

Multi-Task Curriculum Transfer Deep Learning of Clothing Attributes

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1 Introduction

➤ **Problem**

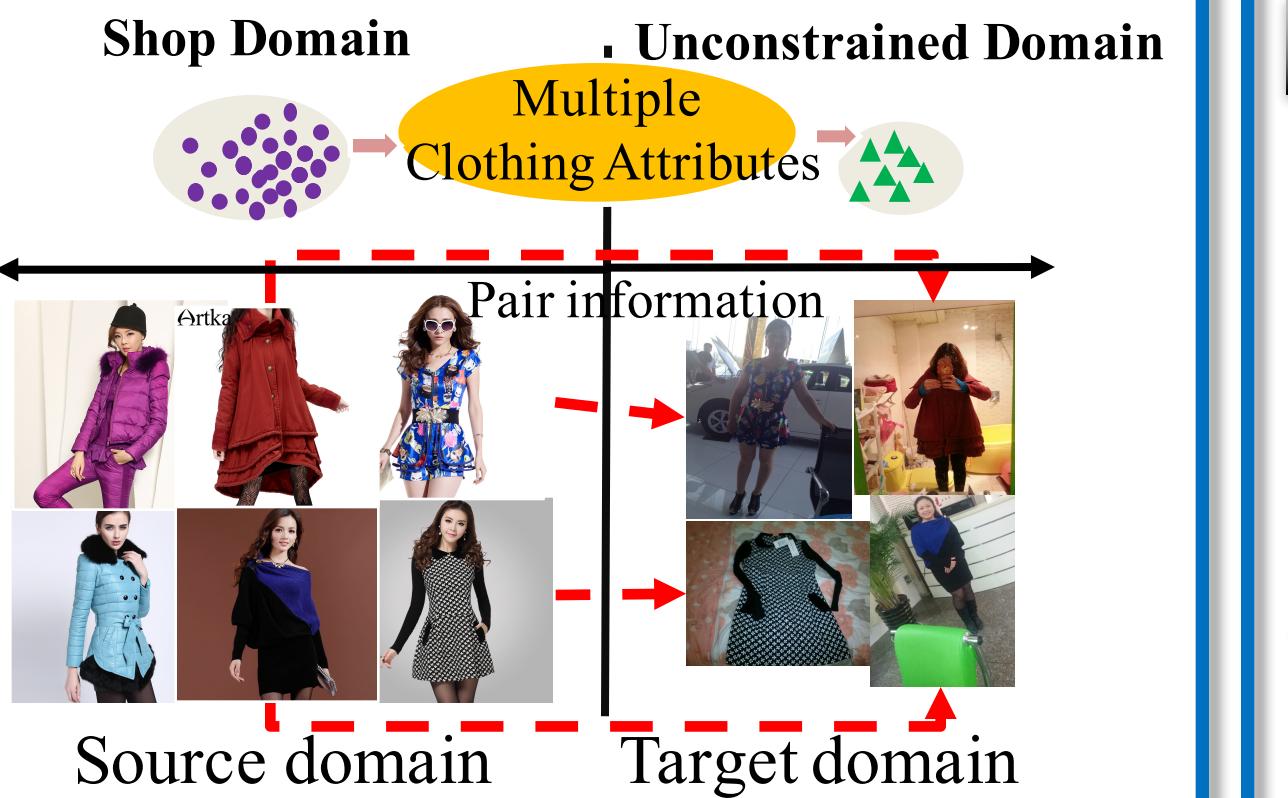
Domain transfer learning for recognising fine-grained multi-label clothing attributes in the street (wild) given limited training data.

➤ **Limitation of Existing Methods**

- Hand crafted features.
- Single task deep learning for multi-label recognition.
- Lack of end-to-end cross domain transfer learning.

➤ **Contributions**

- Novel **Multi-Task Curriculum Transfer (MTCT)** deep learning strategy.
- Effective **Multi-Task Network (MTN)** for learning from sparse target data.



2 Overview of method

➤ **Clothing detection**

Faster R-CNN[4] for clothing detection



➤ **Stage1: Shop domain (clean)**

Pretrain **MTN** on ImageNet and train on shop images.

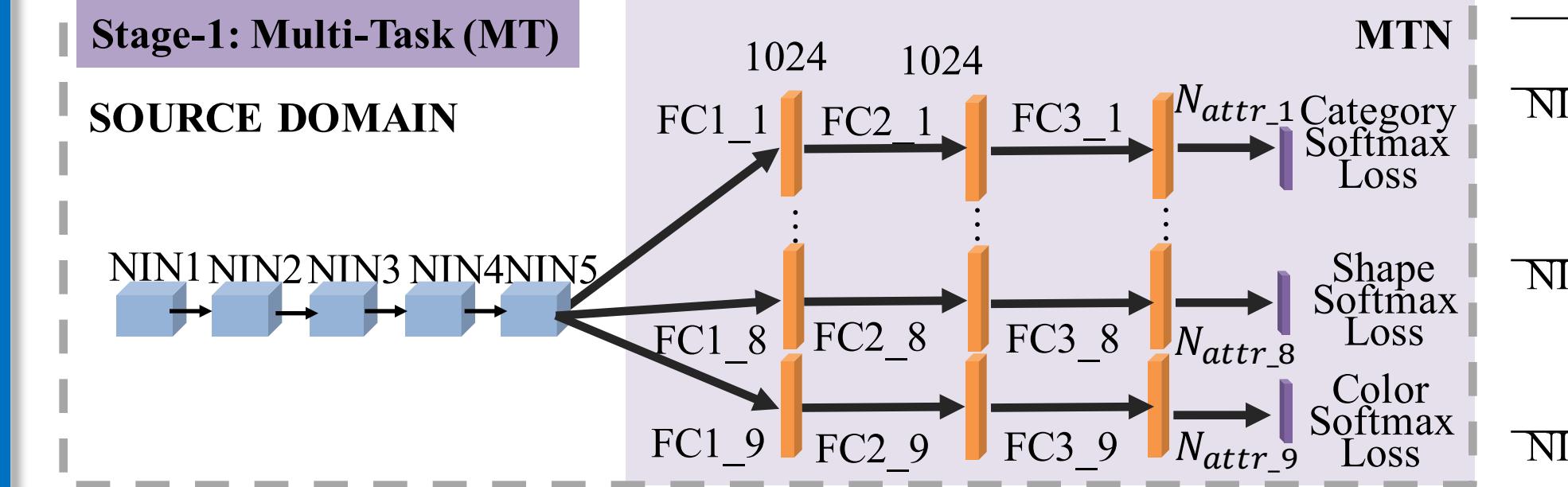
➤ **Stage 2: Street domain (wild)**

Initialize 3MTN by shop domain images trained model and then fine-tune FC layers using cross-domain triplet information for **transfer learning**.

3 Multi-task deep learning

Stage-1: Multi-Task (MT)

SOURCE DOMAIN

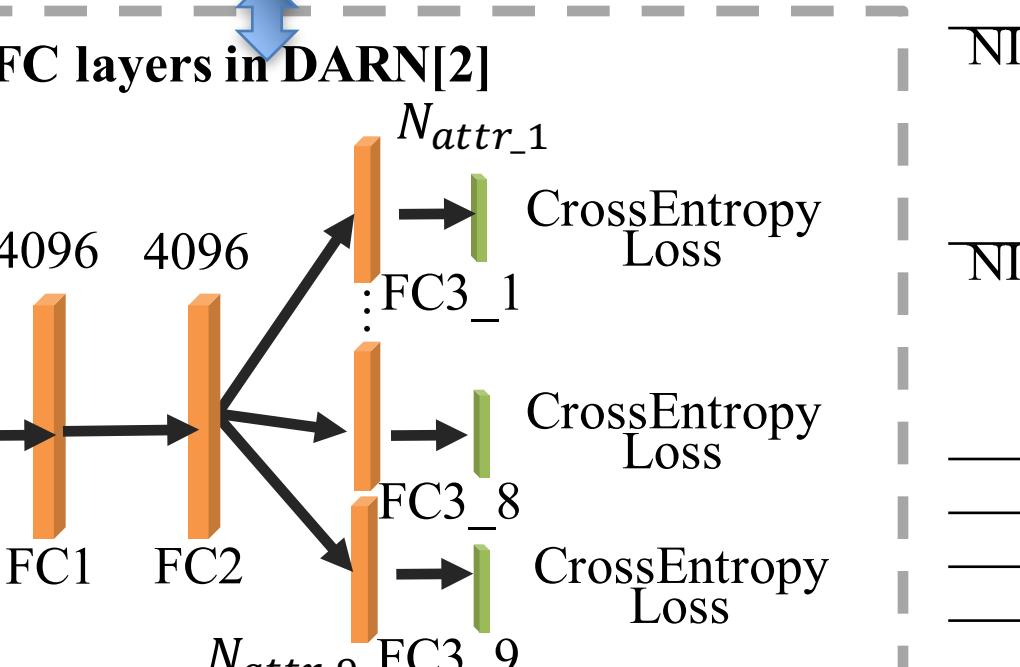


➤ **MTN**

A three-layer branch for learning specifics of each attribute category, with shared learning of generic features in conv layers.

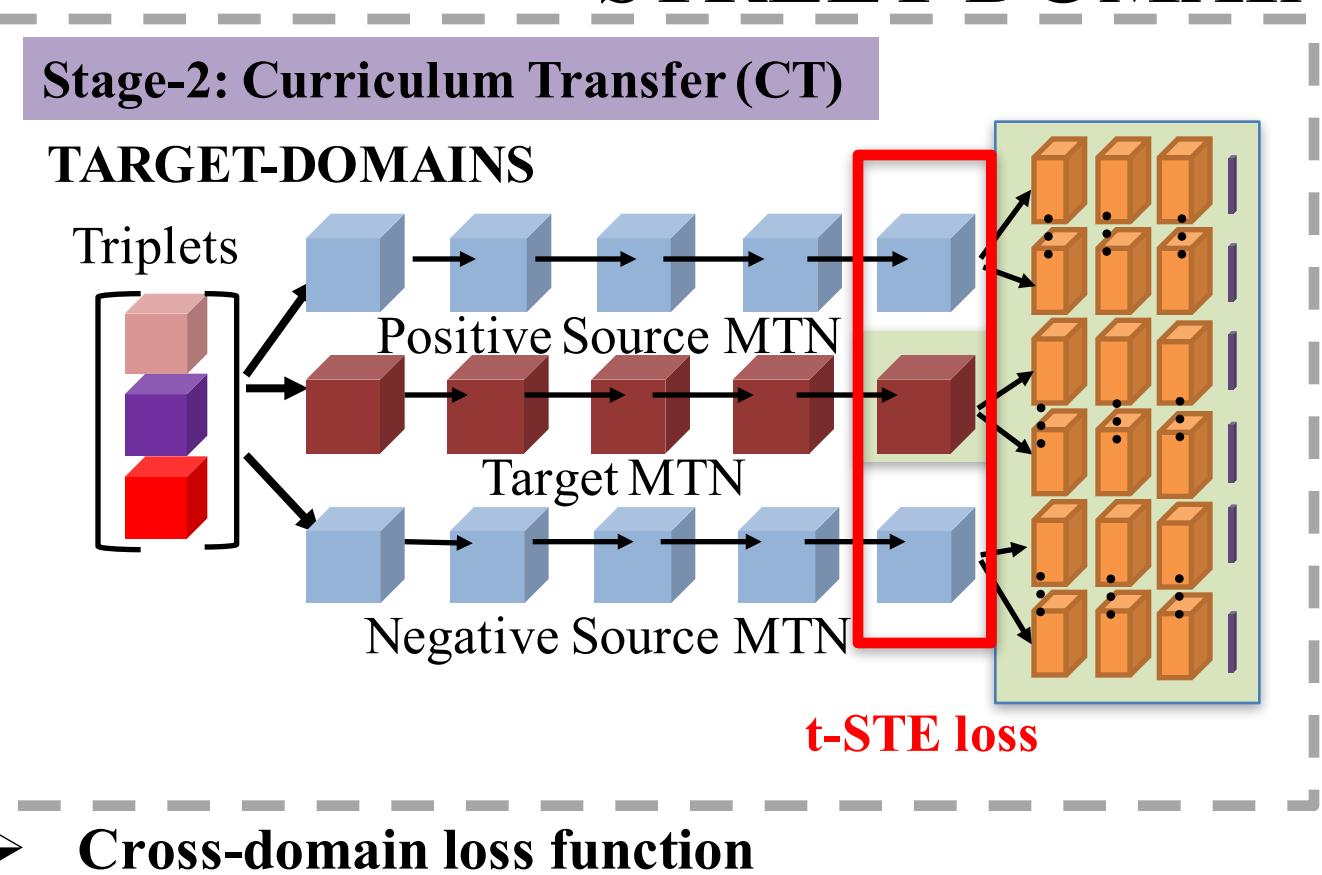
SHOP DOMAIN

	Layer Name	Parameters
NIN1	Conv1	7x7-96-2
	Conv1_1	1x1-96-1
	Conv1_2	1x1-96-1
NIN2	Maxpooling-3x3	
	Conv2	5x5-256-2
	Conv2_1	1x1-256-1
NIN3	Conv2_2	1x1-256-1
	Conv3	3x3-512-1
	Conv3_1	1x1-512-1
NIN4	Conv3_2	1x1-512-1
	Conv4	3x3-1024-1
	Conv4_1	1x1-1024-1
NIN5	Conv4_2	1x1-512-1
	Conv4_3	1x1-384-1
	Conv5	3x3-512-2
FC-1024	Conv5_1	1x1-512-1
	Conv5_2	1x1-512-1
	Maxpooling-3x3	
FC-1024	FC-1024 for any branch	
	FC-1024 for any branch	
	FC- <i>N_{attr}</i> for any branch	
Softmax	FC- <i>N_{attr}</i> for any branch	
	Softmax for any branch	



4 Curriculum transfer learning

STREET DOMAIN



➤ **Cross-domain loss function**

$$l_{t\text{-}STE} = \sum_{\{I_i, I_p, I_n\} \in T} \log \frac{(1 + \frac{\|f_i(I_i) - f_s(I_p)\|^2}{\alpha})^\beta}{(1 + \frac{\|f_i(I_i) - f_s(I_n)\|^2}{\alpha})^\beta + (1 + \frac{\|f_i(I_i) - f_t(I_n)\|^2}{\alpha})^\beta}$$

[1] Q. Chen, J. Huang, R. Feris, L. M. Brown, J. Dong, and S. Yan. Deep domain adaptation for describing people based on fine-grained clothing attributes. CVPR2015.

[2] Huang, R. S. Feris, Q. Chen, and S. Yan. Cross-domain image retrieval with a dual attribute-aware ranking network. ICCV2015.

[3] Z. Liu, P. Luo, S. Qiu, X. Wang, and X. Tang. Deepfashion: Powering robust clothes recognition and retrieval with rich annotations. CVPR2016.

[4] S. Ren, et.al. Faster-r-cnn: Towards real-time object detection with region proposal networks. In Advances in Neural Information Processing Systems, pages 91–99, 2015.

5 Experiments

➤ **Comparison to the State-of-The-Arts**

Methods	Category	Button	Colour	Length	Pattern	Shape	Collar	Slv-Len	SLv-shp	<i>mAP_{cls}</i>	<i>mP_{ins}</i>	<i>mR_{ins}</i>
DDAN[1]	12.56	24.13	20.72	35.91	61.67	47.14	31.17	80.63	73.96	43.10	45.41	52.20
DARN[2]	52.55	37.48	58.24	51.49	67.53	47.70	47.77	82.04	73.72	57.61	57.79	67.29
FashionNet[3]	55.85	39.52	60.33	53.08	68.65	49.79	51.27	83.79	75.34	59.84	59.97	69.74
MTCT	65.96	43.57	66.86	58.27	70.55	51.40	58.79	86.05	77.54	64.35	64.97	75.66

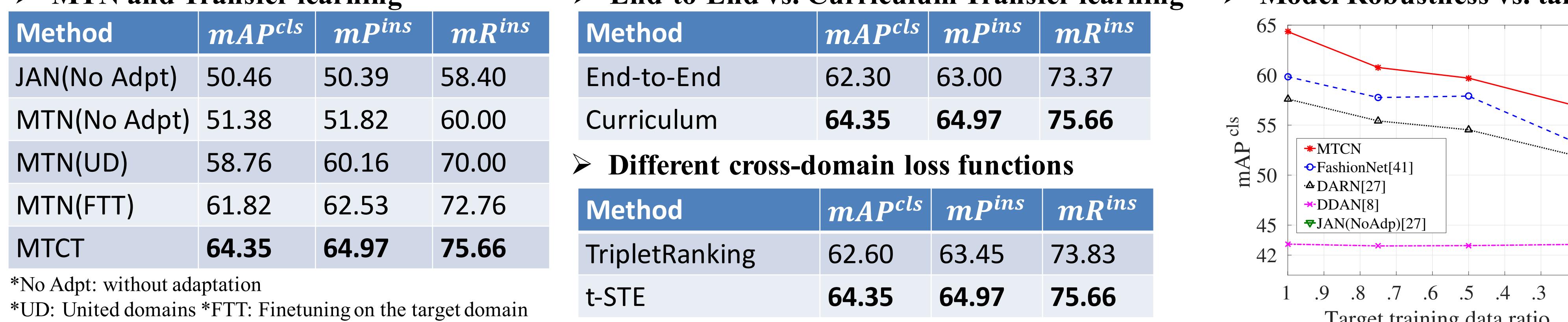
➤ **MTN and Transfer learning**

Method	<i>mAP_{cls}</i>	<i>mP_{ins}</i>	<i>mR_{ins}</i>
JAN(No Adpt)	50.46	50.39	58.40
MTN(No Adpt)	51.38	51.82	60.00
MTN(UD)	58.76	60.16	70.00
MTN(FTT)	61.82	62.53	72.76
MTCT	64.35	64.97	75.66

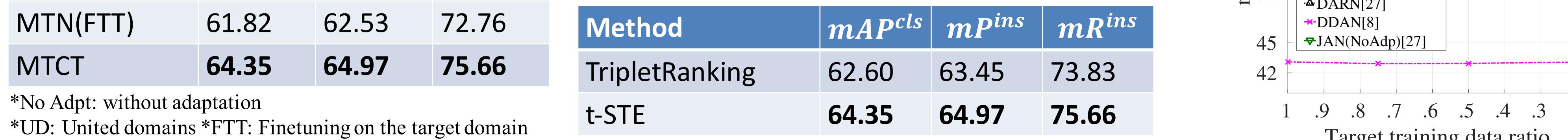
*No Adpt: without adaptation

*UD: United domains *FTT: Finetuning on the target domain

➤ **End-to-End vs. Curriculum Transfer learning**



➤ **Different cross-domain loss functions**



6 A qualitative evaluation of MTCT

