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Unsupervised Domain Adaptation with Residual Transfer Networks

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Outline

- Authors
- Motivation
- Methods
- Experiments

Authors

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1. **Mingsheng Long**, Jianmin Wang, Yue Cao, Jiaguang Sun, Philip S. Yu. **Deep Learning of Transferable Representation for Safe Domain Adaptation**. *IEEE Transactions on Knowledge and Data Engineering (**TKDE**)*, 28(8):2027-2040, 2016.
2. **Mingsheng Long**, Jianmin Wang, Jiaguang Sun, Philip S. Yu. **Domain Invariant Transfer Kernel Learning**. *IEEE Transactions on Knowledge and Data Engineering (**TKDE**)*, 27(6):1519-1532, 2015.
3. **Mingsheng Long**, Jianmin Wang, Guiguang Ding, Dou Shen, Qiang Yang. **Transfer Learning with Graph Co-Regularization**. *IEEE Transactions on Knowledge and Data Engineering (**TKDE**)*, 26(7):1805-1818, 2014.
4. **Mingsheng Long**, Jianmin Wang, Guiguang Ding, Sinno Jialin Pan, Philip S. Yu. **Adaptation Regularization: A General Framework for Transfer Learning**. *IEEE Transactions on Knowledge and Data Engineering (**TKDE**)*, 26(5):1076-1089, 2014.

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Problem description

- Given
  source domain $\mathcal{D}_s = \{(\mathbf{x}_i^s, y_i^s)\}_{i=1}^{n_s}$
  unlabeled target domain $\mathcal{D}_t = \{\mathbf{x}_j^t\}_{j=1}^{n_t}$
- Source domain and target domain are sampled from different probability distributions.
- How to minimize expected target risk
  $R_t(f_t) = \mathbb{E}_{(\mathbf{x},y)\sim q}[f_t(\mathbf{x}) \neq y]$
  by leveraging the source domain supervised data?

Discrepancy

-

distribution discrepancy

$p(\mathbf{x}, y) \neq q(\mathbf{x}, y)$

feature discrepancy

$p(\mathbf{x}) \neq q(\mathbf{x})$

classifier discrepancy

$f_s(\mathbf{x}) \neq f_t(\mathbf{x})$

no label in target domain

Motivation

- Bridge the source classifier $f_S(\mathbf{x})$ and target classifier $f_T(\mathbf{x})$ by residual layers.

- Model discrepancy as a perturbation function

$$f_S\left(\mathbf{x}\right) = f_T\left(\mathbf{x}\right) + \Delta f\left(\mathbf{x}\right),$$

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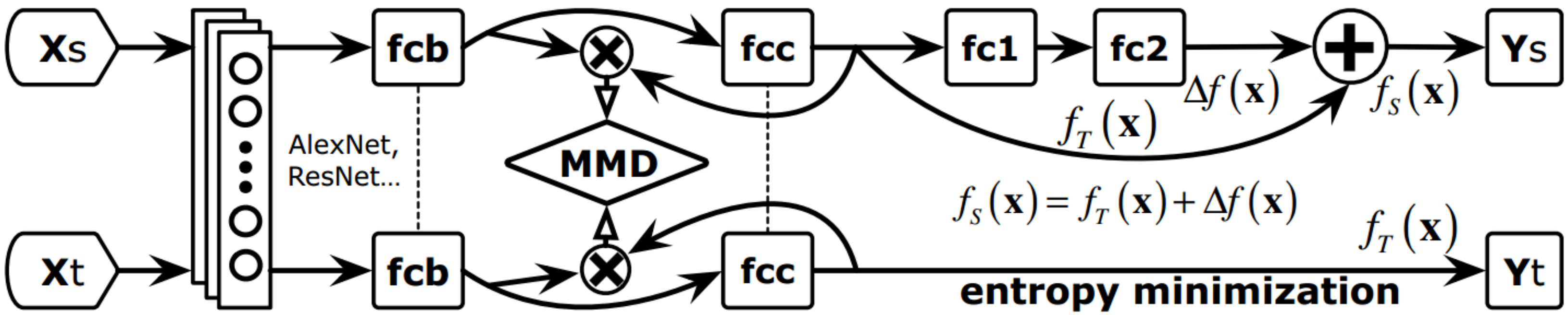
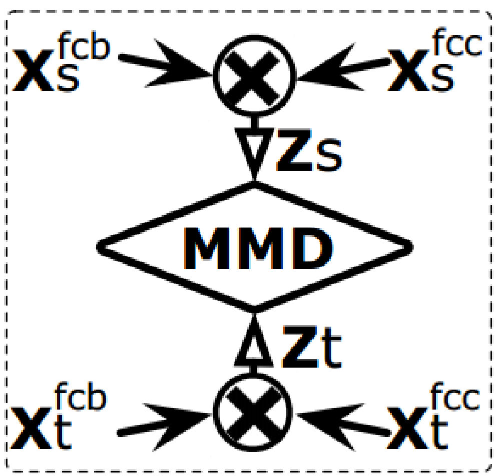
Main method

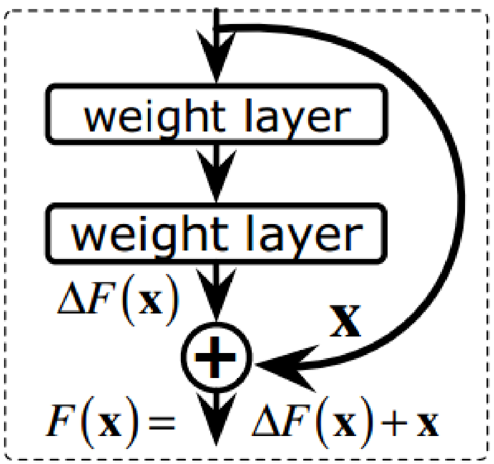
- High-level representation abstract: entropy objective + source domain regularizer

- Feature adaptation: joint training using Maximum Mean Discrepancy (MMD)

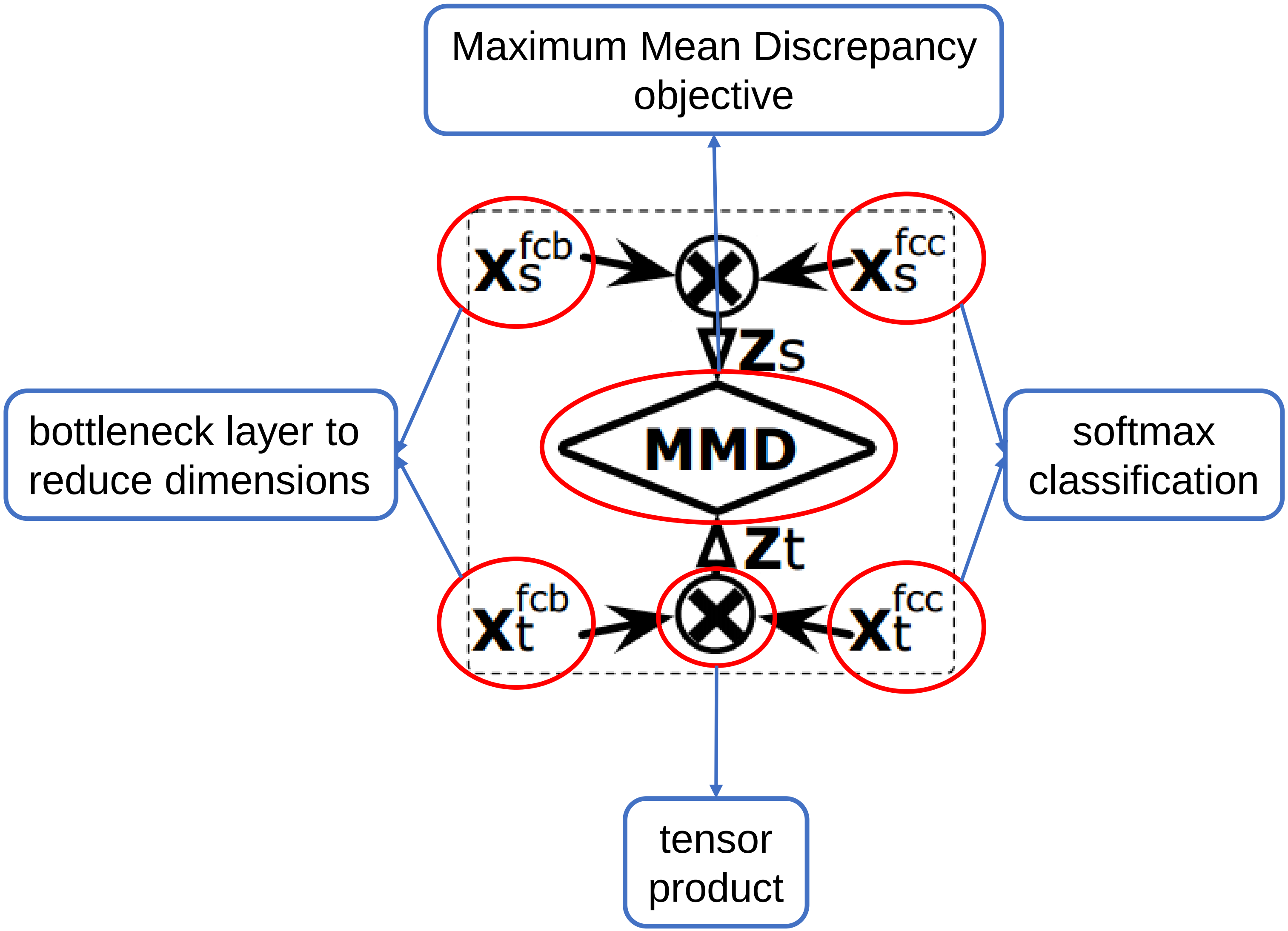
Architecture of Residual Transfer Network







Feature Adaptation



Maximum Mean Discrepancy

Maximum Mean Discrepancy (Fortet and Mourier, 1953)

$$D(p, q, \mathcal{F}) := \sup_{f \in \mathcal{F}} \mathbf{E}_p [f(x)] - \mathbf{E}_q [f(y)]$$

Theorem (via Dudley, 1984)

$D(p, q, \mathcal{F}) = 0$ iff $p = q$, when $\mathcal{F} = C^0(\mathcal{X})$ is the space of continuous, bounded, functions on $\mathcal{X}$.

Theorem (via Steinwart, 2001; Smola et al., 2006)

$D(p, q, \mathcal{F}) = 0$ iff $p = q$, when $\mathcal{F} = \{f | \, \|f\|_{\mathcal{H}} \leq 1\}$ is a unit ball in a Reproducing Kernel Hilbert Space, provided that $\mathcal{H}$ is universal.

Maximum Mean Discrepancy

Optimization Problem

$$\sup_{\|f\|\leq 1} \mathbf{E}_p\left[f(x)\right] - \mathbf{E}_q\left[f(y)\right] = \sup_{\|f\|\leq 1} \langle \mu_p - \mu_q, f\rangle = \|\mu_p - \mu_q\|_{\mathcal{H}}$$

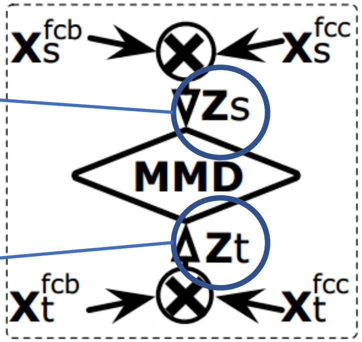
Kernels

$$\begin{aligned}
\|\mu_p - \mu_q\|_{\mathcal{H}}^2 &= \langle \mu_p - \mu_q, \mu_p - \mu_q\rangle \\
&= \mathbf{E}_{p,p}\left\langle k(x,\cdot), k(x',\cdot)\right\rangle - 2\mathbf{E}_{p,q}\left\langle k(x,\cdot), k(y,\cdot)\right\rangle \\
&\quad + \mathbf{E}_{q,q}\left\langle k(y,\cdot), k(y',\cdot)\right\rangle \\
&= \mathbf{E}_{p,p} k(x,x') - 2\mathbf{E}_{p,q} k(x,y) + \mathbf{E}_{q,q} k(y,y')
\end{aligned}$$

Maximum Mean Discrepancy

$$\mathbf{z}_i^s \triangleq \otimes_{\ell \in \mathcal{L}} \mathbf{X}_i^{s\ell}$$

$$\mathbf{z}_j^t \triangleq \otimes_{\ell \in \mathcal{L}} \mathbf{X}_j^{t\ell}.$$



$$k(\mathbf{z}, \mathbf{z}') = e^{-\left\|\mathrm{vec}(\mathbf{z}) - \mathrm{vec}(\mathbf{z}')\right\|^2 / b}$$

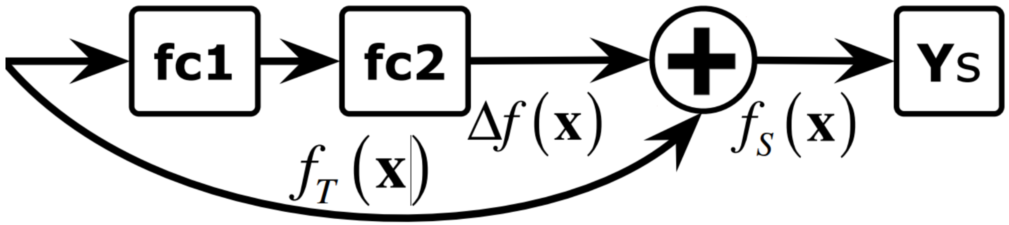
$$\min_{f_s, f_t} D_{\mathcal{L}}\left(\mathcal{D}_s, \mathcal{D}_t\right) = \sum_{i=1}^{n_s}\sum_{j=1}^{n_s} \frac{k\left(\mathbf{z}_i^s, \mathbf{z}_j^s\right)}{n_s^2} + \sum_{i=1}^{n_t}\sum_{j=1}^{n_t} \frac{k\left(\mathbf{z}_i^t, \mathbf{z}_j^t\right)}{n_t^2} - 2\sum_{i=1}^{n_s}\sum_{j=1}^{n_t} \frac{k\left(\mathbf{z}_i^s, \mathbf{z}_j^t\right)}{n_s n_t},$$

Classifier Adaptation

- Assume

$$f_S(\mathbf{x}) = f_T(\mathbf{x}) + \Delta f(\mathbf{x}),$$

- Residual connection



Classifier Adaptation

- Tackle unlabeled target domain data

$$\min_{f_t} \frac{1}{n_t} \sum_{i=1}^{n_t} H\left(f_t\left(\mathbf{x}_i^t\right)\right),$$

$$H\left(f_t\left(\mathbf{x}_i^t\right)\right) = - \sum_{j=1}^{c} f_j^t\left(\mathbf{x}_i^t\right) \log f_j^t\left(\mathbf{x}_i^t\right),$$

Bengio et al., semi supervised learning by entropy minimization

Jointly train：
Residual Transfer Network

$$\min_{f_S=f_T+\Delta f} \frac{1}{n_s} \sum_{i=1}^{n_s} L\left(f_s\left(\mathbf{x}_i^s\right), y_i^s\right) + \frac{\gamma}{n_t} \sum_{i=1}^{n_t} H\left(f_t\left(\mathbf{x}_i^t\right)\right) + \lambda\, D_{\mathcal{L}}\left(\mathcal{D}_s, \mathcal{D}_t\right),$$

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Datasets

- **Office-31：4110 images in 31 classes from three domains**
  Amazon (**A**) *Webcam* (**W**) *DSLR* (**D**)

- **Office-Caltech**
  10 common categories shared by *Office-31* and *Caltech-256* (**C**), 12 transfer tasks

Results

Table 1: Accuracy on *Office-31* dataset using standard protocol [5] for unsupervised adaptation.

Method	A → W	D → W	W → D	A → D	D → A	W → A	Avg
TCA [9]	59.0±0.0	90.2±0.0	88.2±0.0	57.8±0.0	51.6±0.0	47.9±0.0	65.8
GFK [14]	58.4±0.0	93.6±0.0	91.0±0.0	58.6±0.0	**52.4**±0.0	46.1±0.0	66.7
AlexNet [26]	60.6±0.4	95.4±0.2	99.0±0.1	64.2±0.3	45.5±0.5	48.3±0.5	68.8
DDC [4]	61.0±0.5	95.0±0.3	98.5±0.3	64.9±0.4	47.2±0.5	49.4±0.6	69.3
DAN [5]	68.5±0.3	96.0±0.1	99.0±0.1	66.8±0.2	50.0±0.4	49.8±0.3	71.7
RevGrad [6]	73.0±0.6	96.4±0.4	99.2±0.3	-	-	-	-
RTN (mmd)	70.0±0.4	96.1±0.3	99.2±0.3	67.6±0.4	49.8±0.4	50.0±0.3	72.1
RTN (mmd+ent)	71.2±0.3	96.4±0.2	99.2±0.1	69.8±0.2	50.2±0.3	50.7±0.2	72.9
RTN (mmd+ent+res)	**73.3**±0.3	**96.8**±0.2	**99.6**±0.1	**71.0**±0.2	50.5±0.3	**51.0**±0.1	**73.7**

Table 2: Accuracy on *Office-Caltech* dataset using standard protocol [5] for unsupervised adaptation.

Method	A→W	D→W	W→D	A→D	D→A	W→A	A→C	W→C	D→C	C→A	C→W	C→D	Avg
TCA [9]	84.4	96.9	99.4	82.8	90.4	85.6	81.2	75.5	79.6	92.1	88.1	87.9	87.0
GFK [14]	89.5	97.0	98.1	86.0	89.8	88.5	76.2	77.1	77.9	90.7	78.0	77.1	85.5
AlexNet [26]	79.5	97.7	**100.0**	87.4	87.1	83.8	83.0	73.0	79.0	91.9	83.7	87.1	86.1
DDC [4]	83.1	98.1	**100.0**	88.4	89.0	84.9	83.5	73.4	79.2	91.9	85.4	88.8	87.1
DAN [5]	91.8	98.5	**100.0**	91.7	90.0	92.1	84.1	81.2	80.3	92.0	90.6	89.3	90.1
RTN (mmd)	93.2	98.5	**100.0**	91.7	88.0	90.7	84.0	81.3	80.4	91.0	89.8	90.4	90.0
RTN (mmd+ent)	93.8	98.6	**100.0**	92.9	93.6	**92.7**	87.8	84.8	83.4	93.2	96.6	93.9	92.6
RTN (mmd+ent+res)	**95.2**	**99.2**	**100.0**	**95.5**	**93.8**	92.5	**88.1**	**86.6**	**84.6**	**93.7**	**96.9**	**94.2**	**93.4**

Thank you!