Transfer Learning for Action Classification in Racket Games

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Outline

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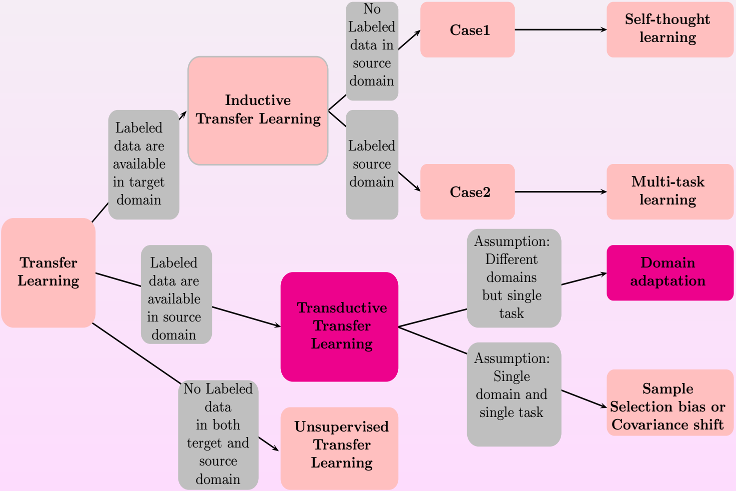

Transfer Learning
Labeled data are available in target domain
Inductive Transfer Learning
No Labeled data in source domain
Case1
Self-thought learning
Labeled source domain
Case2
Multi-task learning
Labeled data are available in source domain
Transductive Transfer Learning
Assumption: Different domains but single task
Domain adaptation
Assumption: Single domain and single task
Sample Selection bias or Covariance shift
No Labeled data in both terget and source domain
Unsupervised Transfer Learning

Arnold et. al's domain adaptation model and its modifications

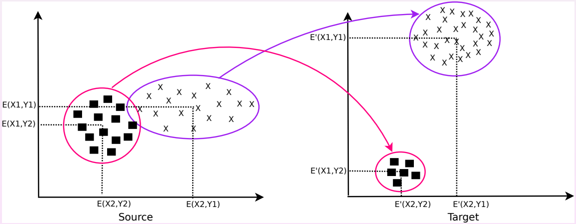
Data

Input $D^{src} = \{(\mathbf{x}^{src}{}_i), y^{src}{}_i\}$, $D^{trg} = \{\mathbf{x}^{trg}{}_i\}$ and KLDA classification parameters
Output $P(y^{trg} \mid \mathbf{x}^{trg})$

Algorithm

1. Estimation of posterior probability for each target sample using source model
2. Compute the transformation matrix for source space
3. Transform the source domain and retrain on this new source space
4. Predict the target labels using the retrained classifier

Scaling



The transformation parameters are derived as: $\forall i = 1 : N^{src}_{train}, \; G(x^i_j) = x^i_j \frac{E^{trg}_{\Lambda_{src}}[x_j, y_i]}{E^{src}[x_j, y_i]}$

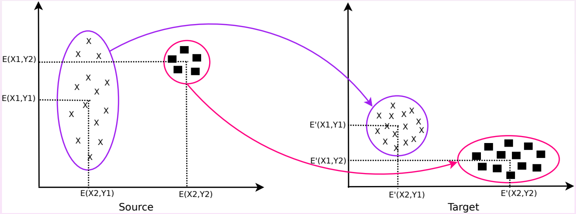
where the x^i_j is the jth feature of sample x^i and Λ_{src} is the classification model learned using source samples and $E^{trg}_{\Lambda_{src}}$ is computed by:

$$E^{trg}[x_j, y] \approx E^{trg}_{\Lambda_{src}}[x_j, y] = \frac{\sum_{i=1}^{N^{trg}_{test}} x^i_j P_{\Lambda_{src}}(y|x_i)}{\sum_{i=1}^{N^{trg}_{test}} P_{\Lambda_{src}}(y|x_i)}$$

A smoothing factor θ has been introduced to control the degree to which we use the target conditional estimates to alter the source conditionals:

$$G'(x^i_j) = (1 - \theta)x^i_j + \theta G(x^i_j)$$

Translating and Scaling



The transformation parameters will be estimated by:

$$\forall i = 1 : N^{src}_{train},\ G(x^i_j) = \frac{x^i_j - E^{src}[x_j, y_i]}{\sigma^{src}_{j,y_i}} \sigma^{trg}_{j,y_i} + E^{trg}_{\Lambda src}[x_j, y_i]$$

where σ^{src}_{j,y_i} is the standard deviation of the feature x_j of the source samples $\mathbf{x}_k$ labeled as y_i and:

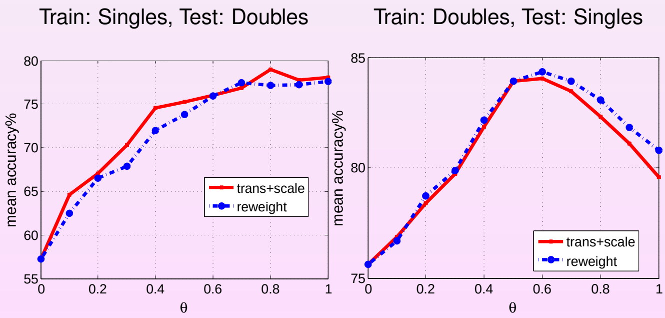
$$\sigma^{trg}_{j,y_i} = \sqrt{\frac{\sum_{k=1}^{N^{trg}_{test}} (x^k_j - E^{trg}_{\Lambda src}[x_j, y_i])^2 P_{\Lambda src}(y_i|\mathbf{x}_k)}{\sum_{k=1}^{N^{trg}_{test}} P_{\Lambda src}(y_i|\mathbf{x}_k)}}$$

Experimental Datasets

- Source domain datasets: Badminton and Aus2003 Tennis Singles
- Target Domain datasets: Aus2003 Tennis Singles, Aus2003 men Tennis Singles, Japan2009 Singles, Aus2009 Tennis Doubles

label	sport	gender	number	competition	year	non-hit	hit	serve
TWSA03	Tennis	Women	Singles	Australian	2003	944	214	72
TMSA03	Tennis	Men	Singles	Australian	2003	1881	469	123
TWDA09	Tennis	Women	Doubles	Australian	2009	1064	135	36
BMSB08	Badminton	Men	Singles	Beijing	2008	706	458	8

Experimental results on Tennis Singles vs. Tennis Doubles



Experimental results on Badminton vs. Tennis Singles

Baseline accuracy results and results with two methods for DA: *reweight*|*trans+scale*, in ‰

	source	target		accuracy per class (‰)			macro
		adaptation	test	non-hit	hit	serve	average
a	TWSA03	–	TWDA09	996	149	571	572
b	TWSA03	test set	TWDA09	939|939	418|433	857|886	738|752
c	TWDA09	–	TWSA03	978	305	986	756
d	TWDA09	test set	TWSA03	870|912	676|634	972|972	839|839
e	TWSA03	–	TMSA03	981	248	549	592
f	TWSA03	test set	TMSA03	975|973	427|442	852|902	751|772
g	BMSB08	–	TMSA03	359	779	0	**379**
h	BMSB08	test set	TMSA03	327|393	886|852	0|0	404|415
i	BMSB08+TWSA03	–	TMSA03	940	357	500	599
j	BMSB08+TWSA03	test set	TMSA03	975|917	427|547	852|942	767|802
k	BMSB08	TWSA03	TMSA03	245|330	983|908	0|0	394|**413**

Results obtained by swapping TMSA03 and TWSA03

	source	target		accuracy per class (‰)			macro
		adaptation	test	non-hit	hit	serve	average
a	TMSA03	–	TWSA03	971	427	931	776
b	TMSA03	test set	TWSA03	931|917	610|671	972|986	838|858
c	BMSB08	–	TWSA03	391	883	0	**425**
d	BMSB08	test set	TWSA03	362|440	930|873	0|0	431|438
e	BMSB08+TMSA03	–	TWSA03	966	488	887	781
f	BMSB08+TMSA03	test set	TWSA03	921|851	709|803	958|972	862|875
g	BMSB08	TMSA03	TWSA03	300|369	945|939	0|0	416|**436**

Discussion

Pros

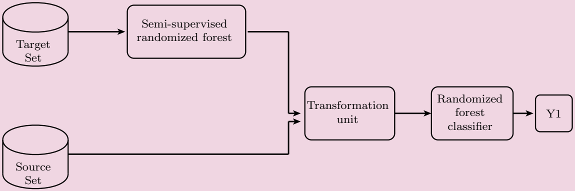
- A straight-forward and fast method
- Satisfying level of enhancement in the case of transferring from Tennis Singles to Tennis Doubles

Cons

- Obtaining poorer results in the case of transferring from Badminton to Tennis Singles in comparison with the Tennis Singles to Doubles
- The transformation model is too simple

Future Work

- Testing our approach on the public routers data set
- The taxonomy for improving our system is as followed:
  1. Use a semi-supervised decision forest to estimate an initial posterior probability for target samples
  2. Use this prediction to compute the transformation for source space
  3. Train a decision forest classifier on the transformed source domain
  4. Predict the labels for the target data points



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Time Complexity Comparison

No Transfer	No re-training	$O(Ker^{src} + Class^{src})$
No Transfer	Added Labeled samples on target	$O(Labeling) + O(Ker^{src+trg} + Class^{src+trg})$
Transfer	Unsupervised	$2 \times O(Ker^{src} + Class^{src}) + O(transfer)$