Taking a Closer Look at Synthesis: Fine-grained Attribute Analysis for Person Re-Identification

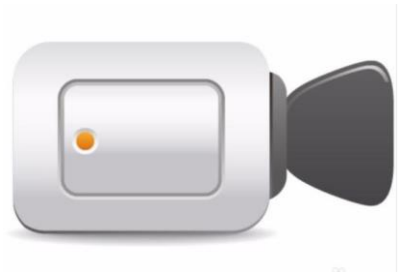
Suncheng Xiang[1], Yuzhuo Fu[1], Guanjie You[2], Ting Liu[1]

[1]*School of Electronic Information and Electrical Engineering, Shanghai Jiao Tong University*
[2]*College of Intelligence Science and Technology, National University of Defense Technology*

https://JeremyXSC.github.io/
https://JeremyXSC.github.io/GPR/

Introduction: Attribute Analysis for Person Re-ID

- Person re-ID is to find the person of interest from different camera views.



Challenges:

- Small-scale datasets
- Lack of diversity in viewpoint, weather, illumination and pose, etc
- Neglecting to explore the potential of performing efficient training

Dataset		#Identities	#Bboxes	#Cameras	#Weathers	#Illuminations
Real	Market-1501	1,501	32,668	6	✗	✗
	CUHK03	1,467	14,096	2	✗	✗
	DukeMTMC-reID	1,404	36,411	8	✗	✗
	MSMT17	4,101	126,441	15	✗	✗
Synthetic	SOMAset	50	100,000	250	✗	✗
	SyRI	100	1,680,000	280	✗	140
	PersonX	1,266	273,456	36	✗	✗
	RandPerson	8,000	1,801,816	19	✗	✗
	GPR+ (Ours)	**808**	**475,104**	**36**	7	7

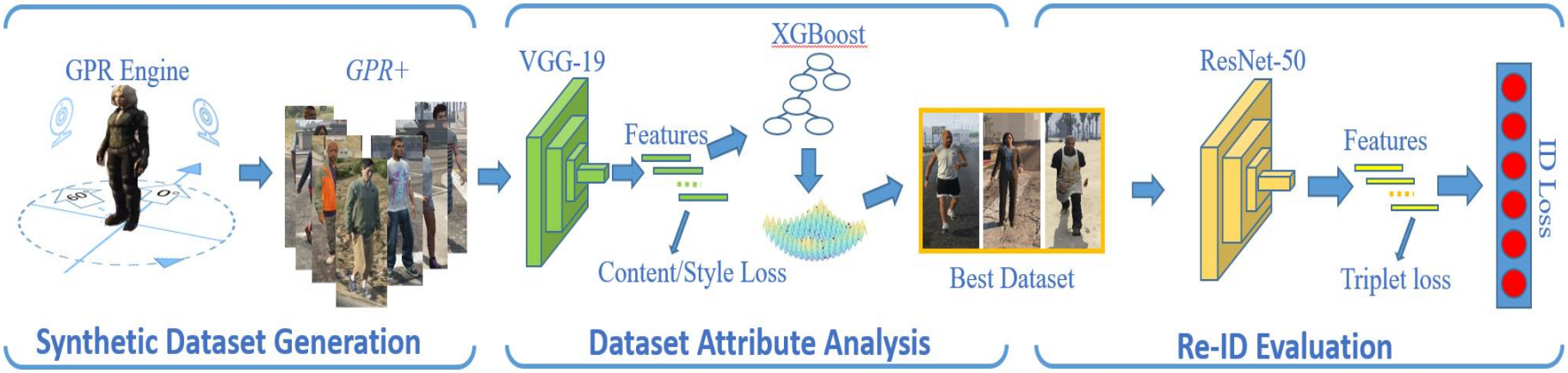
GPR+ dataset

Viewpoint

Weather

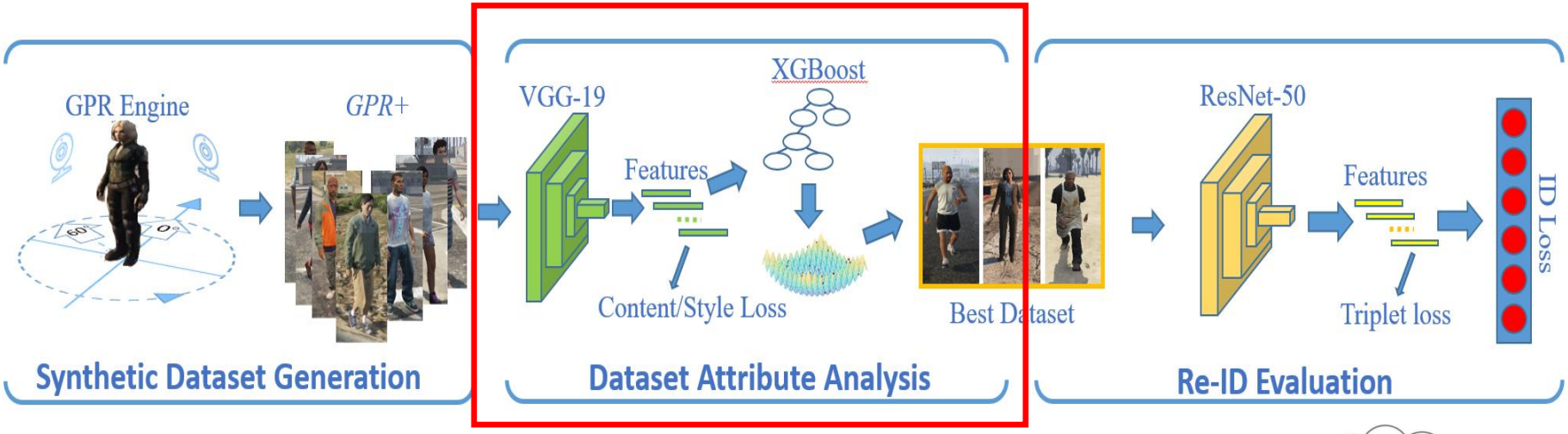
Illumination

Our work



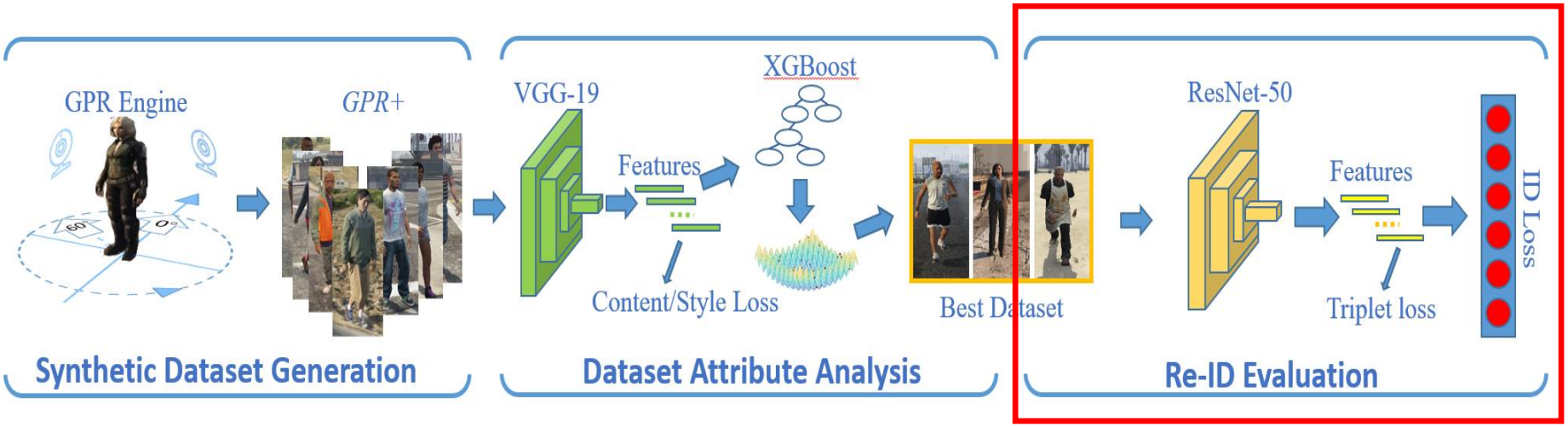
- The procedure of our proposed end-to-end systematic framework

Our work



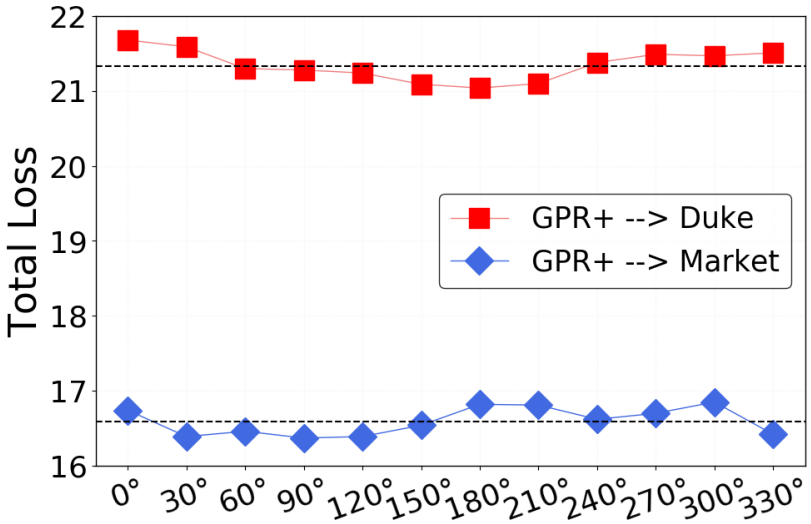
- Content representation $\mathcal{L}_{\text{content}} = \frac{1}{2}\sum_{i,j}\left(F_{ij}^{l} - P_{ij}^{l}\right)^2$
- Style representation $\mathcal{L}_{\text{style}} = \sum_{l=0}^{L} w_l \frac{1}{4N_l^2 M_l^2}\sum_{i,j}\left(G_{ij}^{l} - A_{ij}^{l}\right)^2$
- Total representation $\mathcal{L}_{\text{total}} = \alpha * \mathcal{L}_{\text{style}} + \beta * \mathcal{L}_{\text{content}}$

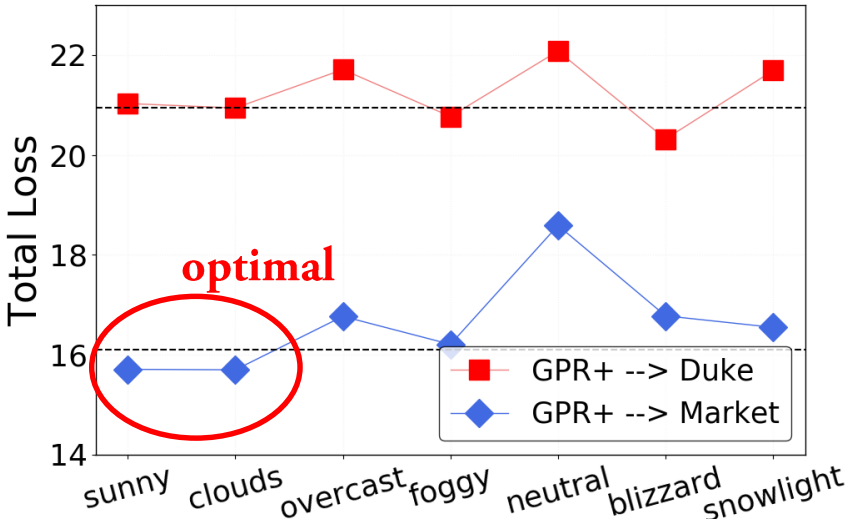
Our work

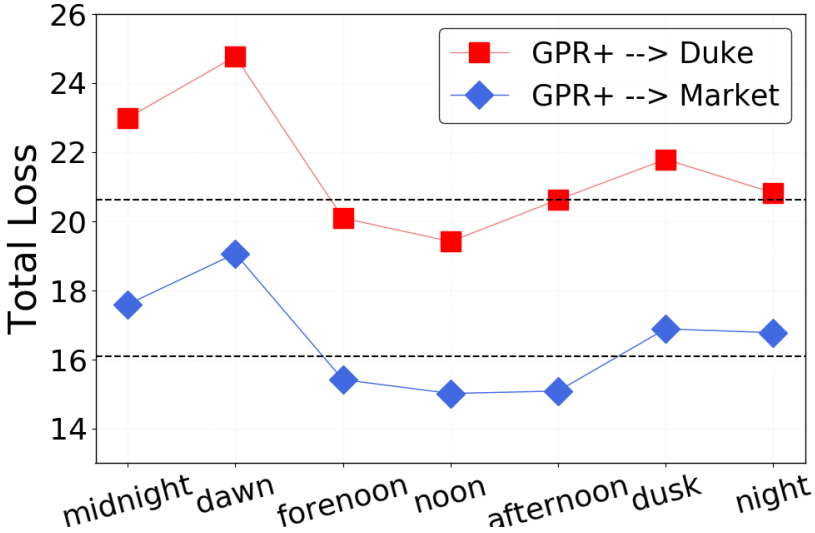


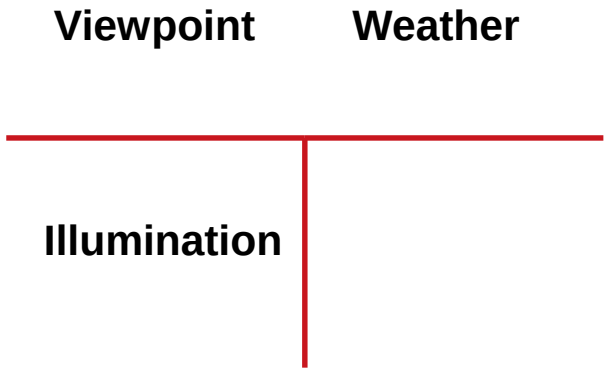
- Adopting a initializing model resnet-50 pre-trained on ImageNet
- Built with commonly used loss functions Triplet loss and ID loss

Loss distribution

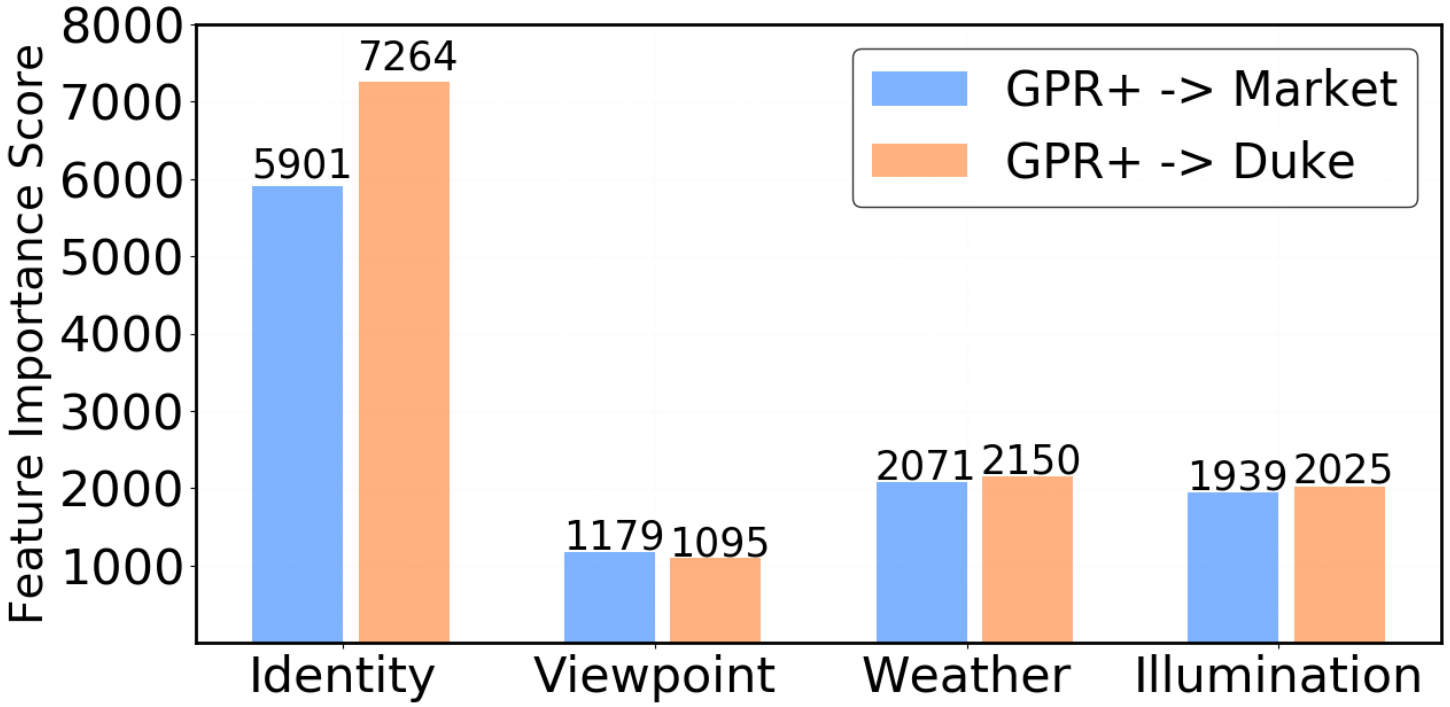








Attribute Importance



Results of Fine-grained Attribute Analysis

+12.6%

#identity	#box	#viewpoint	#weather	#illumination	Time (h)↓	mAP↑	R@1↑	R@5↑
100	58,800	✔	✔	✔	8.3	4.8	15.4	29.3
400	235,200	✔	✔	✔	31.0	13.5	35.7	53.8
800	470,400	✔	✔	✔	61.5	17.4	41.8	60.6
800	134,400	✔	sunny,clouds	✔	18.0	**19.7**	43.3	59.8
800	201,600	✔	✔	forenoon,noon,afternoon	26.5	18.6	41.4	58.8
800	235,200	30°, 60°, 90°,120°,150°, 330°	✔	✔	30.5	19.3	**44.1**	**62.4**
800	28,800	30°, 60°, 90°,120°,150°, 330°	sunny,clouds	forenoon, noon, afternoon	**4.5**	17.4	40.3	56.7

Results on Market dataset

+2.3%

#identity	#box	#viewpoint	#weather	#illumination	time (h)↓	mAP↑	R@1↑	R@5↑
100	58,800	✔	✔	✔	8.3	4.3	13.8	24.2
400	235,200	✔	✔	✔	30.6	10.7	26.3	38.2
800	470,400	✔	✔	✔	60.7	15.1	33.5	48.0
800	134,400	✔	foggy,blizzard	✔	18.0	17.8	33.8	48.3
800	201,600	✔	✔	forenoon,noon,afternoon	26.5	**18.8**	**38.2**	**52.3**
800	235,200	60°,90°,120°,150°,180°, 210°	✔	✔	30.6	17.2	37.7	52.2
800	28,800	60°,90°,120°,150°,180°, 210°	foggy,blizzard	forenoon,noon,afternoon	**4.4**	13.3	25.7	39.1

Results on Duke dataset

- Using more IDs as training samples is always beneficial to the system
- Obtaining some optimal attributes can lead to a more satisfactory performance

Conclusion

Contribution:

- Upgrade and enrich the previous GPR dataset to GPR+.
- Introduce a fine-grained analysis strategy to quantitatively assess the importance of different attributes.
- Conduct comprehensive experiments to explore the influence of various attributes on re-ID task. (a meaningful work)

Future work:

- Construct data from more virtual scenarios/cameras as with richer details.
- Explore the mutual benefits of multiple attributes for fine-grained attribute analysis in re-ID task.

Thank you!