Beyond Appearance: a Semantic Controllable Self-supervised Learning Framework for Human-Centric Visual Tasks

Weihua Chen, Xianzhe Xu, Jian Jia, Hao Luo, Yaohua Wang, Fan Wang, Rong Jin, Xiuyu Sun

Paper ID: 8746

Session Tag: WED-PM-257





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1. MOTIVATION

Background

1. Human-centric tasks are curial in application;

- 2. Massive unlabeled human images available;
- 3. Semantic information is important.

4. Different downstream tasks require different needs of semantic.



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1. MOTIVATION

Background



Main Contributions

1. Human-centric tasks are curial in application;

- 2. Massive unlabeled human images available;
- 3. Semantic information is important.
- 4. Different downstream tasks require different needs of semantic.



1. Build a semantic supervision from human prior to train SOLIDER. 2. Design a semantic controller to adjust the semantic rate in the pre-trained model.



2. METHOD





2. METHOD

3. EXPERIMENTS

3.1. Can SOLIDER learn semantic ?

DINO space: Different parts from same person are closer.

After DINO

Solution Solution Solution Solution Solution Solution Solution State Semigrateries from different people are closer.

After SOLIDER

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3. EXPERIMENTS

3.2. Can λ control semantic rate ?

[Exp 1] With λ increased:

Observation 1. Different parts from same person (intra-distance) gets further. **Observation 2.** Same semantic parts from different people (inter-distance) gets closer.

[Exp 2] With λ increased:

Observation 1. The person re-identification performance is lower. **Observation 2.** The pedestrian detection performance is higher.

3. EXPERIMENTS

3.3. How is Ablation Study and SOTA Comparison?

Ablation Study

Pretrain Methods		Sup	DINO [6]	+ Clustering	+ Clustering&Controller
Pretrain Data		ImageNet	LUP1M	LUP1M	LUP1M
Person Re-identification	Market1501	78.1/90.2	89.6/95.9	89.5/95.5	89.9/96.1
TransReID [36]	MSMT17	49.7/73.6	63.3/83.2	61.6/82.2	63.9/83.8
Attribute Recognition mA ↑ RethinkPAR [38]	PETAzs	72.86	73.64	73.90	74.20
	RAP _{zs}	72.10	73.04	73.16	73.21
	PA100k	80.67	82.98	82.98	84.15
Person Search	CUHK-SYSU	93.0/94.1	93.6/94.3	93.6/94.1	94.0/94.7
SeqNet [45]	PRW	50.0/84.4	52.9/84.7	53.0/84.0	54.1/85.0
Pedestrian Detection MR ⁻² (R/HO)↓ CSP [73]	CityPerson	11.6/43.8	11.4/43.1	11.1/41.7	10.8/40.7
Human Parsing mIOU ↑ SCHP [43]	LIP	51.10	54.45	55.25	55.45
Pose Estimation AP/AR ↑ HRFormer [83]	COCO	72.4/78.2	73.1/78.5	73.4/78.7	74.4/79.7

SOTA Comparison

Person identification hAP/Rank1 ↑		SCSN [16]	ABDNet [9]	TransReID [36]	UP-ReID [81]	PASS [97]	Swin-T	SOLIDER Swin-S	Swin-B
	Market1501	88.5/95.7	88.3/95.6	89.5/95.2	91.1/97.1	93.3/ 96.9	91.6/96.1	93.3/96.6	93.9/96.9
	MSMT17	58.5/83.8	60.8/82.3	69.4/86.2	63.3/84.3	74.3/89.7	67.4/85.9	76.9/90.8	77.1/90.7
Attribute ecognition mA ↑		MsVAA [61]	VAC [30]	ALM [66]	JLAC [65]	RethinkPAR [38]	Swin-T	SOLIDER Swin-S	Swin-B
	PETA _{zs}	71.53	71.91	73.01	73.60	71.62	74.37	76.21	76.43
	RAP _{zs}	72.04	73.70	74.28	76.38	72.32	74.23	76.84	77.06
	PA100k	80.41	79.16	80.68	82.31	81.61	84.14	86.25	86.37
Person Search hAP/Rank1 ↑		NAE+ [7]	AlignPS+ [79]	TCTS [68]	SeqNet [45]	GLCNet [93]	Swin-T	SOLIDER Swin-S	Swin-B
	CUHK-SYSU	92.1/92.9	94.0/94.5	93.9/95.1	94.8/95.7	95.8/96.2	94.9/95.7	95.5/95.8	94.9/95.5
	PRW	44.0/81.1	46.1/82.1	46.8/87.5	47.6/87.6	47.8/ 87.8	56.8/86.8	59.8 /86.7	59.7/86.8
Pedestrian Detection		RepLoss [71]	CSP [73]	NMS-Loss [56]	ACSP [70]	PedesFormer [33]	Swin-T	SOLIDER Swin-S	Swin-B
$R^{-2}(R/HO)\downarrow$	CityPerson	13.2/56.9	11.0/49.3	10.8/-	9.3/46.3	9.2/36.9	10.3/40.8	10.0/39.2	9.7/39.4
Human Parsing mIOU ↑		JPPNet [46]	BraidNet [50]	CE2P [60]	PCNet [87]	SCHP [43]	Swin-T	SOLIDER Swin-S	Swin-B
	LIP	51.37	54.40	53.10	57.03	59.36	57.52	60.21	60.50
Pose Estimation AP/AR ↑		CPN [17]	SimpleBase [75]	TokenPose [44]	HRNet [63]	HRFormer [83]	Swin-T	SOLIDER Swin-S	Swin-B
	COCO	68.6/-	74.3/79.7	75.8/80.9	76.3/81.2	77.2/82.0	74.4/79.6	76.3/81.3	76.6/81.5

4. OPEN CODE

Project Website: https://github.com/tinyvision/SOLIDER

SOLIDER

a Semantic controllable self-superviseD lEaRning framework from Alibaba Group

of the Art	Pedestrian Attribute Recognition on	PA-100K
of the Art	Person Re-Identification on MSMT17	/ (using additional train
ed #3 Per	son Re-Identification on Market-1501	l (using additional train
of the Art	Person Search on PRW [III] Ranked	#6 Pedestrian Detect
of the Art	Semantic Segmentation on LIP val	Ranked #2 Pose E

