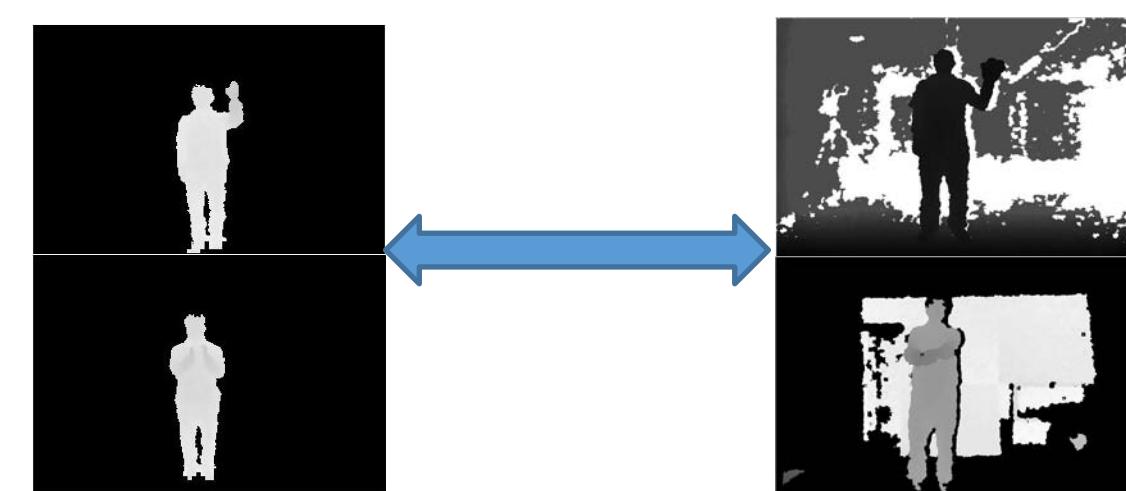
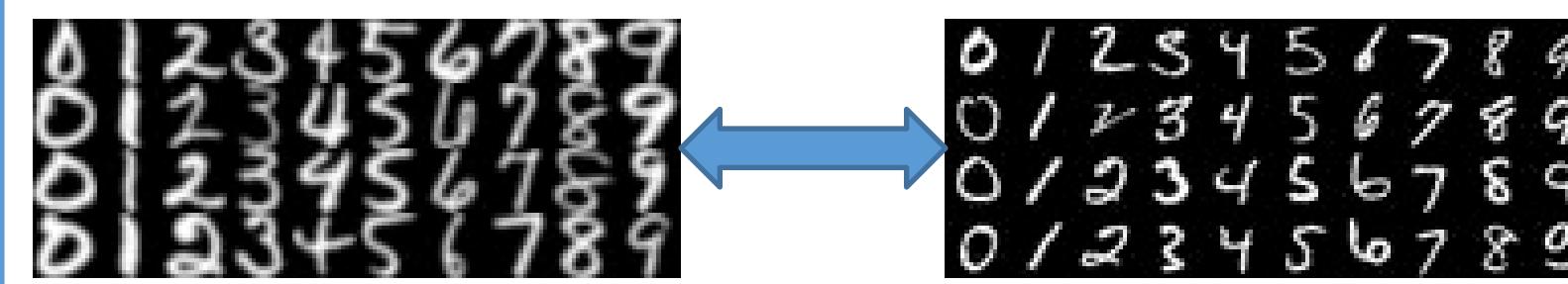
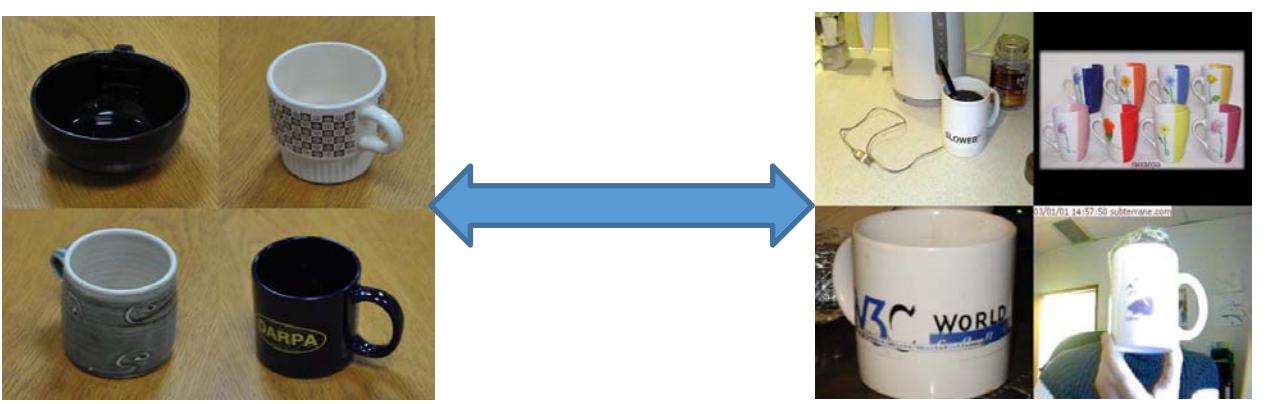


## Introduction

### Motivation

- ✓ Divergence between training and test data



### Unsupervised Domain Adaptation

- ✓ Data: labelled source + unlabeled target
- ✓ Task: recognition on target domain
- ✓ Challenge: distribution discrepancy → performance degeneration

### Solution

- ✓ Data centric approach
- ✓ Subspace centric approach

## Proposed Method

Key Ideas: find two coupled subspaces to obtain new representations of respective domains such that

- ✓ the variance of target domain is maximized,

$$\max_B \text{Tr}(B^T S_t B)$$

- ✓ the discriminative information of source domain is preserved,

$$\max_A \text{Tr}(A^T S_b A), \quad \min_A \text{Tr}(A^T S_w A)$$

- ✓ the distribution shift is small,

$$\min_{A,B} \text{Tr} \left( \begin{bmatrix} A^T & B^T \end{bmatrix} \begin{bmatrix} M_s & M_{st} \\ M_{ts} & M_t \end{bmatrix} \begin{bmatrix} A \\ B \end{bmatrix} \right)$$

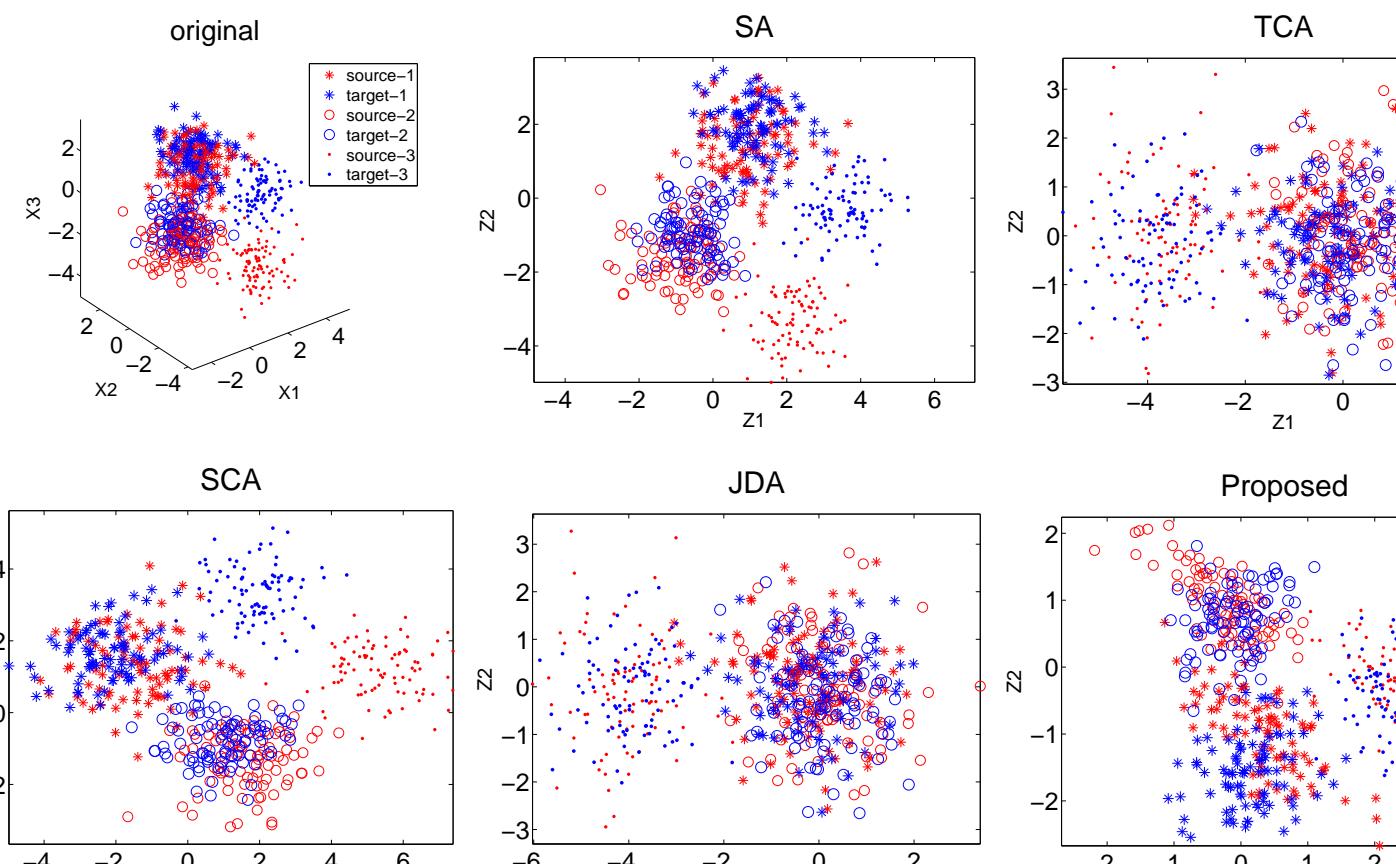
- ✓ the subspace shift is small.

$$\min_{A,B} \|A - B\|_F^2$$

$$\{\text{Var.}^{\text{target}}\} + \{\text{Var.}^{\text{between}}\}$$

$$\text{Overall: } \max_{A,B} \frac{\{\text{Var.}^{\text{target}}\} + \{\text{Var.}^{\text{between}}\}}{\{\text{Dist.shift}\} + \{\text{Sub.shift}\} + \{\text{Var.}^{\text{within}}\}}$$

## Results on Synthetic Data



## Results on Real World Data

### Results on Cross-domain Object Recognition (surf)

Feature	SURF										
	data	Raw	SA	SDA	GFK	TCA	JDA	TJM	SCA	JGSA primal	JGSA linear
C→A	36.01	49.27	49.69	46.03	45.82	45.62	46.76	45.62	51.46	52.30	<b>53.13</b>
C→W	29.15	40.00	38.98	36.95	31.19	41.69	38.98	40.00	45.42	45.76	<b>48.47</b>
C→D	38.22	39.49	40.13	40.76	34.39	45.22	47.13	45.86	44.59	45.86	<b>48.41</b>
A→C	34.19	39.98	39.54	40.69	<b>42.39</b>	39.36	39.45	39.72	41.50	38.11	41.50
A→W	31.19	33.22	30.85	36.95	36.27	37.97	42.03	34.92	45.76	<b>49.49</b>	45.08
A→D	35.67	33.76	40.13	33.76	39.49	45.22	39.49	<b>47.13</b>	45.86	45.22	
W→C	28.76	<b>35.17</b>	34.73	24.76	29.39	31.17	30.19	31.08	33.21	32.68	33.57
W→A	31.63	39.25	39.25	27.56	28.91	32.78	29.96	29.96	39.87	<b>41.02</b>	40.81
W→D	84.71	75.16	75.80	85.35	89.17	89.17	89.17	87.26	<b>90.45</b>	88.54	
D→C	29.56	34.55	<b>35.89</b>	29.30	30.72	31.52	31.43	30.72	29.92	30.19	30.28
D→A	28.29	<b>39.87</b>	38.73	28.71	31.00	33.09	32.78	31.63	38.00	36.01	38.73
D→W	83.73	76.95	76.95	80.34	86.10	89.49	85.42	84.41	91.86	91.86	<b>93.22</b>
Average	40.93	44.72	44.52	43.13	43.26	46.38	46.33	45.16	50.04	50.18	<b>50.58</b>

### Results on Cross-domain Object Recognition (Decaf)

Feature	Decaf <sub>6</sub>				
	data	JDA	OTGL	JGSA primal	JGSA linear
C→A	90.19	<b>92.15</b>	91.44	91.75	91.13
C→W	85.42	84.17	<b>86.78</b>	85.08	83.39
C→D	85.99	87.25	<b>93.63</b>	92.36	92.36
A→C	81.92	<b>85.51</b>	84.86	85.04	84.86
A→W	80.68	83.05	81.02	<b>84.75</b>	80.00
A→D	81.53	85.00	<b>88.54</b>	85.35	84.71
W→C	81.21	81.45	<b>84.95</b>	84.68	84.51
W→A	90.71	90.62	90.71	<b>91.44</b>	91.34
W→D	<b>100</b>	96.25	<b>100</b>	<b>100</b>	<b>100</b>
D→C	80.32	84.11	<b>86.20</b>	85.75	84.77
D→A	91.96	<b>92.31</b>	91.96	92.28	91.96
D→W	99.32	96.29	<b>99.66</b>	98.64	98.64
Average	87.44	88.18	<b>89.98</b>	89.76	88.97

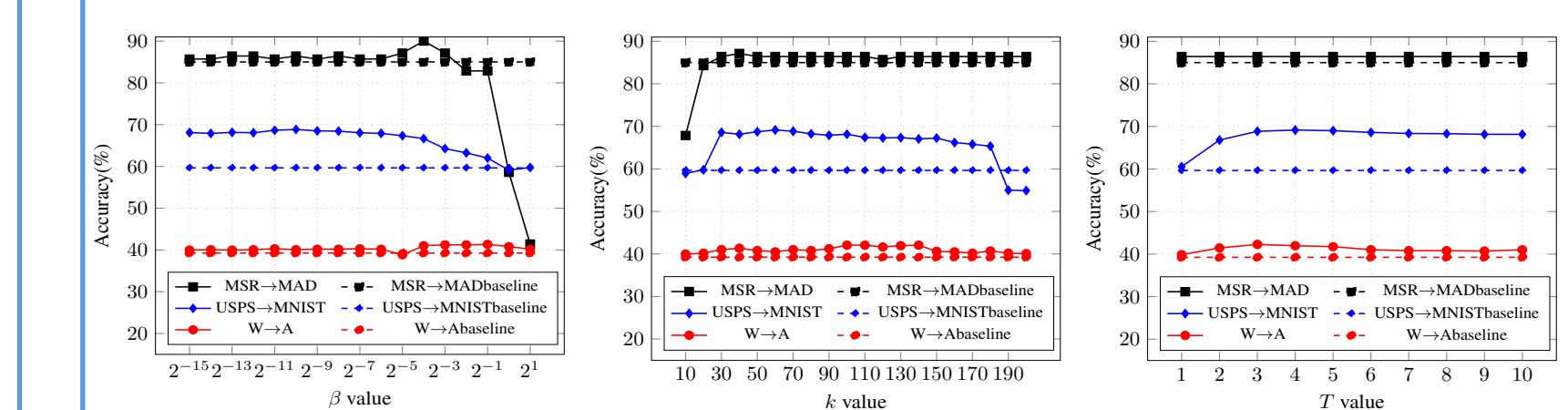
### Results on Cross-domain Digit Recognition

data	Raw	SA	SDA	GFK	TCA	JDA	TJM	SCA	JGSA primal
MNIST→USPS	65.94	67.78	65.00	61.22	56.33	67.28	63.28	65.11	<b>80.44</b>
USPS→MNIST	44.70	48.80	35.70	46.45	51.20	59.65	52.25	48.00	<b>68.15</b>
Average	55.32	58.29	50.35	56.84	53.77	63.47	57.77	56.56	<b>74.30</b>

### Results on Cross-dataset Action Recognition

data	Raw	SA	SDA	GFK	TCA	JDA	TJM	SCA	JGSA linear
MSR→G3D	72.92	77.08	73.96	68.75	82.29	70.83	70.83	<b>89.58</b>	
G3D→MSR	54.47	<b>68.09</b>	67.32	50.58	65.37	63.04	55.25	66.93	
MSR→UTD	66.88	73.75	73.75	65.00	<b>77.50</b>	65.00	64.38	76.88	
UTD→MSR	62.93	<b>67.91</b>	66.67	57.63	61.06	60.12	55.14	61.37	
MSR→MAD	80.71	85.00	83.57	79.29	82.86	82.14	78.57	<b>86.43</b>	
MAD→MSR	80.09	81.48	80.56	81.02	83.33	79.63	79.63	<b>85.65</b>	
Average	69.67	75.55	74.30	67.05	75.40	70.13	67.30	<b>77.81</b>	

## Parameter Sensitivity



## Conclusions

A novel framework for unsupervised domain adaptation is proposed, where

- ✓ both geometrical and statistical shifts are reduced,
- ✓ both shared and specific features are exploited,
- ✓ the state-of-the-art results are obtained on both synthetic data and real world datasets.

## References

- [1] S. J. Pan, I. W. Tsang, J. T. Kwok, and Q. Yang, "Domain adaptation via transfer component analysis," *IEEE Transactions on Neural Networks*, 2011.
- [2] B. Fernando, A. Habrard, M. Sebban, and T. Tuytelaars, "Unsupervised visual domain adaptation using subspace alignment," *IEEE ICCV*, 2013.
- [3] M. Ghifary, D. Balduzzi, W. B. Kleijn, and M. Zhang, "Scatter component analysis: A unified framework for domain adaptation and domain generalization," *IEEE TPAMI*, 2016.
- [4] M. Long, J. Wang, G. Ding, J. Sun, and P. Yu, "Transfer feature learning with joint distribution adaptation," *IEEE ICCV*, 2013.