Learning Transferable Features with Deep Adaptation Networks

Mingsheng Long[12], Yue Cao[1], Jianmin Wang[1], and Michael I. Jordan[2]

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Introduction

- Goal: Enhance the transferability of features from task-specific layers
- Proposed a Deep Adaptation Network DAN architecture
  - General features can generalize well to a novel task; however, for specific features they cannot bridge the domain discrepancy
- Some ways to enhance feature transferability:
  - By mean-embedding matching, feature transferability can be enhanced substantially
  - Utilizing multi-layer representations across domains in a reproducing kernel Hilbert space

Main Breakthrough

- *Generalizes deep CNN to the domain adaptation*
- Deep adaptation of multiple task-specific layers, including output
- Optimal adaptation using multiple kernel two-sample matching

Deep Learning For Domain Adaptation

- None or very weak supervision in the *target* task (new domain)
  - Target classifier cannot be reliably trained due to over-fitting
  - Fine-tuning is impossible as it requires substantial supervision
- Generalize related supervised source task to the target task
  - Deep networks can learn transferable features for adaptation
- Hard to find big source task for learning deep features from scratch
  - Transfer from deep networks pre-trained on unrelated big dataset
  - Transferring features from distant tasks better than random features

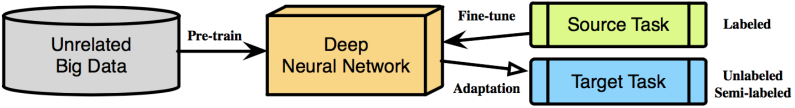

Figure: *Deep Learning for Domain Adaptation Workflow*

How Transferable Are Deep Features?

- Transferability is restricted by (Yosinski et al. 2014; Glorot et al. 2011)
- Specialization of higher layer neurons to original task (new task)
- Disentangling of variations in higher layers enlarges task discrepancy
- Transferability of features decreases while task discrepancy increases

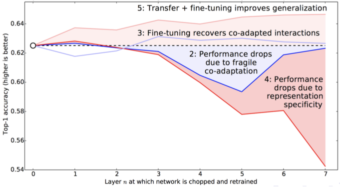

Figure: Transferability of features decreases while task discrepancy increases

Deep Adaptation Network (DAN)

Key Observations (AlexNet) (Krizhevsky et al. 2012)

- Comprised of five convolutional layers $conv1 - conv5$ and three fully connected layers $fc6 - fc8$
- Convolutional layers learn general features: safely transferable
  - Safely freeze $conv1 - conv3$ & fine tuned $conv4 - conv5$
- Fully-connected layers fit task specificicy: NOT safely transferable
  - Deeply adapt $fc6 - fc8$ using statistically optimal two-sample matching

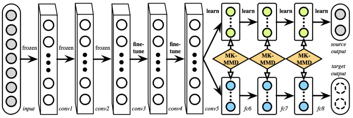

Figure: The DAN architecture for learning transferable features

Objective Function

Main Problems

- Feature transferability decreases with increasing task discrepancy
- Higher layers are tailored to specific tasks, NOT safely transferable
- Adaptation effect may vanish in back-propagation of deep networks

Deep Adaptation with Optimal Matching

- Deep adaptation: match distributions in multiple layers includingoutput
- Optimal matching: maximize two-sample test of multiple kernels

$$\min_{\Theta} \max_{\kappa} \frac{1}{n_a} \sum_{i=1}^{n_a} J(\theta(x_i^a), y_i^a) + \lambda \sum_{\ell=l_1}^{l_2} d_k^2(D_s^\ell, D_t^\ell) \tag{1}$$

$\lambda > 0$ is a penality, $D_*^\ell = \{h_i^{*\ell}\}$ is the ℓ-th layer hidden representaion

MK-MMD

Theorem (Two-Sample Test (Gretton et al. 2012))

- $p = q$ iff $d_k^2(p,q) = 0$ (In practice, $d_k^2(p,q) < \epsilon$)
- $\max_{k \in \kappa} d_k^2(D_s^\ell, D_t^\ell)\sigma_k^{-2} \Leftrightarrow$ minType II Error ($d_k^2(p,q) < \epsilon$ when $p \neq q$)

Multiple Kernel Maximum Mean Discrepancy (MK-MMD)

$\triangleq$ RKHS distance between kernel embeddings of distributions p and q

$$d_k^2(p,q) \triangleq \| E_p[\phi(x^s)] - E_q[\phi(x^t)] \|_{\mathcal{H}_k}^2 \tag{2}$$

$k(\mathbf{x}^s, \mathbf{x}^t) = \langle \phi(\mathbf{x}^s), \phi(\mathbf{x}^t) \rangle$ is a convex combination of m PSD kernels

$$\kappa \triangleq \left\{ k = \sum_{u=1}^{m} \beta_u k_u : \sum_{u=1}^{m} \beta_u = 1, \beta_u \geq 0, \forall u \right\} \tag{3}$$

Learning CNN

Linear-Time Algorithm of MK-MMD (Streaming Algorithm)

$O(n^2) : d_k^2(p,q) = \mathbf{E}_{\mathbf{x}^s\mathbf{x}'^s} k(\mathbf{x}^s, \mathbf{x}'^s) + \mathbf{E}_{\mathbf{x}^t\mathbf{x}'^t} k(\mathbf{x}^t, \mathbf{x}'^t) - 2\mathbf{E}_{\mathbf{x}^s\mathbf{x}^t} k(\mathbf{x}^s, \mathbf{x}^t)$

$d_k^2(p,q) = \frac{2}{n_s} \sum_{i=1}^{\frac{n_s}{2}} g_k(\mathbf{z}_i) \rightarrow$ linear-time unbiased estimate

- Quad-tuple: $\mathbf{z}_i \triangleq (\mathbf{x}_{2i-1}^s, \mathbf{x}_{2i}^s, \mathbf{x}_{2i-1}^t, \mathbf{x}_{2i}^t)$
- $g_k(\mathbf{z}_i) \triangleq k(\mathbf{x}_{2i-1}^s, \mathbf{x}_{2i}^s) + k(\mathbf{x}_{2i-1}^t, \mathbf{x}_{2i}^t) - k(\mathbf{x}_{2i-1}^s, \mathbf{x}_{2i}^t) - k(\mathbf{x}_{2i}^s, \mathbf{x}_{2i-1}^t)$

Stochastic Gradient Descent(SGD)

For each layer ℓ and for each quad-tuple $\mathbf{z}_i \triangleq (\mathbf{x}_{2i-1}^s, \mathbf{x}_{2i}^s, \mathbf{x}_{2i-1}^t, \mathbf{x}_{2i}^t)$

$$\nabla_{\Theta^\ell} = \frac{\partial J(z_i)}{\partial \Theta^\ell} + \lambda \frac{\partial g_k(z_i^\ell)}{\partial \Theta^\ell} \tag{4}$$

Learning Kernel

Learning optimal kernel $k = \sum_{u=1}^{m} \beta_u k_u$

Maximizing test power $\triangleq$ minimizing Type II error (Gretton et al. 2012)

$$\max_{k \in \kappa} d_k^2(D_s^\ell, D_t^\ell)\sigma_k^{-2} \tag{5}$$

where $\sigma_k^2 = \mathbf{E}_\mathbf{z} g_k^2(\mathbf{z}) - [\mathbf{E}_z g_k(\mathbf{z})]^2$ is the estimation variance.

Quadratic Program (QP), scaling linearly to sample size: $\mathrm{O}(m^{2n} + m^3)$

$$\min_{d^T\beta=1, \beta\geq 0} \beta^T(Q + \epsilon I)\beta \tag{6}$$

where $\mathbf{d} = (d_1, d_2, ..., d_m)^T$, and each d_u is MMD using base kernel k_u.

Analysis

Theorem (Adaptation Bound)

(Ben-David et al. 2010) Let $\theta \in H$ be a hypothesis, $\epsilon_s(\theta)$ and $\epsilon_t(\theta)$ be the expected risks of source and target respectively, then

$$\epsilon_t(\theta) \leq \epsilon_s(\theta) + 2d_k(p, q) + C \tag{7}$$

where C is a constant for the complexity of hypothesis space, the empirical estimate of **H**-divergence, and the risk of an ideal hypothesis for both tasks.

Two-Sample Classifier: Nonparametric vs. Parametric

- Nonparametric MMD directly approximates $d_{\mathcal{H}}(p, q)$
- Parametric classifier: adversarial training to approximate $d_{\mathcal{H}}(p, q)$

Experiment Setup

- Datasets: pre-trained on ImageNet, fined-tuned on Office&Caltech
- Tasks: 12 adaptation tasks ⇒ An unbiased look at dataset bias
- Variants: DAN; single-layer: DAN_7, DAN_8; single-kernel: DAN_{SK}
- Protocols: unsupervised adaptation vs semi-supervised adaptation
- Parameter selection: cross-validation by jointly assessing
    - test errors of source classifier and two-sample classifier (MK-MMD)

Figure: *the proposed DAN model is trained by fine-tuning from the AlexNet model (Krizhevsky et al., 2012) pre-trained on ImageNet, implemented in Caffe.*

Results & Discussion

Learning transferable features by deep adaptation and optimal matching

- Deep adaptation of multiple domain-specific layers (DAN) vs. shallow adaptation of one hard-to-tweak layer (DDC)
- Two samples can be matched better by MK-MMD vs. SK-MMD

Table 1. Accuracy on *Office-31* dataset with standard unsupervised adaptation protocol (Gong et al., 2013).

Method	$A \to W$	$D \to W$	$W \to D$	$A \to D$	$D \to A$	$W \to A$	Average
TCA	21.5 ± 0.0	50.1 ± 0.0	58.4 ± 0.0	11.4 ± 0.0	8.0 ± 0.0	14.6 ± 0.0	27.3
GFK	19.7 ± 0.0	49.7 ± 0.0	63.1 ± 0.0	10.6 ± 0.0	7.9 ± 0.0	15.8 ± 0.0	27.8
CNN	61.6 ± 0.5	95.4 ± 0.3	$\underline{99.0} \pm 0.2$	63.8 ± 0.5	51.1 ± 0.6	49.8 ± 0.4	70.1
LapCNN	60.4 ± 0.3	94.7 ± 0.5	$\mathbf{99.1} \pm 0.2$	63.1 ± 0.6	51.6 ± 0.4	48.2 ± 0.5	69.5
DDC	61.8 ± 0.4	95.0 ± 0.5	98.5 ± 0.4	64.4 ± 0.3	52.1 ± 0.8	$\underline{52.2} \pm 0.4$	70.6
DAN_7	63.2 ± 0.2	94.8 ± 0.4	98.9 ± 0.3	65.2 ± 0.4	52.3 ± 0.4	52.1 ± 0.4	71.1
DAN_8	$\underline{63.8} \pm 0.4$	94.6 ± 0.5	98.8 ± 0.6	65.8 ± 0.4	52.8 ± 0.4	51.9 ± 0.5	71.3
DAN_{SK}	63.3 ± 0.3	$\underline{95.6} \pm 0.2$	$\underline{99.0} \pm 0.4$	$\underline{65.9} \pm 0.7$	$\underline{53.2} \pm 0.5$	52.1 ± 0.4	$\underline{71.5}$
DAN	$\mathbf{68.5} \pm 0.4$	$\mathbf{96.0} \pm 0.3$	$\underline{99.0} \pm 0.2$	$\mathbf{67.0} \pm 0.4$	$\mathbf{54.0} \pm 0.4$	$\mathbf{53.1} \pm 0.3$	**72.9**

Figure: Table 1. Accuracy on Office-31 dataset with standard unsupervised adaptation protocol

Results & Discussion

Semi-supervised adaptation: source supervision vs. target supervision?

- Limited target supervision is prone to over-fitting the target task
- Source supervision can provide strong but inaccurate inductive bias
- Two-sample matching is more effective for bridging dissimilar tasks

Table 2. Accuracy on *Office-10* + *Caltech-10* dataset with standard unsupervised adaptation protocol (Gong et al., 2013).

Method	A → C	W → C	D → C	C → A	C → W	C → D	Average
TCA	42.7 ± 0.0	34.1 ± 0.0	35.4 ± 0.0	54.7 ± 0.0	50.5 ± 0.0	50.3 ± 0.0	44.6
GFK	41.4 ± 0.0	26.4 ± 0.0	36.4 ± 0.0	56.2 ± 0.0	43.7 ± 0.0	42.0 ± 0.0	41.0
CNN	83.8 ± 0.3	76.1 ± 0.5	80.8 ± 0.4	91.1 ± 0.2	83.1 ± 0.3	89.0 ± 0.3	84.0
LapCNN	83.6 ± 0.6	77.8 ± 0.5	80.6 ± 0.4	**92.1** ± 0.3	81.6 ± 0.4	87.8 ± 0.4	83.9
DDC	84.3 ± 0.5	76.9 ± 0.4	80.5 ± 0.2	91.3 ± 0.3	85.5 ± 0.3	89.1 ± 0.3	84.6
DAN_7	<u>84.7</u> ± 0.3	78.2 ± 0.5	<u>81.8</u> ± 0.3	91.6 ± 0.4	87.4 ± 0.3	88.9 ± 0.5	85.4
DAN_8	84.4 ± 0.3	<u>80.8</u> ± 0.4	81.7 ± 0.2	91.7 ± 0.3	<u>90.5</u> ± 0.4	89.1 ± 0.4	<u>86.4</u>
DAN_{SK}	84.1 ± 0.4	79.9 ± 0.4	81.1 ± 0.5	91.4 ± 0.3	86.9 ± 0.5	<u>89.5</u> ± 0.3	85.5
DAN	**86.0** ± 0.5	**81.5** ± 0.3	**82.0** ± 0.4	<u>92.0</u> ± 0.3	**92.0** ± 0.4	**90.5** ± 0.2	**87.3**

Figure: Table 2. Accuracy on Office-10 + Caltech-10 dataset with standard unsupervised adaptation protocol

Data Visualization

How transferable are DAN features? t-SNE embedding for visualization

- target points form clearer class boundaries
- target points can be classified more accurately
- Source and target categories are aligned better

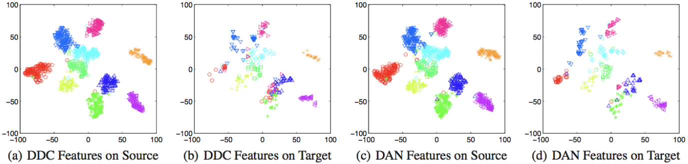

Figure: t-SNE of DDC features on source (a) and target (b) versus. t-SNE of DAN features on source (c) and target (d)

Empirical Analysis

How is generalization performance related to two-sample discrepancy?

- $\hat{d}_A$ on CNN & DAN features $>$ $\hat{d}_A$ on Raw features
- $\Rightarrow$ $\hat{d}_A$ on DAN feature is much smaller than $\hat{d}_A$ on CNN feature
- $\hat{d}_A$ on DAN feature $<$ $\hat{d}_A$ on CNN feature
- $\Rightarrow$Domain adaptation can be boosted by reducing domain discrepancy

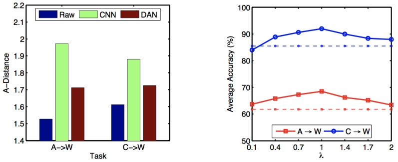

Figure: (e) A-Distance of CNN & DAN features; (f) sensitivity of λ

Summary

- DAN: A deep adaptation network for learning transferable features
- Deep adaptation of multiple task-specific layers (including output)
- Optimal adaptation using multiple kernel two-sample matching
- *A brief analysis of learning bound for the proposed deep network*