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Distant Domain Transfer Learning[a]

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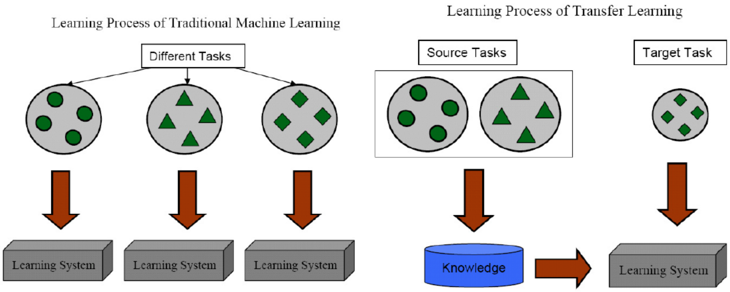
[a]This slide is based on AAAI-17 paper: *Ben Tan, Yu Zhao, Sinno Jialin Pan and Qiang Yang: Distant domain transfer learning*.

Content

Problems

- Building every model from scratch is time-consuming and expensive.
- But there are many existing knowledge. Can we reuse them?



(a) Traditional Machine Learning (b) Transfer Learning

Common Definition

- Wikipedia: research problem in machine learning that focuses on storing knowledge gained while solving one problem and applying it to a **different** but **related** problem [wik].

TL vs Traditional ML

Traditional ML:

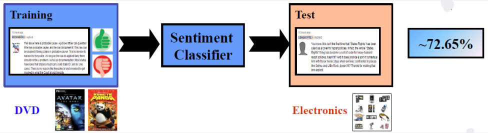
- Training and testing samples must be in the **same** feature distributions.
- Training samples must be **enough**.

Transfer learning:

- Source and target domains do **not** need to be in the same distributions.
- **Less** training samples, even **none**.

Example: sentiment classification

DVD $\rightarrow$ Electronics: Only got sentiment on DVD, how to transfer it to electronics?

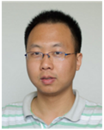


Proceedings

- Data mining: ACM SIGKDD, IEEE ICDM, PKDD
- ML & AI: ICML, NIPS, AAAI, IJCAI, ECML
- Applications: ACM TIST, ACM SIGIR, WWW, ACL, IEEE TKDE

Many apps include image classification, natural language processing, activity recognition, and Wifi localization.

There are 4 authors of this paper:



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- Google scholar citations: 4,000+
- `http://www.ntu.edu.sg/home/sinnopan/`

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- Head of CSE HKUST
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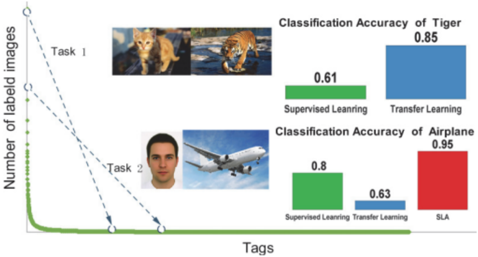
- Google scholar citations: 30,000+
- `http://www.cs.ust.hk/~qyang/`

Traditional TL: the source and target domain are **close** [PY10]
DDTL: the source and target domain can be **totally different**!



- Task 1: Cat $\rightarrow$ Tiger, good performance for traditional TL.
- Task 2: Face $\rightarrow$ Airplane, bad performance for traditional TL.

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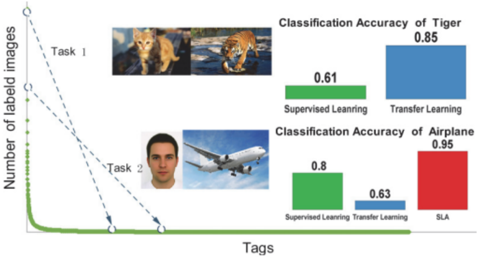

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How to conduct transfer learning in such scenario when source and target domain are totally different?

Distant domain transfer learning (DDTL): exploit the unlabeled data in the intermediate domains to build a bridge between source and target domain.

Input:

- Labeled source domain $\mathcal{S} = \{(\mathbf{x}_S^1, y_S^1), \cdots, (\mathbf{x}_S^{n_S}, y_S^{n_S})\}$
- Unlabeled target domain $\mathcal{T} = \{(\mathbf{x}_T^1, y_T^1), \cdots, (\mathbf{x}_T^{n_T}, y_T^{n_T})\}$
- Mixture of unlabeled intermediate domains: $\mathcal{I} = \{(\mathbf{x}_I^1), \cdots, (\mathbf{x}_I^{n_I})\}$

Output:

- labels of target domain

Constraints:

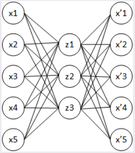
- $p_T(\mathbf{x}) \neq p_S(\mathbf{x}), p_T(\mathbf{x}) \neq p_I(\mathbf{x})$ and $p_T(y|\mathbf{x}) \neq p_S(y|\mathbf{x})$
- similarity between $\mathcal{S}$ and $\mathcal{T}$ is very small

Selective Learning Algorithm (SLA) is proposed to solve the DDTL problem, which is based on autoencoder.

Autoencoder

An unsupervised feed-forward neural network with an input layer, hidden layer and output layer.

- Encoding: $\mathbf{h} = f_e(\mathbf{x})$
- Decoding: $\hat{\mathbf{x}} = f_d(\mathbf{h})$
- Objective: $\min \sum_{i=1}^{n} ||\hat{\mathbf{x}}_i - \mathbf{x}_i||_2^2$



To capture spatial information, a convolutional autoencoder is desired.

SLA algorithm

Instance selection via reconstruction error

Motivation: if data from source / intermediate domain is similar and useful to the target domain, then one should be able to find a pair of encoding and decoding functions that have small reconstruction error.

Objective: learn a pair of encoding and decoding functions by minimizing reconstruction errors on source, intermediate and target domain simultaneously.

SLA algorithm
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$$\mathcal{J}_1(f_e, f_d, v_S, v_T) = \frac{1}{n_S} v_S^i ||\hat{x}_S^i - x_S^i||_2^2 + \frac{1}{n_I} v_I^i ||\hat{x}_I^i - x_I^i||_2^2 + \frac{1}{n_T} ||\hat{x}_T^i - x_T^i||_2^2 + R(v_S, v_T) \tag{1}$$

v_S and v_T are selection indicators. $R(\cdot,\cdot)$ is the regularization term.

$$R(v_S, v_T) = -\frac{\lambda_S}{n_S} \sum_{i=1}^{n_S} v_S^i - \frac{\lambda_T}{n_T} \sum_{i=1}^{n_T} v_T^i \tag{2}$$

Learning in Eq. (1) is in unsupervised manner, consider to add some **side information**:

$$\mathcal{J}_2(f_c, f_e, f_d) = \frac{1}{n_S}\sum_{i=1}^{n_S} v_S^i \mathcal{L}(y_S^i, f_c(\mathbf{h}_S^i)) + \frac{1}{n_T}\sum_{i=1}^{n_T} v_T^i \mathcal{L}(y_T^i, f_c(\mathbf{h}_T^i)) + \frac{1}{n_I}\sum_{i=1}^{n_I} v_I^i g(f_c(\mathbf{h}_I^i)) \tag{3}$$

$f_c(\cdot)$ is a classification function, $g(\cdot)$ is the entropy function: $g(z) = -z\ln z - (1-z)\ln(1-z)$ for $0 \leq z \leq 1$.

Overall objective function:

$$\begin{aligned} &\min_{\Theta, v} \mathcal{J} = \mathcal{J}_1 + \mathcal{J}_2 \\ &s.t. \quad v_S^i, v_T^i \in \{0, 1\} \end{aligned} \tag{4}$$

Where Θ denotes all parameters ($f_c(\cdot), f_d(\cdot), f_e(\cdot)$) and $v = \{v_S, v_T\}$.

Technique: **Block Coordinate Decent (BCD)**, where in each iteration, variables in each block are optimized sequentially while keeping other variables fixed.

- fix v, update Θ using back propagation;
- fix Θ, obtain v as follows:

$$v_S^i = \begin{cases} 1 & \text{if } \mathcal{L}(y_s^i, f_c(f_e(x_S^i))) + ||\hat{x}_S^i - x_S^i||_2^2 < \lambda_S \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

$$v_T^i = \begin{cases} 1 & \text{if } ||\hat{x}_I^i - x_I^i||_2^2 + g(f_c(f_e(x_I^i))) < \lambda_I \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

Based on the above equations, only samples with low reconstruction error and high prediction confidence will be selected and used.

Learning Algorithm

The learning algorithm is as follows:

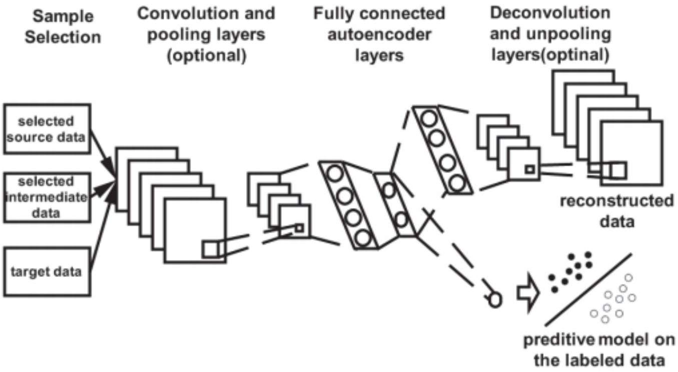
Algorithm 1 The Selective Learning Algorithm (SLA)

1: **Input**: Data in $\mathcal{S}$, $\mathcal{T}$ and $\mathcal{I}$, and parameters λ_S, λ_I, and T;
2: Initialize $\mathbf{\Theta}$, $\boldsymbol{v}_S = \mathbf{1}$, $\boldsymbol{v}_I = \mathbf{0}$; *// All source data are used*
3: **while** $t < T$ **do**
4:     Update $\mathbf{\Theta}$ via the BP algorithm; *// Update the network*
5:     Update $\boldsymbol{v}$ by Eqs. (4) and (5); *// Select "useful" instances*
6:     $t = t + 1$
7: **end while**
8: **Output**: $\mathbf{\Theta}$ and $\boldsymbol{v}$.

Add convolution layers to the network, it can be viewed as a generalized autoencoder or convolutional autoencoder with side information.

SAN: supervised autoencoder, only autoencoder

SCAN: supervised convolutional autoencoder, using convolution



2 datasets

- **Caltech-256**: 30,607 images from 256 classes
- **Animals with Attributes (AwA)**: 30,475 images with 50 classes

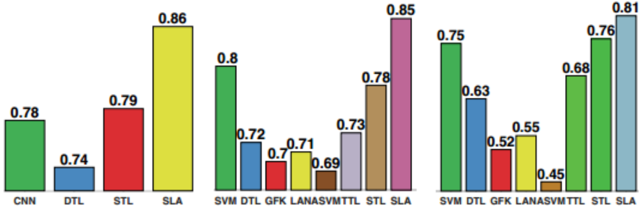
3 categories of baseline methods

- **Supervised learning**: SVM and CNN
- **Transfer learning**: ASVM, GFK, LAN, DTL and TTL
- **Self-taught learning method**

3 experiments

- Source and target domain are distant
- Visualize some intermediate domain data
- Evaluate the learning order of SLA

Average accuracies of different algorithms on Caltech-256 and AwA:

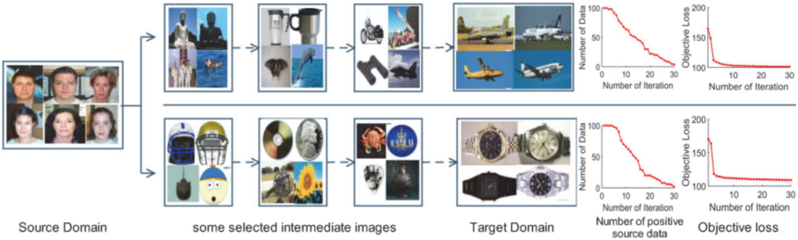


(a) Caltech (Tensor) (b) Caltech (SIFT) (c) AwA (SIFT)

	SVM	DTL	GFK	LAN	ASVM	TTL	STL	SLA
'horse-to-face'	84 ± 2	88 ± 2	77 ± 3	79 ± 2	76 ± 4	78 ± 2	86 ± 3	$\mathbf{92} \pm 2$
'airplane-to-gorilla'	75 ± 1	62 ± 3	67 ± 5	66 ± 4	51 ± 2	65 ± 2	76 ± 3	$\mathbf{84} \pm 2$
'face-to-watch'	75 ± 7	68 ± 3	61 ± 4	63 ± 4	60 ± 5	67 ± 4	75 ± 5	$\mathbf{88} \pm 4$
'zebra-to-collie'	71 ± 3	69 ± 2	56 ± 2	57 ± 3	59 ± 2	70 ± 3	72 ± 3	$\mathbf{76} \pm 2$

Conclusion: For distant domains, SLA algorithm **outperforms** other methods.

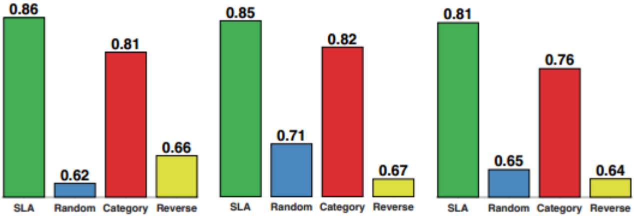
Visualization of the selected intermediate data over iterations of `face-to-airplane` and `face-to-watch`:



Conclusion:

- At the beginning, the intermediate domains are similar to **source domain**. In the end, it's more similar to the **target domain**.
- The number of positive examples in source domain **decreases**, and the value of objective function also **decreases**

Comparison results with different learning orders on the Caltech-256 and AwA datasets (Orders of intermediate domains changed):



(a) Caltech (Tensor) (b) Caltech (SIFT) (c) AwA (SIFT)

Conclusion: Three types of different orders obtain worse results than SLA, and `Category` is close to SLA because this strategy is close to SLA.

Related Work

DDTL is a novel difficult problem with many state-of-the-art methods **not applying** to it.

- **Typical transfer learning** approaches like instance reweighting [DYXY07] and feature mapping [PTKY11] do not apply to this problem, as they assume the domains are close.
- **Transitive transfer learning** [TSZY15]: manually select one intermediate domain as the bridge; **ours** automatically select many domains.
- **TLMS** [MMR09]: all the source domains in TLMS are labeled and closely related to the target domain.
- **Self-taught learning** [RBL$^+$07]: use all domain data to learn; ours use intermediate domains.
- **Semi-supervised autoencoder** [WRMC12]: uses labeled and unlabeled data for learning; ours use intermediate domains and we use convolutional layers.

Conclusion

Contributions of this paper

- **First** work to study DDTL problem using mixture intermediate domains
- Propose **SLA** algorithm for DDTL problem
- Extensive experiments on real-world datasets show the **effectiveness** of SLA

What we should learn from this paper

- Good layout, consider it as a template for **algorithm-paper**
- Introduction, tables and figures are good
- Experiment: **more datasets, more analysis**

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Q & A

Thank you for your listening