Nonconvex and discriminative transfer subspace learning for unsupervised domain adaptation

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Problems & Ideas

- Problems of TSL:
  - To preserve data structural information, the traditional methods often impose low-rank constraints, i.e., trace norm on reconstruction matrix, making its solutions deviate from the original optimums.
  - The traditional methods directly use the strict labels of source domain, which is difficult to deal with label noise.
- Ideas: we propose a novel nonconvex and discriminative transfer subspace learning method named NDTSL by incorporating Schatten-p norm and soft label.

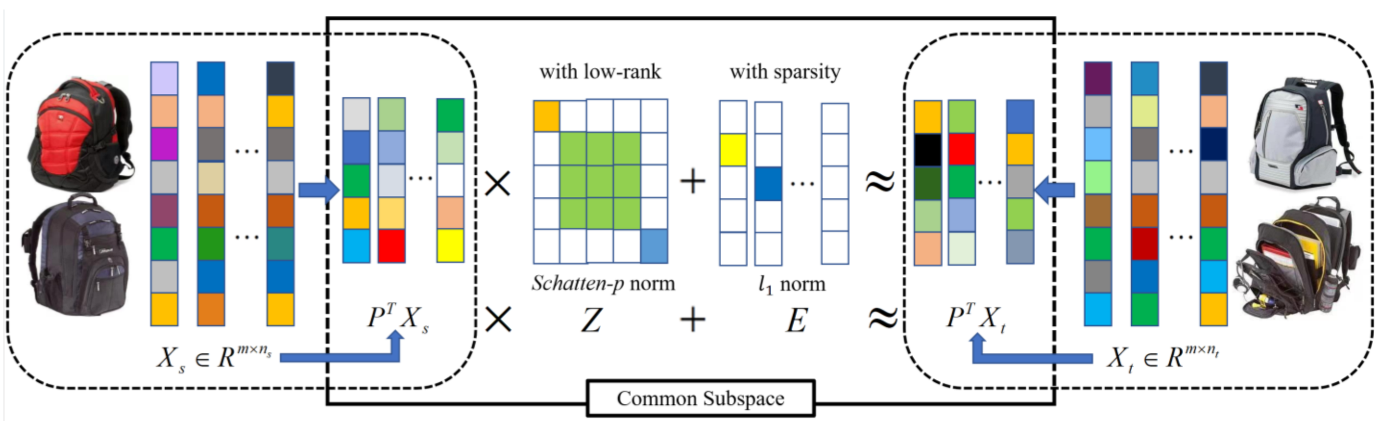

Figure 1 A framework of NDTSL method. Schatten-p norm is used to impose a low-rank constraint on Z for preserving the original data structure; $l_1$norm is adopted to make noise matrix E sparsity and ensure the robustness of our model.

Main Contributions

- Contributions:
  - ◆ We design NDTSL to transfer knowledge from source domain to target domain and extract the discriminative features in subspace by incorporating Schatten-p norm and a soft label matrix.
  - ◆ A fast and efficient alternative algorithm is designed to solve the nonconvex objective function.
  - ◆ The extensive experimental results verified the effectiveness of our proposed NDTSL.

Table 4 Four evaluation metrics: Accuracy, Precision, Recall, and Macro-F1 of different methods on VSL by NN classifier. The best results on each row are bolded, and •/⊙/◦ means that the NDTSL method is better/tied/worse than other methods

Dataset	Measures	NN	TCA	JDA	W-BDA	JPDA	GFK	DTSL	FSSP	JLRFS	PAS	LRRCA	NDTSL
	Accuracy	.6297±.0144•	.5314±.0143•	.5591±.0170•	.5728±.0113•	.5530±.0095•	.5814±.0092•	.6740±.0094⊙	.5743±.0146•	.6699±.0121•	.5615±.0151•	.6746±.0125•	**.6769±.0113**
V→S	Precision	.4131±.0125•	.3831±.0128•	.3856±.0130•	.3836±.0087•	.3801±.0098•	.4004±.0085•	.4774±.0194⊙	.3804±.0130•	**.4882±.0411**⊙	.4547±.0176•	.4812±.0271•	.4837±.0270
	Recall	.4584±.0303•	.4078±.0450•	.4064±.0442•	.3937±.0272•	.4189±.0408•	.4681±.0361•	**.5908±.0496**⊙	.4198±.0296•	.5332±.0619•	.5890±.0347⊙	.5808±.0634•	.5830±.0636
	Macro-F1	.4154±.0158•	.3629±.0131•	.3743±.0159•	.3759±.0117•	.3741±.0143•	.3995±.0121•	.4954±.0230⊙	.3825±.0170•	.4914±.0374⊙	.3920±.0215•	.4957±.0312•	**.4985±.0310**
	Accuracy	.5469±.0193•	.4446±.0158•	.5086±.0177•	.5171±.0139•	.5528±.0130•	.5297±.0156•	.5716±.0143⊙	.4810±.0191•	.5698±.0164⊙	.4063±.0185•	.5709±.0143⊙	**.5735±.0142**
V→L	Precision	.4915±.0280⊙	.2741±.0096•	.3281±.0298•	.3920±.0409•	.3742±.0279•	.3996±.0232•	.4874±.0268⊙	.3313±.0344•	**.5042±.0238**◦	.4039±.0466•	.4869±.0268⊙	.4891±.0216
	Recall	.4314±.0318•	.3168±.0175•	.3581±.0361•	.3734±.0387•	.3863±.0311•	.3993±.0386•	.4762±.0294•	.3338±.0363•	.4789±.0267•	.4361±.0327•	.4759±.0294•	**.4861±.0307**
	Macro-F1	.4231±.0261•	.2646±.0109•	.3296±.0295•	.3575±.0358•	.3673±.0279•	.3766±.0267•	.4477±.0246⊙	.3036±.0333•	**.4615±.0206**⊙	.2961±.0247•	.4473±.0245⊙	.4564±.0221
	Accuracy	.5341±.0133•	.5219±.0142•	.5422±.0159•	.5414±.0148•	.5339±.0157•	.5498±.0156•	.5541±.0154•	**.6321±.0167**◦	.5470±.0119•	.3681±.0114•	.5575±.0153⊙	.5614±.0143
S→V	Precision	.5382±.0340⊙	.4276±.0498•	.4269±.0360•	.4076±.0482•	.4442±.0455•	.5502±.0345⊙	.5915±.0531◦	**.6527±.0177**◦	.5148±.1309⊙	.4335±.0116•	.5884±.0537◦	.5543±.0295
	Recall	.4387±.0139•	.3967±.0098•	.4171±.0111•	.4011±.0112•	.4020±.0121•	.4313±.0152•	.4237±.0113•	**.5629±.0188**◦	.4052±.0076•	.4448±.0123⊙	.4269±.0108•	.4474±.0135
	Macro-F1	.4226±.0195•	.3560±.0112•	.3731±.0114•	.3667±.0109•	.3723±.0145•	.4226±.0180•	.3990±.0143•	**.5833±.0189**◦	.3597±.0094•	.3917±.0109•	.4019±.0143•	.4362±.0166
	Accuracy	.5128±.0144•	.5044±.0213•	.5169±.0165•	.5367±.0157•	.5361±.0180•	.5214±.0147•	.5724±.0156⊙	.5052±.0167•	.5652±.0208•	.2672±.0105•	.5719±.0164⊙	**.5739±.0169**
S→L	Precision	.3446±.0834•	.2781±.0353•	.2966±.0411•	.3114±.0630•	.3754±.0810⊙	.3839±.0985⊙	.4385±.1490⊙	.2469±.0283•	.4184±.1566⊙	.2979±.0121•	**.4387±.1493**⊙	.4136±.1350
	Recall	.2705±.0201•	.2800±.0275⊙	.2597±.0167•	.2619±.0159•	.2909±.0175⊙	**.2912±.0279**⊙	.2842±.0133•	.2524±.0185•	.2910±.0209⊙	.1894±.0203•	.2840±.0135⊙	.2907±.0153
	Macro-F1	.2466±.0255•	.2594±.0227•	.2491±.0154•	.2467±.0123•	.2642±.0158•	.2767±.0304⊙	.2764±.0198⊙	.2296±.0160•	.2793±.0268⊙	.2007±.0103•	.2764±.0201⊙	**.2820±.0222**
	Accuracy	.5478±.0126•	.4606±.0147•	.5118±.0134•	.5348±.0153•	.4733±.0148•	.5452±.0147•	.5479±.0141•	.5247±.0124•	.5355±.0162•	.1850±.0109•	.5448±.0145•	**.5568±.0141**
L→V	Precision	.5286±.0147•	.3793±.0260•	.4347±.0157•	.4444±.0178•	.4508±.0228•	.4841±.0140•	.5366±.0178•	.4778±.0167•	.3546±.0151•	.3143±.0119•	.5380±.0177•	**.5444±.0176**
	Recall	**.4947±.0100**◦	.3302±.0118•	.4365±.0144•	.4085±.0087•	.3988±.0124•	.4806±.0134⊙	.4740±.0132•	.4791±.0156⊙	.4281±.0106•	.2866±.0080•	.4647±.0135•	.4813±.0159
	Macro-F1	**.4824±.0104**⊙	.3109±.0136•	.4306±.0148•	.4022±.0104•	.3861±.0145•	.4787±.0134⊙	.4820±.0135⊙	.4773±.0154⊙	.3788±.0107•	.2093±.0093•	.4707±.0139•	.4815±.0158
	Accuracy	.4402±.0118•	.3980±.0151•	.4512±.0186•	.4700±.0131•	.4499±.0122•	.4684±.0134•	.4899±.0152•	.4672±.0154•	.4337±.0121•	.3864±.0150•	.4902±.0144•	**.5034±.0136**
L→S	Precision	.3320±.0175•	.2755±.0146•	.3232±.0147•	.3318±.0079•	.3332±.0116•	.3477±.0129•	.3500±.0226•	.3345±.0129•	**.3805±.0267**◦	.3342±.0170•	.3505±.0231•	.3599±.0219
	Recall	.3553±.0483•	.2590±.0293•	3213±.0353•	.3383±.0266•	.3642±.0609•	.4003±.0412⊙	.3659±.0399•	.3281±.0328•	.3389±.0487•	**.4401±.0280**◦	.3661±.0393•	.3963±.0357
	Macro-F1	.3000±.0197	.2322±.0141•	.2986±.0172•	.3106±.0097•	.2986±.0122•	.3231±.0143•	.3325±.0196•	.3071±.0164•	.2606±.0190•	.2417±.0107•	.3328±.0200•	**.3509±.0211**
win/tie/loss		20/3/1	23/1/0	24/0/0	24/0/0	22/2/0	18/6/0	12/11/1	18/2/4	14/8/2	21/2/1	15/8/1	-