

Addressing the Elephant in the Room: Robust Animal Re-Identification with Unsupervised Part-Based Feature Alignment



Yingxue Yu, Vidit Vidit, Andrey Davydov, Martin Engilberge, Pascal Fua École Polytechnique Fédérale de Lausanne (EPFL)

Code: https://github.com/Chloe-Yu/Animal-Re-ID

Introduction

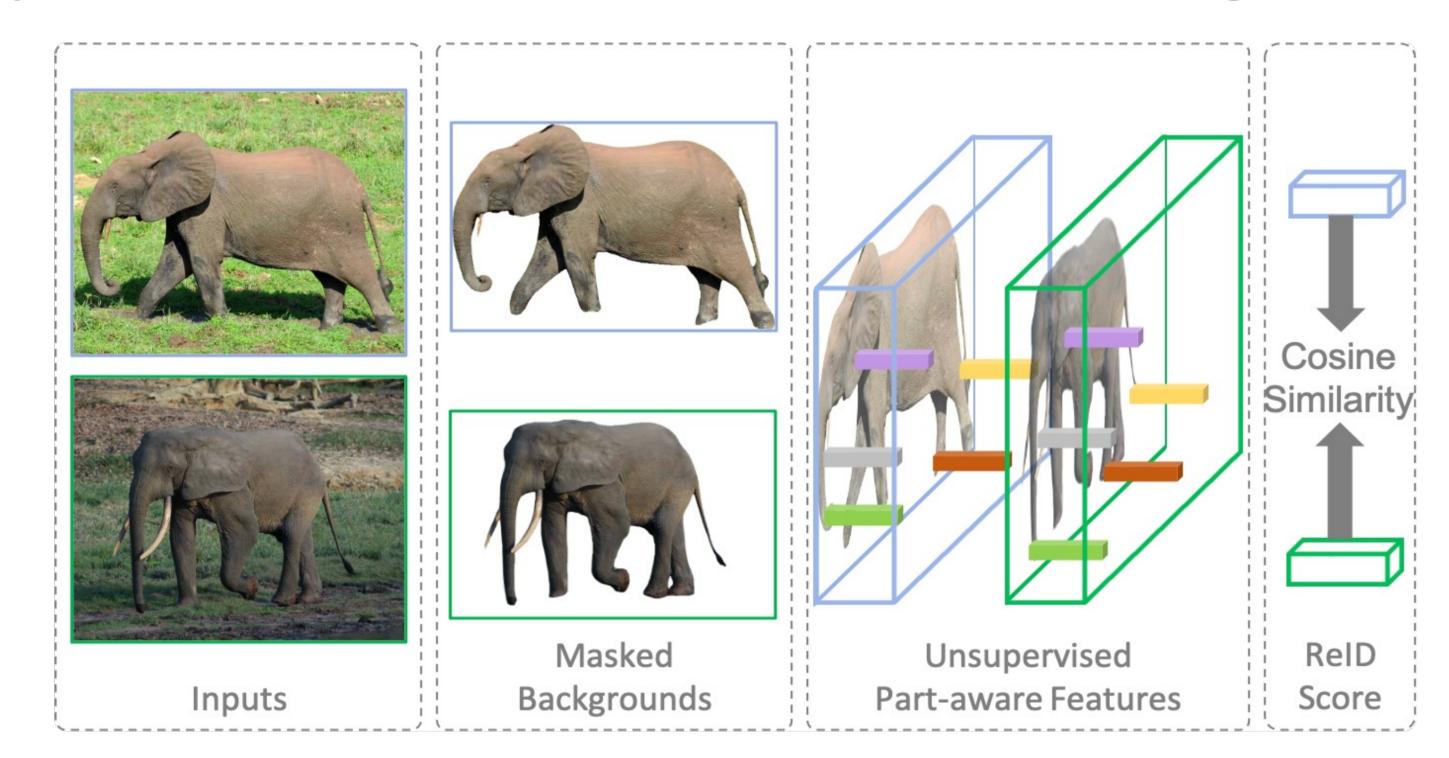
Motivation

Problem with Animal Re-ID Tasks

- Great variations within an individual
- Small variations between different individuals
- Few part-labeled images

Our Solution

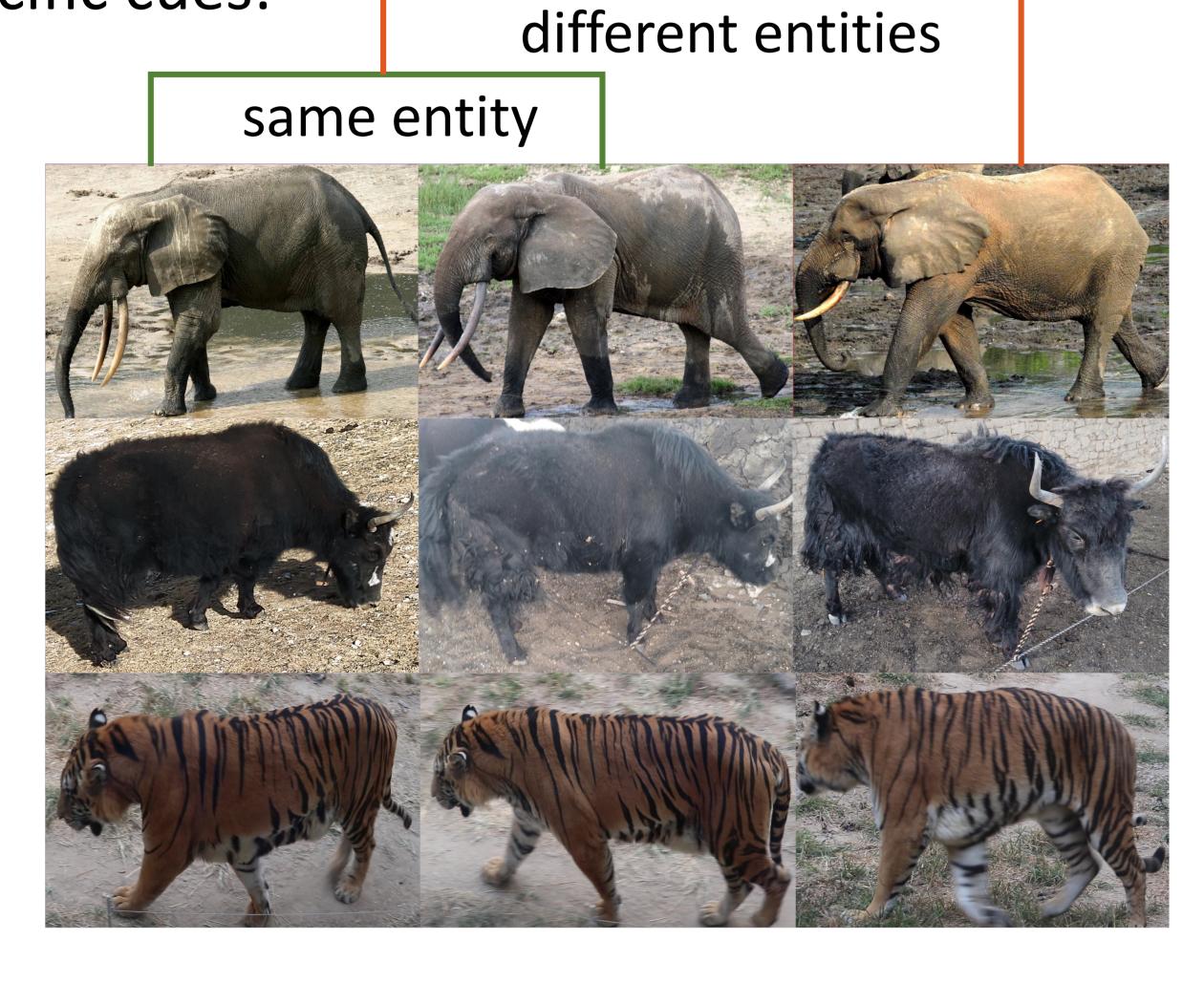
Unsupervised Part-aware model on Background-Free images



Learning Part-aware Features

Subtle species specific cues:

- tusk
- horn
- stripes



Background Removal

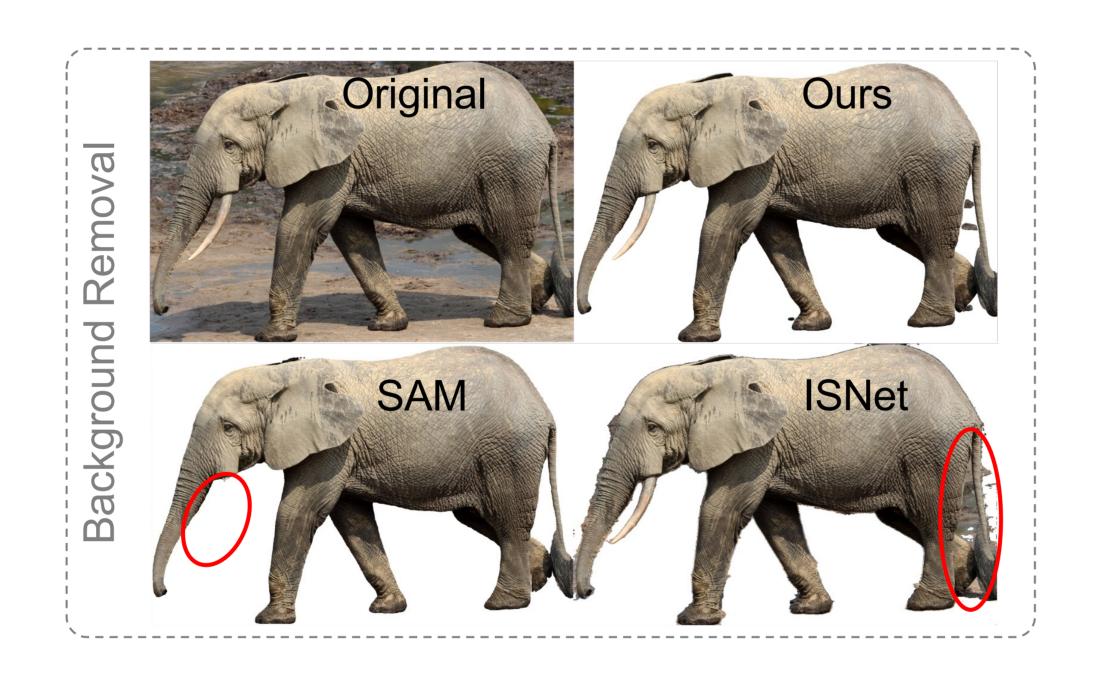
Background overfitting:

- Existing methods overly rely on background
- Clustering shows:
 - Grouping by background
 - Multiple IDs in the the same cluster

Background Overfitting

Our Solution

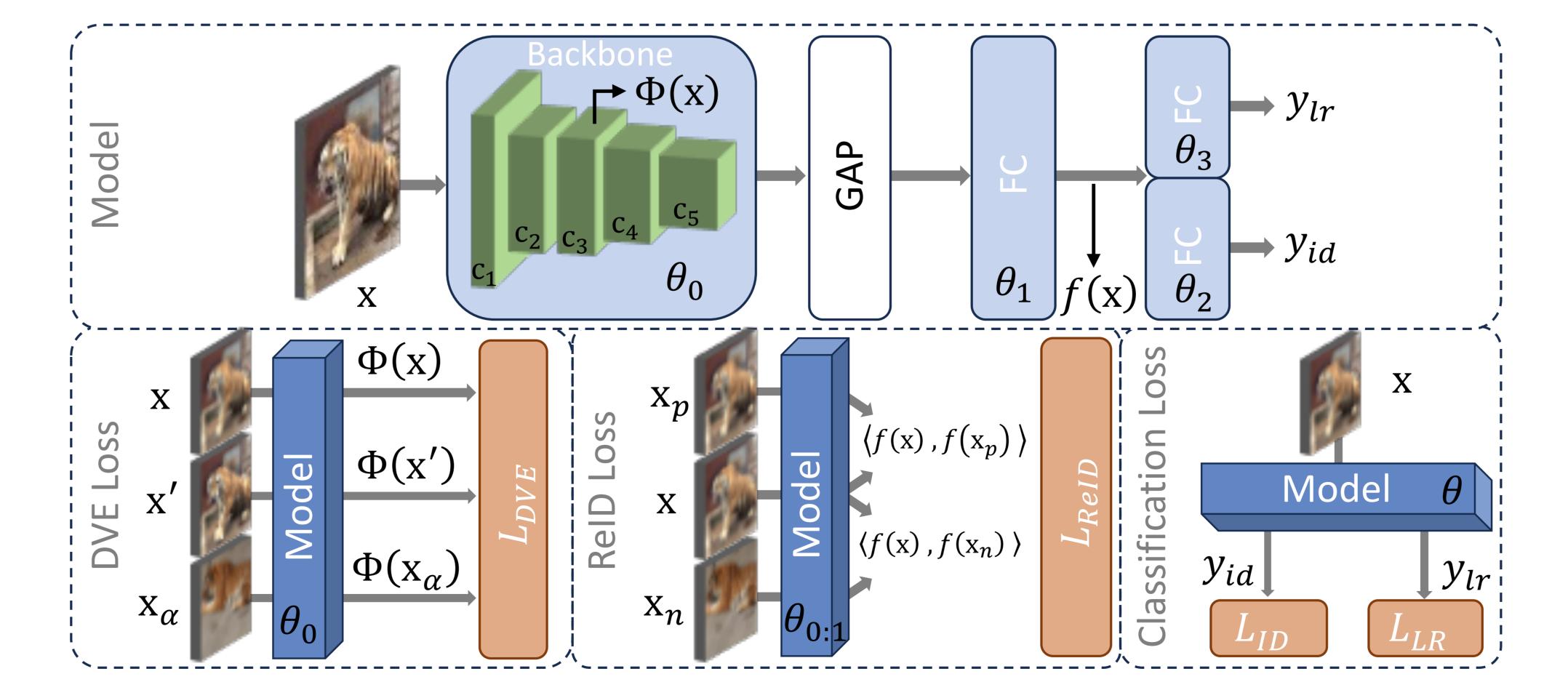
- Remove background both at training and testing time
- True evaluation of identity



Masked Backgrounds		ATRW			
Train	Test	$\overline{\mathrm{mmAP}}$	R@1(s)	R@1(c)	
		74.5	95.7	90.3	
	\checkmark	60.2	88.6	83.4	
\checkmark	\checkmark	66.9	90.8	86.3	
√		73.4	96.9	89.7	

Model Architecture

- Joint training
- Three losses
 - Part alignment DVE
 - ReID Circle loss
 - Attribute classification
 - Orientation
 - ID



 L_{DVE} : Unsupervised technique for feature alignment across body parts and pose variations [1]

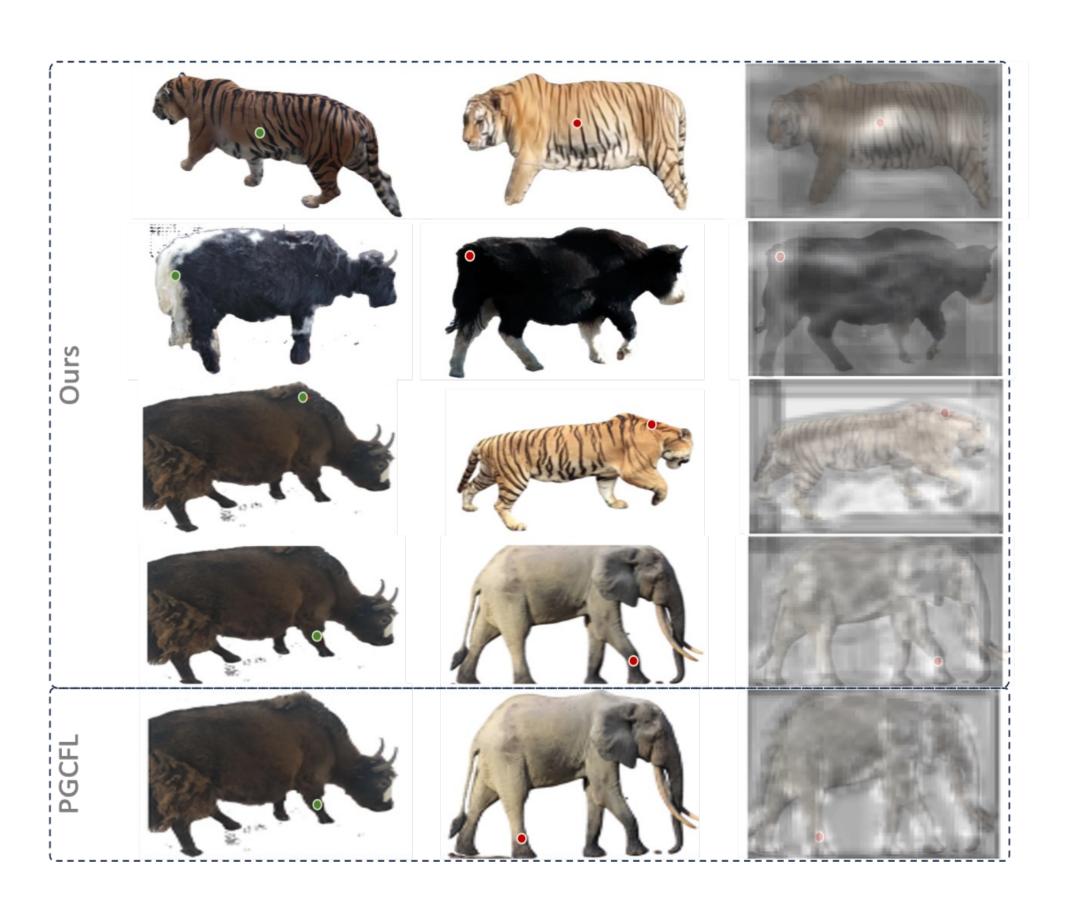
Evaluation

Comparison with SOTA

			ATRW		YakReID-103		ELPephants		
Methods	Org. Re-ID Task	Pose GT	$\overline{\text{mmAP}}$	R@1(s)	R@1(c)	$\overline{\mathrm{mAP}}$	R@1	$\overline{\mathrm{mAP}}$	R@1
CLIP-Re-ID ViT	[2] Person	X	56.5	86.3	72.0	49.8	82.2	12.7	25.3
PPGNet R-50 [3]	${ m Animal}$	\checkmark	68.3	81.2	81.1	-	-	-	_
ResNet50 [4]	Animal	X	65.9	91.1	83.4	60.9	86.0	20.0	33.9
ViT [5]	Animal	×	65.5	90.3	79.4	61.3	88.4	20.6	36.8
PGCFL[6]	${ m Animal}$	×	66.9	90.8	86.3	55.8	82.7	18.5	33.4
Ours	Animal	X	68.6	92.0	84.6	61.0	89.4	24.3	38.7

Feature Visualization

Ablation Study



	Model Components					ATRW		
L_{DVE}	L_{ID}	L_{ReID}	L_{LR}	B.S.	$ \overline{\text{mAP}} $	R@1(c)		
	\checkmark				54.6	74.9		
		\checkmark			56.3	72.0		
	\checkmark	\checkmark			$\boxed{54.4}$	69.7		
	\checkmark		\checkmark		61.4	81.1		
		\checkmark	\checkmark		60.5	76.6		
	\checkmark	\checkmark	\checkmark		63.4	78.9		
\checkmark	\checkmark	\checkmark	\checkmark		63.4	78.3		
	\checkmark	\checkmark	\checkmark	\checkmark	63.2	80.6		
√	\checkmark	\checkmark	\checkmark	\checkmark	64.9	82.9		

References

- [1] Thewlis, J., Albanie, S., Bilen, H., & Vedaldi, A. Unsupervised Learning of Landmarks by Descriptor Vector Exchange. 2019 ICCV
- [2] Siyuan Li, Li Sun, and Qingli Li. Clip-reid: exploiting vision-language model for image re-identification without concrete text labels. AAAI 2023
- [3] Cen Liu, Rong Zhang, and Lijun Guo. Part-pose guided amur tiger re-identification. CVPR 2019.
- [4] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. CVPR 2016
- [5] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. arXiv
- [6] Ning Liu, Qijun Zhao, Nan Zhang, Xinhua Cheng, and Jianing Zhu. Pose-guided complementary features learning for amur tiger re-identification. CVPR workshops, 2019