Transferability vs. Discriminability:
Batch Spectral Penalization for Adversarial Domain Adaptation

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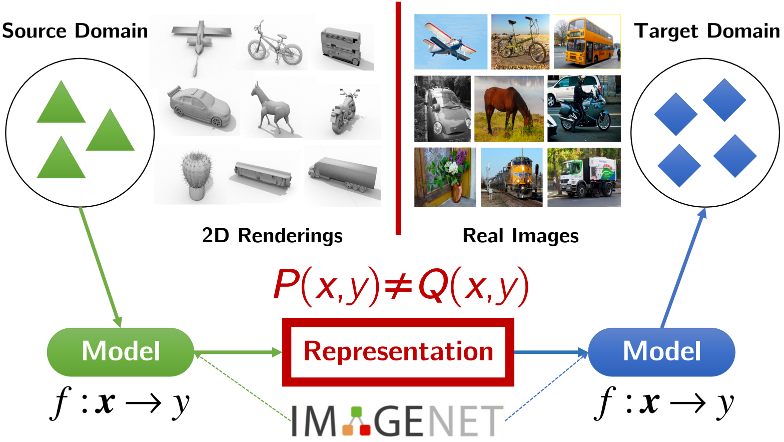
Transfer Learning: Unsupervised Domain Adaptation

- Non-IID distributions $P \neq Q$
- Only unlabeled data in target domain



Adversarial Domain Adaption

Matching distributions across source and target domains s.t. $P \approx Q$

Adversarial adaptation: learning features indistinguishable across domains

$$\begin{aligned} &\min_{F,G} \mathcal{E}(F,G) + \gamma \mathrm{dis}_{P \leftrightarrow Q}(F,D) \\ &\max_{D} \ \mathrm{dis}_{P \leftrightarrow Q}(F,D), \end{aligned} \tag{1}$$

We analysis features extracted by DANN[1] with a ResNet-50[2] pretrained on Imagenet

$$\begin{aligned} \mathcal{E}(F,G) &= \mathbb{E}_{(\mathbf{x}_i^s,\mathbf{y}_i^s)\sim P} L(G(F(\mathbf{x}_i^s)),\mathbf{y}_i^s) \\ \mathrm{dist}_{P \leftrightarrow Q}(F,D) &= \mathbb{E}_{\mathbf{x}_i^s \sim P} \log[D(\mathbf{f}_i^s)] \\ &+ \mathbb{E}_{\mathbf{x}_i^t \sim Q} \log[1 - D(\mathbf{f}_i^t)] \end{aligned} \tag{2}$$

[1] *Ganin et al. Unsupervised domain adaptation by backpropagation. ICML '15.*

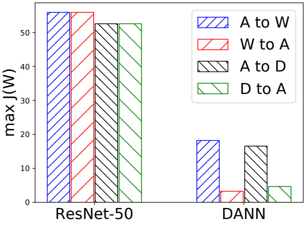
[2] *He et al. Deep residual learning for image recognition. CVPR '15.*

Discriminability of Feature Representations

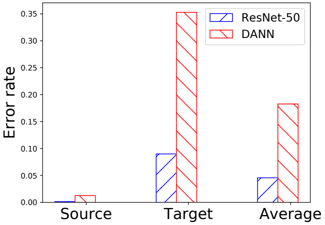
Two key criteria that characterize the goodness of feature representations

- Transferability: the ability of feature to bridge the discrepancy across domains
- Discriminability: the easiness of separating different categories by a supervised classifier trained over the feature representations

Discriminability of features extracted by DANN, worse discriminability is found:



(a) max $J(W)$

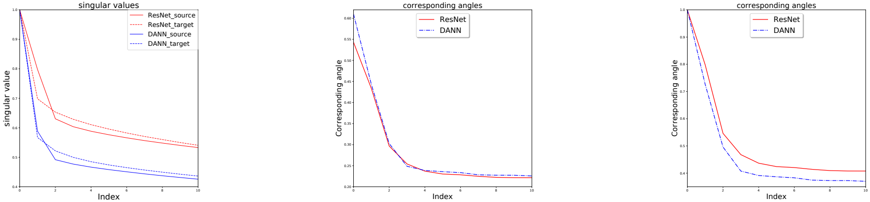


(b) Classification error rate

Figure: Analysis of discriminability of feature: (a) LDA, (b) MLP.

Why Discriminability Is Weakened?

- Corresponding Angles: corresponding angle is the angle between two eigenvectors corresponding to the same singular value index, which are equally important in their feature matrices.

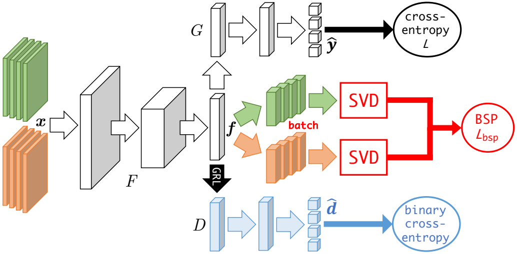


(a) σ (b) $\cos(\psi)$ (c) $\cos(\psi)$

Figure: SVD analysis. We compute (a) the singular values (normalized version); (b) corresponding angles (unnormalized version); (c) corresponding angles (normalized version). In normalized version we scale all values so that the largest value is 1.

- Only the eigenvectors with largest singular values tend to carry transferable knowledge

BSP: Batch Spectral Penalization



BSP combined with DANN to strengthen discriminability of feature

$$\min_{F,G} \mathcal{E}(F,G) + \gamma \mathrm{dis}_{P \leftrightarrow Q}(F,D) + \beta L_{\mathrm{bsp}}(F)$$
$$\max_{D} \ \mathrm{dis}_{P \leftrightarrow Q}(F,D), \tag{3}$$

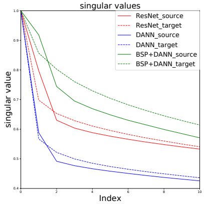
$$L_{\mathrm{bsp}}(F) = \sum_{i=1}^{k} (\sigma_{s,i}^2 + \sigma_{t,i}^2), \tag{4}$$

Results

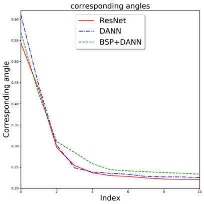
Table: Accuracy (%) on *Office-31* for unsupervised domain adaptation

Method	A → W	D → W	W → D	A → D	D → A	W → A	Avg
ResNet-50	68.4 ± 0.2	96.7 ± 0.1	99.3 ± 0.1	68.9 ± 0.2	62.5 ± 0.3	60.7 ± 0.3	76.1
DAN	80.5 ± 0.4	97.1 ± 0.2	99.6 ± 0.1	78.6 ± 0.2	63.6 ± 0.3	62.8 ± 0.2	80.4
DANN	82.0 ± 0.4	96.9 ± 0.2	99.1 ± 0.1	79.7 ± 0.4	68.2 ± 0.4	67.4 ± 0.5	82.2
JAN	85.4 ± 0.3	97.4 ± 0.2	99.8 ± 0.2	84.7 ± 0.3	68.6 ± 0.3	70.0 ± 0.4	84.3
GTA	89.5 ± 0.5	97.9 ± 0.3	99.8 ± 0.4	87.7 ± 0.5	72.8 ± 0.3	71.4 ± 0.4	86.5
CDAN	93.1 ± 0.2	98.2 ± 0.2	**100.0** ± 0.0	89.8 ± 0.3	70.1 ± 0.4	68.0 ± 0.4	86.6
CDAN+E	**94.1** ± 0.1	**98.6** ± 0.1	**100.0** ± 0.0	92.9 ± 0.2	71.0 ± 0.3	69.3 ± 0.3	87.7
BSP+DANN (Proposed)	93.0 ± 0.2	98.0 ± 0.2	**100.0** ± 0.0	90.0 ± 0.4	71.9 ± 0.3	**73.0** ± 0.3	87.7
BSP+CDAN (Proposed)	93.3 ± 0.2	98.2 ± 0.2	**100.0** ± 0.0	**93.0** ± 0.2	**73.6** ± 0.3	72.6 ± 0.3	**88.5**

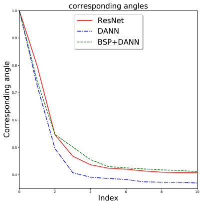
Analysis



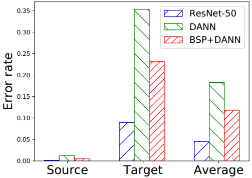
(a) σ



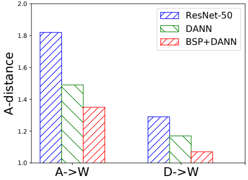
(b) $\cos(\psi)$



(c) $\cos(\psi)$



(d) Classification error



(e) A-distance

Thanks!

Poster: tonight at Pacific Ballroom #256