancy Minimization) [72], DTA (Drop to Adapt) [73], SHOT (Source HypOthesis Transfer) [74], STAR (STochastic clAssifieRs) [75], ADDA (Adversarial Discriminative Domain Adaptation) [50], MIMTFL (Mutual Information Maximisation and Transferable Feature Learning) [76], and SCDA (Semantic Concentration for Domain Adaptation) [77]. These above TAL algorithms on 10 mainstream benchmarks are presented in Table I, II, III, IV, V, VI, and VII, respectively.

III. Discussion and Summary

In this work, to summarize the cross-domain image classification tasks in evaluating the TAL models, 14 benchmarks constructed based on some popular datasets in computer vision

TABLE I
RECOGNITION ACCURACIES (%) ON MULTI-PIE, COIL-20 AND MNIST+USPS. THE BEST RESULTS ARE HIGHLIGHTED IN RED AND THE SECOND BEST IN BLUE.

Datasets	Tasks	Compared TL/DA Methods										
		NN	PCA	GFK	TCA	TSL	JDA	DTSL	CDML	RTML	DICD	DIPDA
Multi-PIE	C05 → C07	26.09	24.80	26.15	40.76	44.08	58.81	65.87	53.22	60.12	72.99	85.69
	C05 → C09	26.59	25.18	27.27	41.79	47.49	54.23	64.09	53.12	55.21	72.00	81.25
	C05 → C27	30.67	29.26	31.15	59.63	62.78	84.50	82.03	80.12	85.19	92.22	95.73
	C05 → C29	16.67	16.30	17.59	29.35	36.15	49.75	54.90	48.23	52.98	66.85	67.04
	C07 → C05	24.49	24.22	25.24	41.81	46.28	57.62	45.04	52.39	58.13	69.93	88.62
	C07 → C09	46.63	45.53	47.37	51.47	57.60	62.93	53.49	54.23	63.92	65.87	84.62
	C07 → C27	54.07	53.35	54.25	64.73	71.43	75.82	71.43	68.36	76.16	85.25	93.39
	C07 → C29	26.53	25.43	27.08	33.70	35.66	39.89	47.97	37.34	40.38	48.71	72.73
	C09 → C05	21.37	20.95	21.82	34.69	36.94	50.96	52.49	43.54	53.12	69.36	84.12
	C09 → C07	41.01	40.45	43.16	47.70	47.02	57.95	55.56	54.87	58.67	65.44	83.19
	C09 → C27	46.53	46.14	46.41	56.23	59.45	68.45	77.50	62.76	69.81	83.39	95.67
	C09 → C29	26.23	25.31	26.78	33.15	36.34	39.95	54.11	38.21	42.13	61.40	77.12
	C27 → C05	32.95	31.96	34.24	55.64	63.66	80.58	81.54	75.12	81.12	93.13	96.93
	C27 → C07	62.68	60.96	62.92	67.83	72.68	82.63	85.39	80.53	83.92	90.12	97.05
	C27 → C09	73.22	72.18	73.35	75.86	83.52	87.25	82.23	83.72	89.51	88.97	92.95
	C27 → C29	37.19	35.11	37.38	40.26	44.79	54.66	72.61	52.78	56.26	75.61	86.76
	C29 → C05	18.49	18.85	20.35	26.98	33.28	46.46	52.19	27.34	29.11	62.88	74.81
	C29 → C07	24.19	23.39	24.62	29.90	34.13	42.05	49.41	30.82	33.28	57.03	76.97
	C29 → C09	28.31	27.12	28.49	29.90	36.58	53.31	58.45	36.34	39.85	65.87	78.30
	C29 → C27	31.24	30.34	31.33	33.64	38.75	57.01	64.31	40.61	47.13	74.77	86.99
COIL-20	COIL1 → COIL2	83.61	84.72	72.50	88.47	88.06	89.31	88.61	88.93	91.23	95.69	99.86
	COIL2 → COIL1	82.78	84.03	74.17	85.83	87.92	88.47	89.17	87.32	90.22	93.33	99.16
MNIST+USPS	USPS → MNIST	44.70	44.95	46.45	51.05	53.75	59.65	55.50	52.25	61.82	65.20	67.85
	MNIST → USPS	65.94	66.22	67.22	56.28	66.06	67.28	52.33	63.28	69.52	77.83	84.11

TABLE II
RECOGNITION ACCURACIES (%) ON OFFICE+CALTECH-10 (4DA) WITH SURF FEATURE. THE BEST RESULTS ARE HIGHLIGHTED IN RED AND THE SECOND BEST IN BLUE.

Tasks	Compared TL/DA Methods														
	NN	PCA	GFK	TCA	TSL	JDA	DTSL	CDML	RTML	GSL	DICD	SCA	VDA	KOT	LDA
C → A	23.70	36.95	41.02	38.20	44.47	44.78	51.25	47.28	49.26	56.60	47.29	45.62	46.14	52.92	53.03
C → W	25.76	32.54	40.68	38.64	34.24	41.69	38.64	36.91	44.72	55.90	46.44	40.00	46.10	45.76	49.49
C → D	25.48	38.22	38.85	41.40	43.31	45.22	47.13	43.93	47.56	49.70	49.68	47.13	51.59	52.23	50.32
A → C	26.00	34.73	40.25	37.76	37.58	39.36	43.37	41.72	43.68	45.40	42.39	39.72	42.21	44.88	44.61
A → W	29.83	35.59	38.98	37.63	33.90	37.97	36.61	38.25	44.32	41.70	45.08	34.92	51.19	43.73	42.03
A → D	25.48	27.39	36.31	33.12	26.11	39.49	38.85	35.92	43.86	44.00	38.85	39.49	48.41	43.95	50.32
W → C	19.86	26.36	30.72	29.30	29.83	31.17	29.83	31.14	34.83	35.30	33.57	31.08	27.60	34.02	37.40
W → A	22.96	31.00	29.75	30.06	30.27	32.78	34.13	32.26	35.28	40.70	34.13	29.96	26.10	36.85	38.52
W → D	59.24	77.07	80.89	87.26	87.26	89.17	82.80	84.84	91.02	88.50	89.81	87.26	89.18	84.71	87.26
D → C	26.27	29.65	30.28	31.7	28.50	31.52	30.11	32.63	34.58	31.80	34.64	30.72	31.26	38.02	32.24
D → A	28.50	32.05	32.05	32.15	27.56	33.09	32.05	29.87	33.26	34.80	34.45	31.63	37.68	38.94	42.07
D → W	63.39	75.93	75.59	86.10	85.42	89.49	72.20	82.34	89.68	84.10	91.19	84.41	90.85	85.76	81.02
Average	31.37	39.79	42.95	43.61	42.37	46.31	44.75	44.80	49.34	50.71	48.96	45.16	49.03	50.15	50.69

TABLE III
RECOGNITION ACCURACIES (%) ON OFFICE-31 (3DA) WITH RESNET-50. THE BEST RESULTS ARE HIGHLIGHTED IN RED AND THE SECOND BEST IN BLUE.

Tasks	Compared Methods														
	ResNet-50	DAN	DANN	ADDA	JAN	GTA	CDAN	MDD	ETD	DWL	DADA	GVB	CAN	SRDC	RADA
A → D	68.9	78.6	79.7	77.8	84.7	87.7	89.8	93.5	88.0	91.2	93.9	95.0	95.0	95.8	96.1
A → W	68.4	80.5	82.0	86.2	85.4	89.5	93.1	94.5	92.1	89.2	92.3	94.8	94.5	95.7	96.2
D → W	96.7	97.1	96.9	96.2	97.4	97.9	98.2	98.4	100.0	99.2	99.2	98.7	99.1	99.2	99.3
W → D	99.3	99.6	99.1	98.4	99.8	99.8	100.0	100.0	100.0	100.0	100.0	100.0	99.8	100.0	100.0
D → A	62.5	63.6	68.2	69.5	68.6	72.8	70.1	74.6	71.0	73.1	74.4	73.4	78.0	76.7	77.5
W → A	60.7	62.8	67.4	68.9	70.0	71.4	68.0	72.2	67.8	69.8	74.2	73.7	77.0	77.0	77.4
Average	76.1	80.4	82.2	82.9	84.3	86.5	86.6	88.9	86.2	87.1	89.0	89.3	90.6	90.8	91.1

TABLE IV
RECOGNITION ACCURACIES (%) ON OFFICE HOME WITH RESNET-50. THE BEST RESULTS ARE HIGHLIGHTED IN RED AND THE SECOND BEST IN BLUE.

Methods	Tasks												
	Ar→Cl	Ar→Pr	Ar→Rw	Cl→Ar	Cl→Pr	Cl→Rw	Pr→Ar	Pr→Cl	Pr→Rw	Rw→Ar	Rw→Cl	Rw→Pr	Average
ResNet-50	34.9	50.0	58.0	37.4	41.9	46.2	38.5	31.2	60.4	53.9	41.2	59.9	46.1
DAN	43.6	57.0	67.9	45.8	56.5	60.4	44.0	43.6	67.7	63.1	51.5	74.3	56.3
DANN	45.6	59.3	70.1	47.0	58.5	60.9	46.1	43.7	68.5	63.2	51.8	76.8	57.6
MCD	48.9	68.3	74.6	61.3	67.6	68.8	57.0	47.1	75.1	69.1	52.2	79.6	64.1
CDAN	50.7	70.6	76.0	57.6	70.0	70.0	57.4	50.9	77.3	70.9	56.7	81.6	65.8
SymNets	47.7	72.9	78.5	64.2	71.3	74.2	63.6	47.6	79.4	73.8	50.8	82.6	67.2
ETD	51.3	71.9	85.7	57.6	69.2	73.7	57.8	51.2	79.3	70.2	57.5	82.1	67.3
BNM	52.3	73.9	80.0	63.3	72.9	74.9	61.7	49.5	79.7	70.5	53.6	82.2	67.9
MDD	54.9	73.7	77.8	60.0	71.4	71.8	61.2	53.6	78.1	72.5	60.2	82.3	68.1
MEDM	57.1	76.1	80.0	62.0	72.7	76.0	62.3	53.4	81.2	69.9	59.8	83.9	69.5
CADA	56.9	76.4	80.7	61.3	75.2	75.2	63.2	54.5	80.7	73.9	61.5	84.1	70.2
GSDA	61.3	76.1	79.4	65.4	73.3	74.3	65.0	53.2	80.0	72.2	60.6	83.1	70.3
DCAN	54.5	75.7	81.2	67.4	74.0	76.3	67.4	52.7	80.6	74.1	59.1	83.5	70.5
TCM	58.6	74.4	79.6	64.5	74.0	75.1	64.6	56.2	80.9	74.6	60.7	84.7	70.7
MetaAlign	59.3	76.0	80.2	65.7	74.7	75.1	65.7	56.5	81.6	74.1	61.1	85.2	71.3

TABLE V
RECOGNITION ACCURACIES (%) ON IMAGECLEF WITH RESNET-50. THE BEST RESULTS ARE HIGHLIGHTED IN RED AND THE SECOND BEST IN BLUE.

Tasks	Compared Methods													
	ResNet-50	DAN	RTN	DANN	MADA	JAN	HAFN	CAT	CDAN	BCDM	A^2LP	SymNets	ETD	TCM	DWL
I → P	74.8	74.5	75.6	75.0	75.0	76.8	76.9	76.7	77.7	79.5	79.6	80.2	81.0	79.9	82.3
P → I	83.9	82.2	86.8	86.0	87.9	88.0	89.0	89.0	90.7	93.2	92.7	93.6	91.7	94.2	94.8
I → C	91.5	92.8	95.3	96.2	96.0	94.7	94.4	94.5	97.7	96.8	96.7	97.0	97.9	97.8	98.1
C → I	78.0	86.3	86.9	87.0	88.8	89.5	89.6	89.8	91.3	91.3	92.5	93.4	93.3	93.8	92.8
C → P	65.5	69.2	72.7	74.3	75.2	74.2	74.9	74.0	74.2	78.9	78.9	78.7	79.5	79.9	77.9
P → C	91.2	89.8	92.2	91.5	92.2	91.7	92.9	93.7	94.3	95.8	96.0	96.4	95.0	96.9	97.2
Average	80.7	82.5	84.9	85.0	85.8	85.8	86.3	86.3	87.7	89.3	89.4	89.9	89.7	90.5	90.5

TABLE VI
RECOGNITION ACCURACIES (%) ON VISDA-2017 WITH RESNET-101. THE BEST RESULTS ARE HIGHLIGHTED IN RED AND THE SECOND BEST IN BLUE.

Methods	Classes												
	plane	bcycl	bus	car	horse	knife	mcycl	person	plant	sktbrd	train	truck	Average
ResNet	55.1	53.3	61.9	59.1	80.6	17.9	79.7	31.2	81.0	26.5	73.5	8.5	52.4
MinEnt	80.3	75.5	75.8	48.3	77.9	27.3	69.7	40.2	46.5	46.6	79.3	16.0	57.0
DAN	87.1	63.0	76.5	42.0	90.3	42.9	85.9	53.1	49.7	36.3	85.8	20.7	61.1
DANN	81.9	77.7	82.8	44.3	81.2	29.5	65.1	28.6	51.9	54.6	82.8	7.8	57.4
CDAN	85.2	66.9	83.0	50.8	84.2	74.9	88.1	74.5	83.4	76.0	81.9	38.0	73.9
ADR	87.8	79.5	83.7	65.3	92.3	61.8	88.9	73.2	87.8	60.0	85.5	32.3	74.8
JADA	91.9	78.0	81.5	68.7	90.2	84.1	84.0	73.6	88.2	67.2	79.0	38.0	77.0
TPN	93.7	85.1	69.2	81.6	93.5	61.9	89.3	81.4	93.5	81.6	84.5	49.9	80..4
AFN	93.6	61.3	84.1	70.6	94.1	79.0	91.8	79.6	89.9	55.6	89.0	24.4	76.1
BNM	89.6	61.5	76.9	55.0	89.3	69.1	81.3	65.5	90.0	47.3	89.1	30.1	70.4
MCD	87.0	60.9	83.7	64.0	88.9	79.6	84.7	76.9	88.6	40.3	83.0	25.8	71.9
GICT	87.6	60.6	81.6	72.1	87.8	62.9	89.7	68.5	88.8	76.1	83.2	20.0	73.1
LPJT	93.0	80.3	66.5	56.3	95.8	70.3	74.2	83.8	91.7	40.0	78.7	57.6	74.0
BSP	92.4	61.0	81.0	57.5	89.0	80.6	90.1	77.0	84.2	77.9	82.1	38.4	75.9
SWD	90.8	82.5	81.7	70.5	91.7	69.5	86.3	77.5	87.4	63.6	85.6	29.2	76.4
DWL	90.7	80.2	86.1	67.6	92.4	81.5	86.8	78.0	90.6	57.1	85.6	28.7	77.1
DTA	93.7	82.2	85.6	83.8	93.0	81.0	90.7	82.1	95.1	78.1	86.4	32.1	81.5
CGDM	93.4	82.7	73.2	68.4	92.9	94.5	88.7	82.1	93.4	82.5	86.8	49.2	82.3
SHOT	94.3	88.5	80.1	57.3	93.1	94.9	80.7	80.3	91.5	89.1	86.3	58.2	82.9
STAR	95.0	84.0	84.6	73.0	91.6	91.8	85.9	78.4	94.4	84.7	87.0	42.2	82.7
BCDM	95.1	87.6	81.2	73.2	92.7	95.4	86.9	82.5	95.1	84.8	88.1	39.5	83.4

TABLE VII

RECOGNITION ACCURACIES (%) ON DOMAINNET WITH RESNET-101. IN EACH SUB-TABLE, THE COLUMN-WISE DOMAINS ARE DENOTED AS THE SOURCE DOMAIN AND THE ROW-WISE DOMAINS ARE DENOTED AS THE TARGET DOMAIN. THE NAMES OF METHODS ARE MARKED IN RED AND DOMAINS IN BLUE.

ADDA	clp	inf	pnt	qdr	rel	skt	Avg.
clp	-	11.2	24.1	3.2	41.9	30.7	22.2
inf	19.1	-	16.4	3.2	26.9	14.6	16.0
pnt	31.2	9.5	-	8.4	39.1	25.4	22.7
qdr	15.7	2.6	5.4	-	9.9	11.9	9.1
rel	39.5	14.5	29.1	12.1	-	25.7	24.2
skt	35.3	8.9	25.2	14.9	37.6	-	25.4
Avg.	28.2	9.3	20.1	8.4	31.1	21.7	19.8

MCD	clp	inf	pnt	qdr	rel	skt	Avg.
clp	-	14.2	26.1	1.6	45.0	33.8	24.1
inf	23.6	-	21.2	1.5	36.7	18.0	20.2
pnt	34.4	14.8	-	1.9	50.5	28.4	26.0
qdr	15.0	3.0	7.0	-	11.5	10.2	9.3
rel	42.6	19.6	42.6	2.2	-	29.3	27.2
skt	41.2	13.7	27.6	3.8	34.8	-	24.2
Avg.	31.4	13.1	24.9	2.2	35.7	23.9	21.9

DANN	clp	inf	pnt	qdr	rel	skt	Avg.
clp	-	15.5	34.8	9.5	50.8	41.4	30.4
inf	31.8	-	30.2	3.8	44.8	25.7	27.3
pnt	39.6	15.1	-	5.5	54.6	35.1	30.0
qdr	11.8	2.0	4.4	-	9.8	8.4	7.3
rel	47.5	17.9	47.0	6.3	-	37.3	31.2
skt	47.9	13.9	34.5	10.4	46.8	-	30.7
Avg.	35.7	12.9	30.2	7.1	41.4	29.6	26.1

ResNet	clp	inf	pnt	qdr	rel	skt	Avg.
clp	-	19.3	37.5	11.1	52.2	41.0	32.2
inf	30.2	-	31.2	3.6	44.0	27.9	27.4
pnt	39.6	18.7	-	4.9	54.5	36.3	30.8
qdr	7.0	0.9	1.4	-	4.1	8.3	4.3
rel	48.4	22.2	49.4	6.4	-	38.8	33.0
skt	46.9	15.4	37.0	10.9	47.0	-	31.4
Avg.	34.4	15.3	31.3	7.4	40.4	30.5	26.5

CDAN	clp	inf	pnt	qdr	rel	skt	Avg.
clp	-	17.8	35.7	15.3	51.3	37.2	31.4
inf	25.4	-	28.9	5.8	38.2	22.8	24.2
pnt	37.1	17.9	-	7.9	51.4	34.0	29.7
qdr	20.5	2.3	7.7	-	14.6	12.6	11.5
rel	43.6	19.4	46.1	8.3	-	33.2	30.1
skt	45.4	18.3	40.4	14.5	48.3	-	33.4
Avg.	34.4	15.1	31.7	10.4	40.8	27.9	26.7

SWD	clp	inf	pnt	qdr	rel	skt	Avg.
clp	-	16.6	35.3	12.8	48.7	41.0	30.9
inf	26.9	-	27.6	2.7	38.1	25.4	24.1
pnt	37.3	16.9	-	5.9	48.7	34.6	28.7
qdr	19.3	3.0	8.1	-	14.2	13.3	11.6
rel	47.0	19.9	47.1	6.1	-	36.8	31.4
skt	48.8	17.3	41.1	12.2	49.1	-	33.7
Avg.	35.9	14.7	31.8	7.9	39.8	30.2	26.7

BNM	clp	inf	pnt	qdr	rel	skt	Avg.
clp	-	19.4	35.6	16.1	49.8	36.3	31.4
inf	24.6	-	27.8	7.9	35.0	22.0	23.5
pnt	36.0	20.2	-	9.7	51.8	34.2	30.4
qdr	21.3	3.8	10.5	-	14.0	12.9	12.5
rel	43.4	21.7	47.0	9.9	-	32.9	31.0
skt	43.1	19.1	39.5	15.6	47.0	-	32.7
Avg.	33.7	16.8	32.1	11.8	39.6	27.7	26.9

MIMTFL	clp	inf	pnt	qdr	rel	skt	Avg.
clp	-	15.1	35.6	10.7	51.5	43.1	31.2
inf	32.1	-	31.0	2.9	48.5	31.0	29.1
pnt	40.1	14.7	-	4.2	55.4	36.8	30.2
qdr	18.8	3.1	5.0	-	16.0	13.8	11.3
rel	48.5	19.0	47.6	5.8	-	39.4	32.1
skt	51.7	16.5	40.3	12.3	53.5	-	34.9
Avg.	38.2	13.7	31.9	7.2	45.0	32.8	28.1

MDD	clp	inf	pnt	qdr	rel	skt	Avg.
clp	-	20.5	40.7	6.2	52.5	42.1	32.4
inf	33.0	-	33.8	2.6	46.2	24.5	28.0
pnt	43.7	20.4	-	2.8	51.2	41.7	32.0
qdr	18.4	3.0	8.1	-	12.9	11.8	10.8
rel	52.8	21.6	47.8	4.2	-	41.2	33.5
skt	54.3	17.5	43.1	5.7	54.2	-	35.0
Avg.	40.4	16.6	34.7	4.3	43.4	32.3	28.6

SCDA	clp	inf	pnt	qdr	rel	skt	Avg.
clp	-	18.6	39.3	5.1	55.0	44.1	32.4
inf	29.6	-	34.0	1.4	46.3	25.4	27.3
pnt	44.1	19.0	-	2.6	56.2	42.0	32.8
qdr	30.0	4.9	15.0	-	25.4	19.8	19.0
rel	54.0	22.5	51.9	2.3	-	42.5	34.6
skt	55.6	18.5	44.7	6.4	53.2	-	35.7
Avg.	42.6	16.7	37.0	3.6	47.2	34.8	30.3

BCDM	clp	inf	pnt	qdr	rel	skt	Avg.
clp	-	19.9	38.5	15.1	53.2	43.9	34.1
inf	31.9	-	32.7	6.9	44.7	28.5	28.9
pnt	42.5	19.8	-	7.9	54.5	38.5	32.6
qdr	23.0	4.0	9.5	-	16.9	16.2	13.9
rel	51.9	24.9	51.2	8.7	-	40.6	35.5
skt	53.7	20.5	46.0	13.1	53.4	-	37.1
Avg.	40.6	17.8	35.6	10.3	44.3	33.5	30.4

MDD+SCDA	clp	inf	pnt	qdr	rel	skt	Avg.
clp	-	20.4	43.3	15.2	59.3	46.5	36.9
inf	32.7	-	34.5	6.3	47.6	29.2	30.1
pnt	46.4	19.9	-	8.1	58.8	42.9	35.2
qdr	31.1	6.6	18.0	-	28.8	22.0	21.3
rel	55.5	23.7	52.9	9.5	-	45.2	37.4
skt	55.8	20.1	46.5	15.0	56.7	-	38.8
Avg.	44.3	18.1	39.0	10.8	50.2	37.2	33.3

are presented, such as ImageNet, ILSVRC, PASCAL VOC, Caltech-256, multi-PIE and MNIST. It is noteworthy that, despite these endeavors made by researchers, more benchmarks in cross-domain vision understanding problems we could see, namely: object detection, semantic segmentation, visual relation modeling, scene parsing, etc. are still future challenges for more universal and safe applications. These can better testify the practicality of TAL methodologies. In this work, in order to show the status of TAL, only cross-domain image classification based benchmarks and performances are summarized for the overview.

The performance on the benchmarks has taken a big step forward. However, we have to denote a fact that the existing unsupervised domain adaptation setting has always used target data for training (even without labels), which, inevitably leads to overfitting and loses fairness. Therefore, we must be aware of this, and a reasonable and scientific training and testing protocol may promote this community. Considering the necessity of target data, a possible solution is that, as few-shot learning does, partial unlabeled target samples are used as seen samples (training) for determining an ideal hypothesis h^* with small joint error $\lambda = \epsilon_S(h^*)+\epsilon_T(h^*)$, and the unseen target samples (test) are used for model evaluation. This meets another more practical challenge of domain generalization (DG), where the task is to generalize a model trained on single/multiple source domains to unseen target domains. DG is another independent branch deserved further research and not the focus of this work, and hence not discussed.

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