Person Re-IDentification

Related work and project status
First milestone

UNIVERSITÀ DI TRENTO

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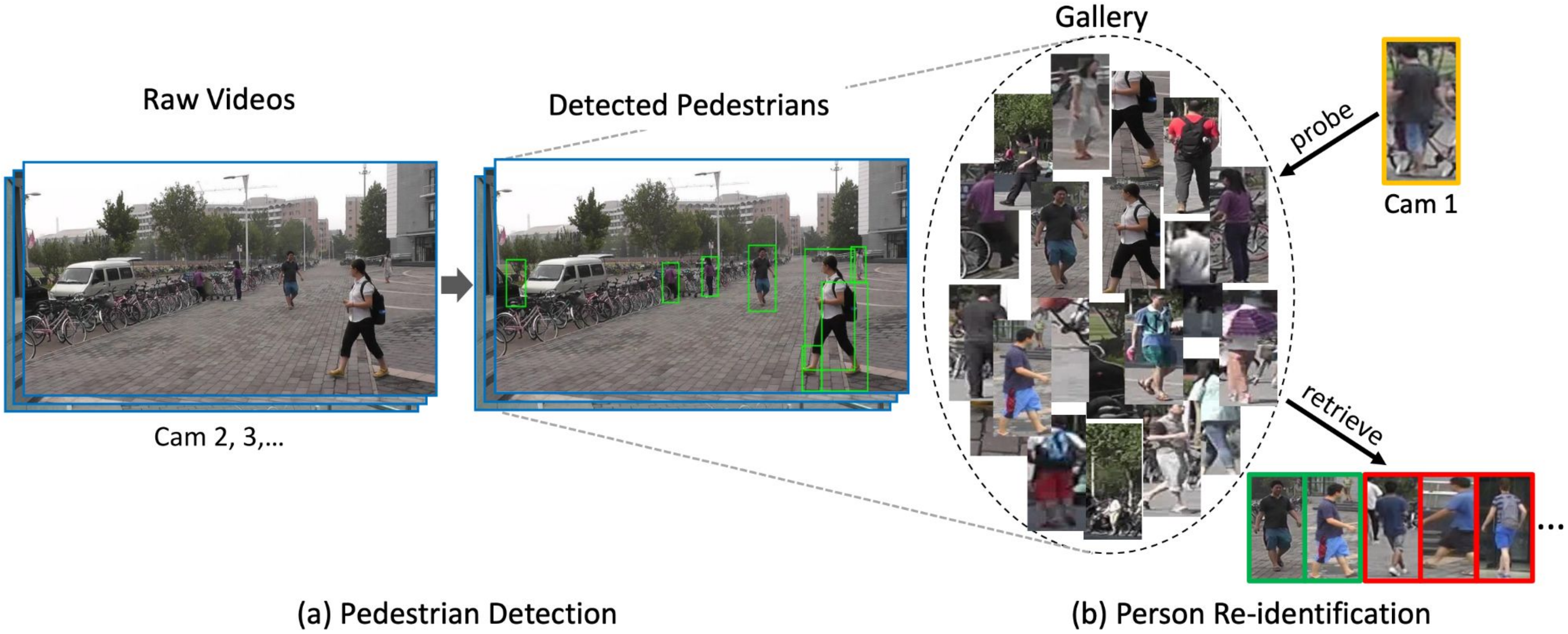
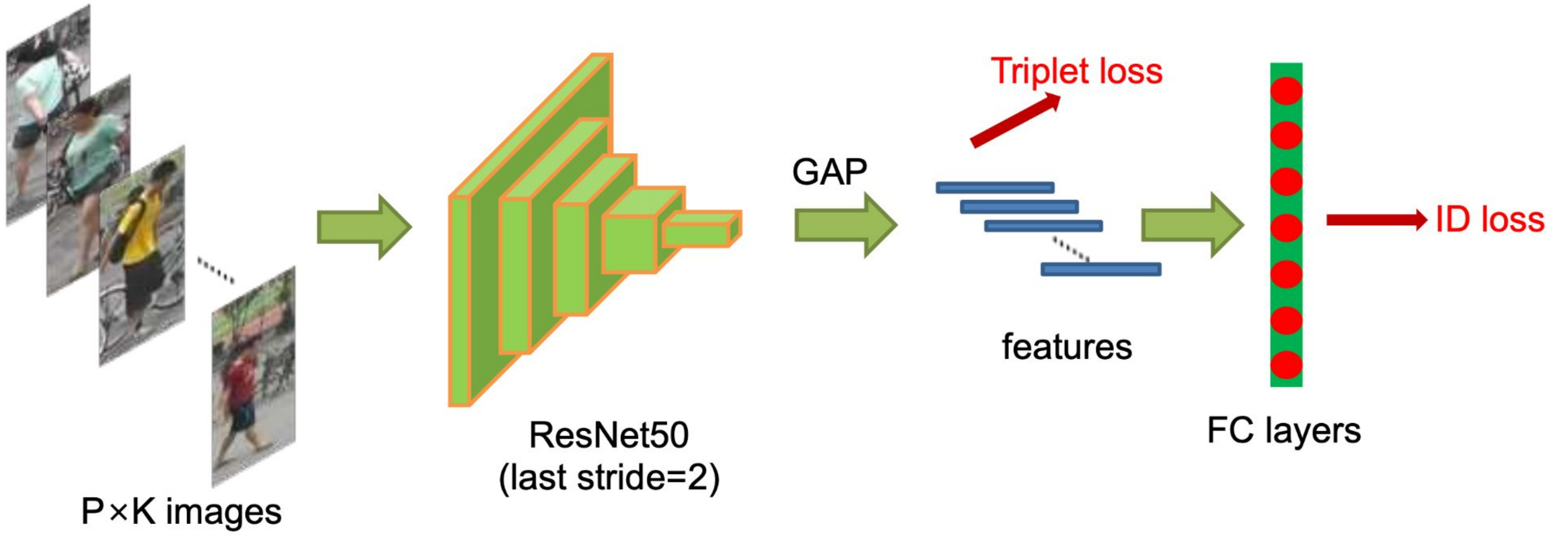
Trends and Applications of Computer Vision
Academic Year 2022/2023

What is Person Re-ID?



Deep Person Re-ID



github.com/Cysu/open-reid

BoT-BS: *Bag of Tricks and a Strong Baseline for Deep Person Re-identification*

1st Paper

He, Tong and Zhang, Zhi and Zhang, Hang and Zhang, Zhongyue and Xie, Junyuan and Li, Mu. Bag of Tricks for Image Classification with Convolutional Neural Networks. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR),* pages 4321-4329, 2019.

BoT-BS | Introduction

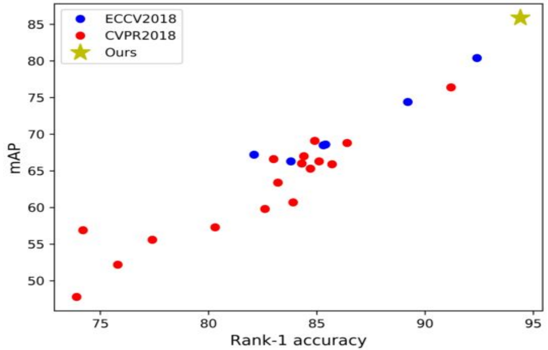
Problem

Complex network structure and a concatenation of multi-branch features

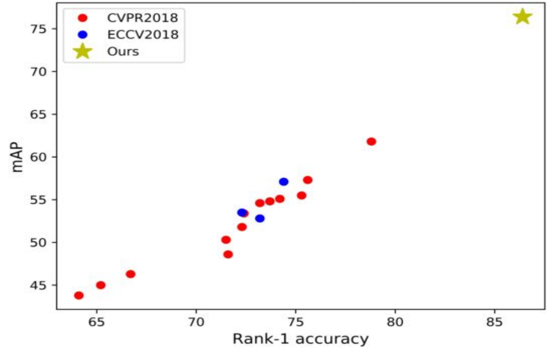
Solution

Improve performance and provide a stronger baseline for future research, for the industry and for the community

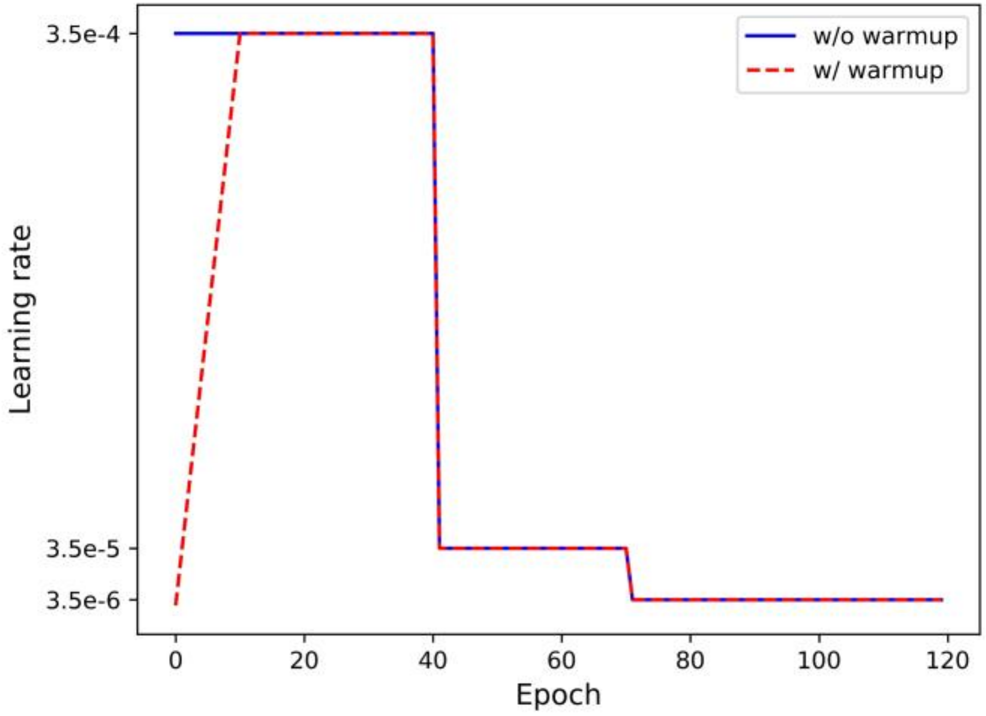
Market1501



DukeMTMC



1st | Warmup Learning Rate



2nd | Random Erasing Augmentation (REA)

Each image in the dataset have a probability p_e of undergoing Random Erasing

➔ In this paper, p_e=0.5

But, REA does harm to models in **cross-domain** ReID task, it decreases its performances by:

>34%
Market1501 → DukeMTMC-reID

>13%
DukeMTMC-reID → Market1501

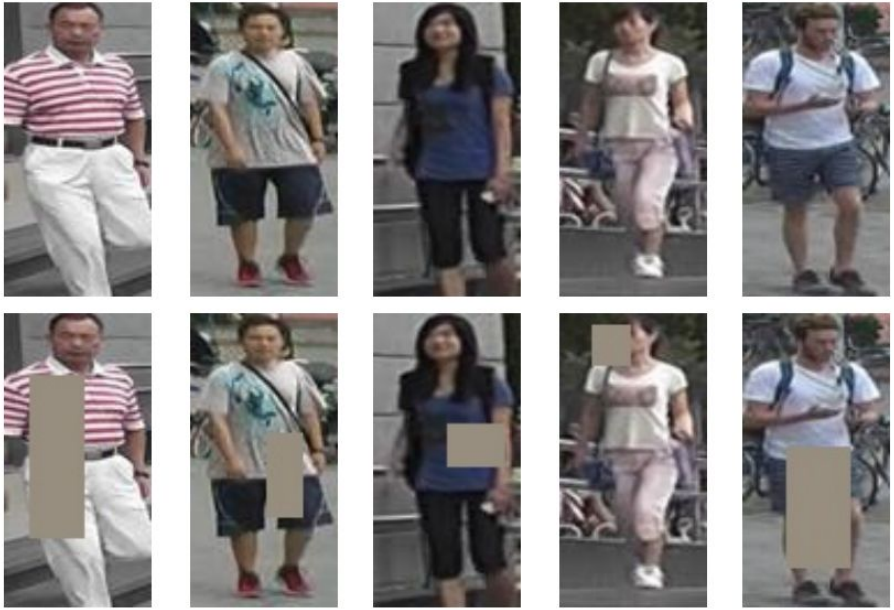
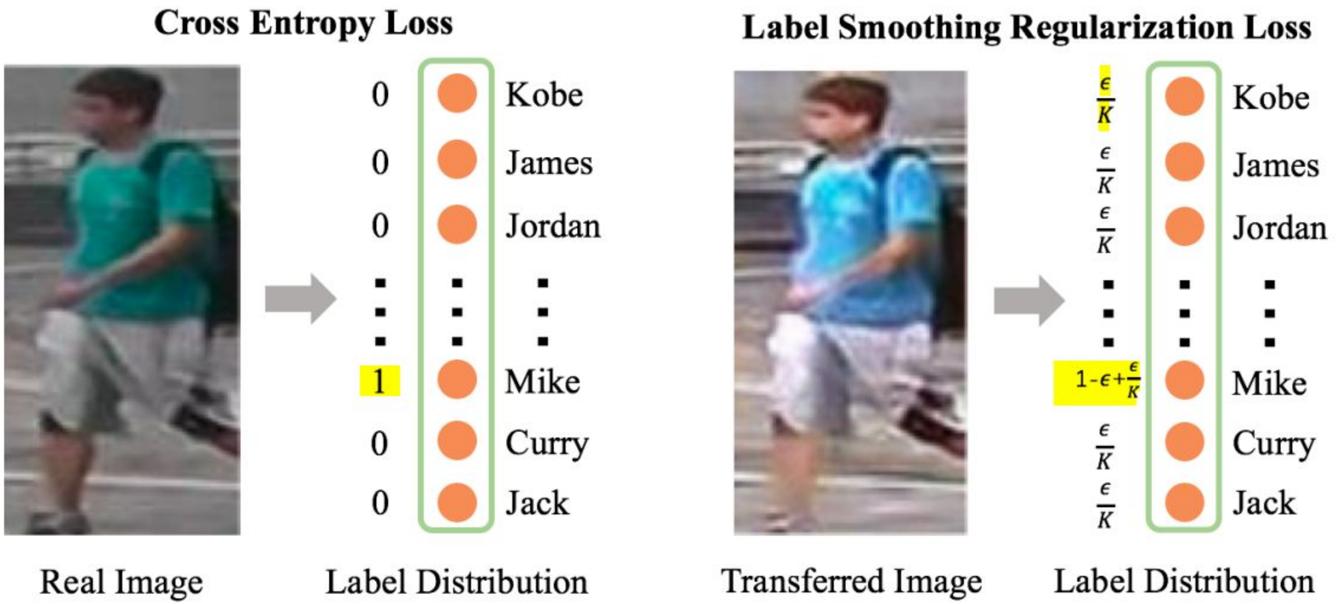


Figure 4. Sampled examples of random erasing augmentation. The first row shows five original training images. The processed images are presented in the second low.

3rd | Label Smoothing



$$L(ID) = \sum_{i=1}^{N} -q_i \log(p_i) \begin{cases} q_i = 0, y \neq i \\ q_i = 1, y = i \end{cases}$$

$$q_i = \begin{cases} 1 - \frac{N-1}{N}\varepsilon & \text{if } i = y \\ \varepsilon / N & \text{otherwise,} \end{cases}$$

Encourages the model to be less confident, to regularize it and make it more adaptable

4th | Last Stride

Hint

Higher spatial resolution always enriches the granularity of the features

ResNet 50
Last Stride=2

ResNet 50
Last Stride=1

5th | BNNeck

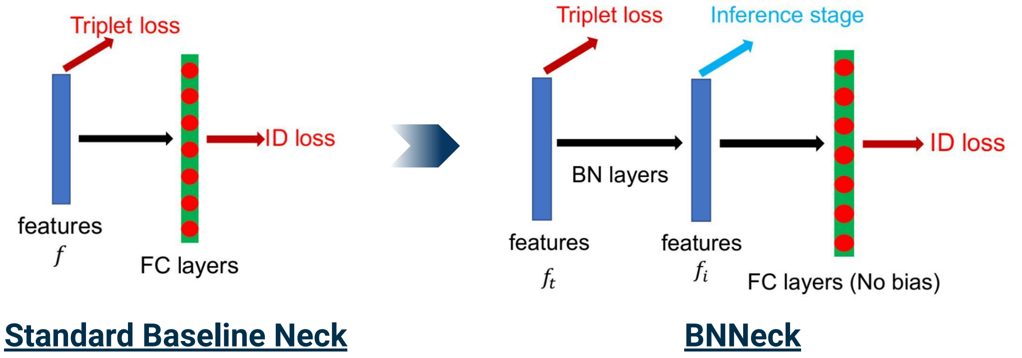
Problem

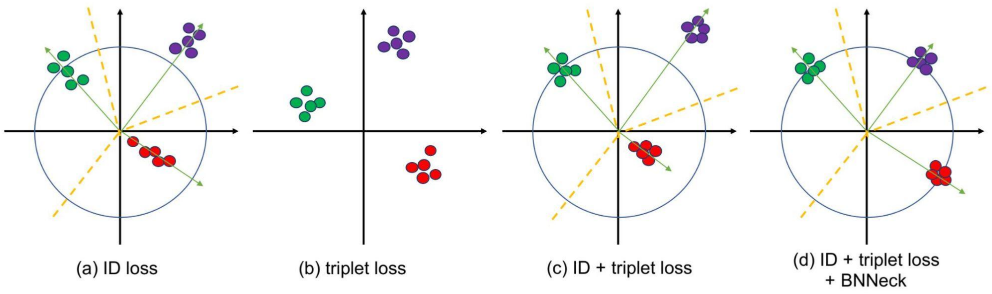
Targets of triplet loss and ID loss are inconsistent in the embedding space

Solution

BNNeck

It adds a batch normalization (BN) layer after features and before the classifier FC layers





Two-dimensional visualization of sample distribution in the embedding space, points of different colors represent embedding features from different classes

6th | Loss

$$L = L_{ID} + L_{Triplet} + \beta L_C$$

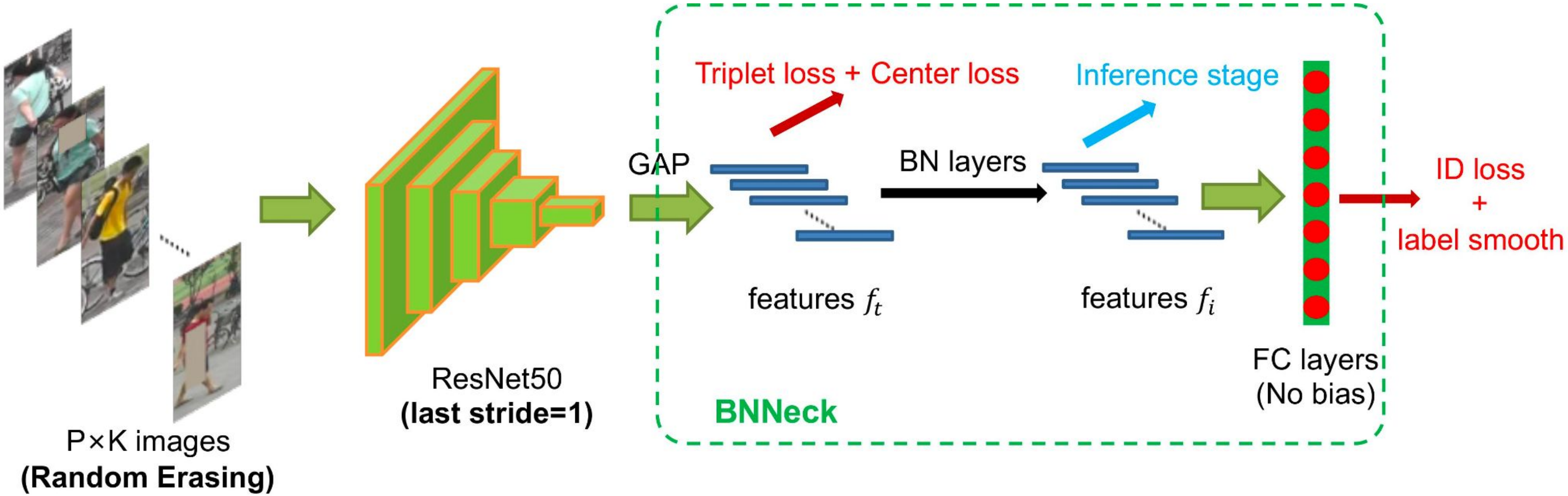
$$L_C = \frac{1}{2}\sum_{j=1}^{B} \left\| f_{t_j} - c_{y_j} \right\|_2^2$$

$$L_{Triplet} = [d_p - d_n + \alpha]_+$$

y_j: Label of the j-th image in a mini batch

c_{yj}: Denotes the y-th class center of deep features

BoT-BS | Illustration



github.com/michuanhaohao/reid-strong-baseline

NFormer: *Robust Person Re-identification with Neighbor Transformer*

2nd Paper

Wang, Haochen and Shen, Jiayi and Liu, Yongtuo and Gao, Yan and Gavves, Efstratios. NFormer: Robust Person Re-identification with Neighbor Transformer.
In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR),* pages 7297-7307, 2022.

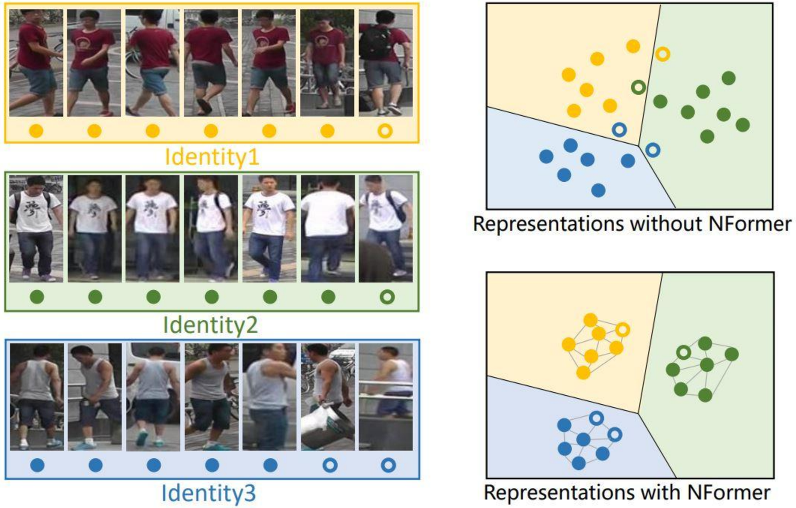
NFormer | Introduction

Problem

Learning representation from single images, ignoring any interactions between them

Solution

<u>**NFormer**</u>
Modeling and learning from **relations** between images



NFormer | Neighbor Transformer Network

Affinity matrix

Model relations between person representations

+

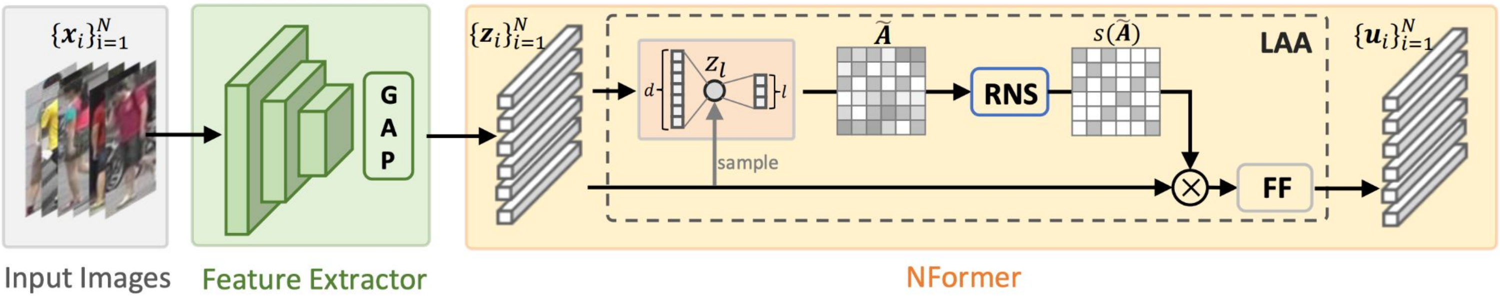
LAA

Reduce the computational cost of the large affinity matrix

+

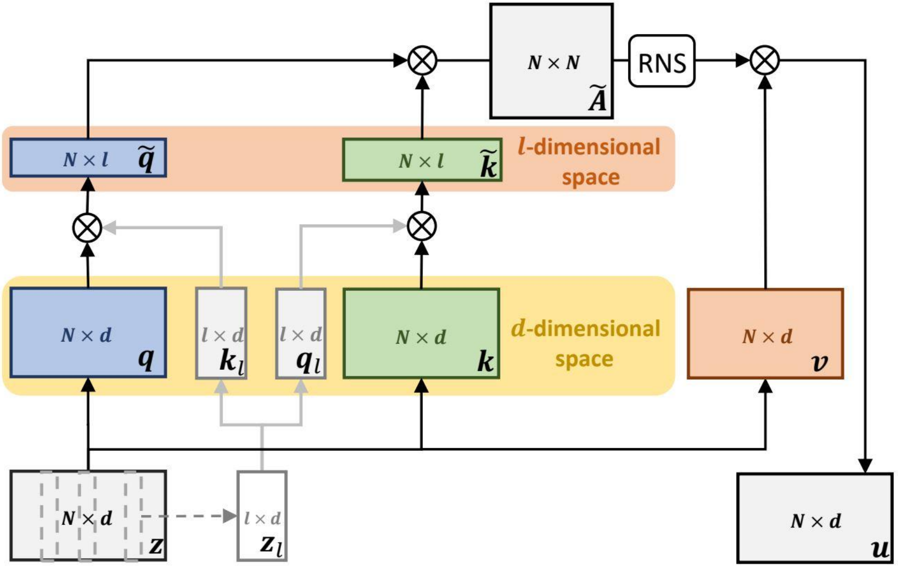
RNS

Strengthen interactions between relevant persons



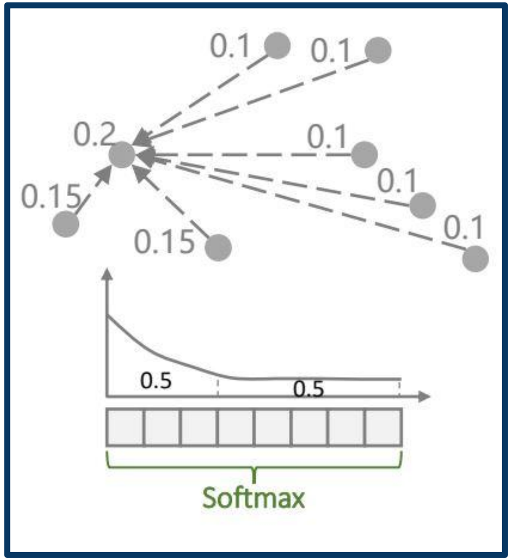
github.com/haochenheheda/NFormer

NFormer | Landmark Agent Attention

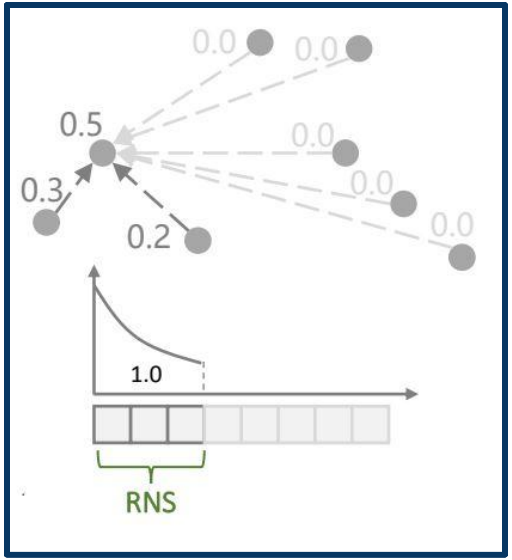


NFormer | Reciprocal Neighbor Softmax

Normal Softmax



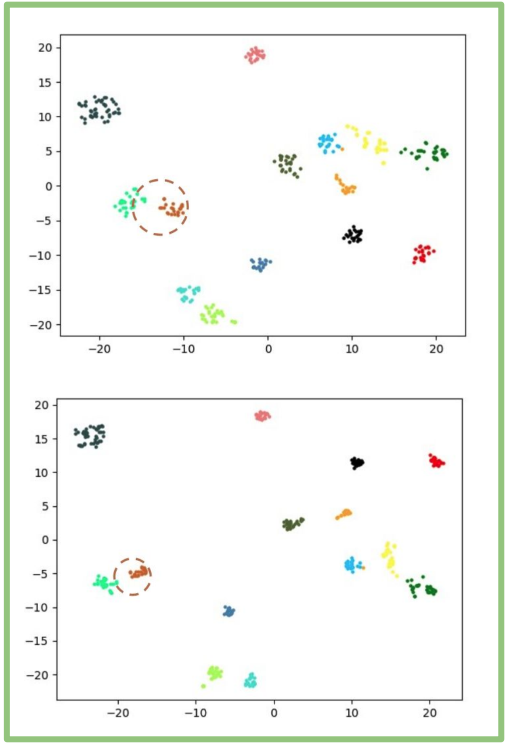
RNS

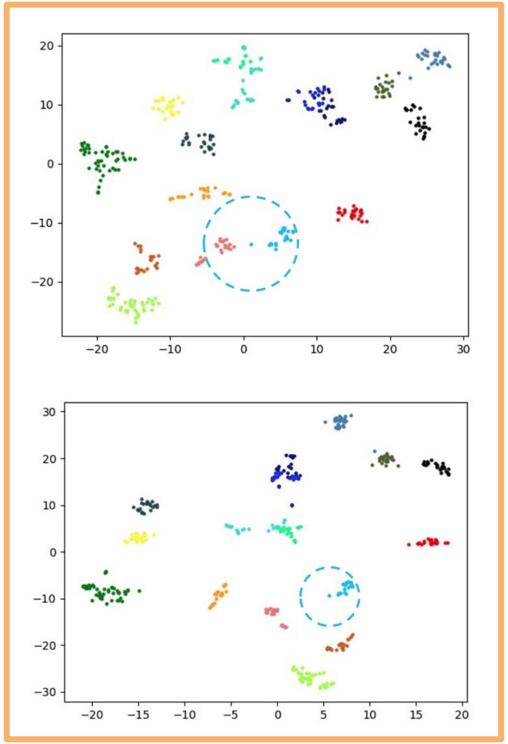


NFormer | Representation vectors

Without NFormer

With NFormer





Market1501

DukeMTMC

Multi-Domain Learning and Identity Mining for **Vehicle Re-Identification**

3rd Paper

S. He, H. Luo, W. Chen, M. Zhang, Y. Zhang, F. Wang, H. Li, and W. Jiang, “Multi-domain learning and identity mining for vehicle re-identification.” [Online]. Available: https://arxiv.org/abs/2004.10547

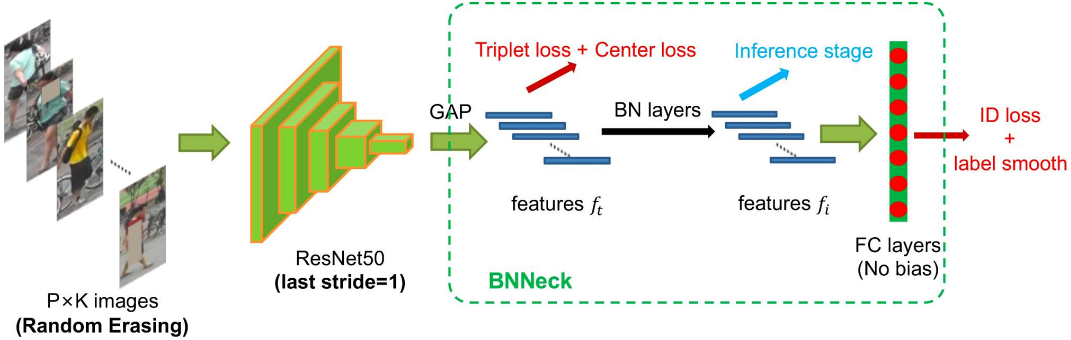
Vehicle re-Identification | Why?

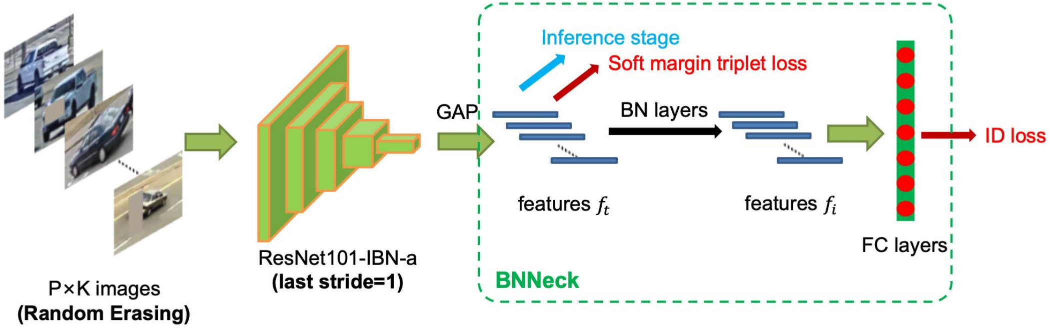
Person Re-ID		Vehicles Re-ID
BoT-BS	→	Multi-Domain Learning and Identity Mining for Vehicle Re-Identification

Without changing implementation

Dataset	Rank-1	mAP
VeRi-776	95.8 %	79.9 %

Vehicle re-Identification | What is changed?





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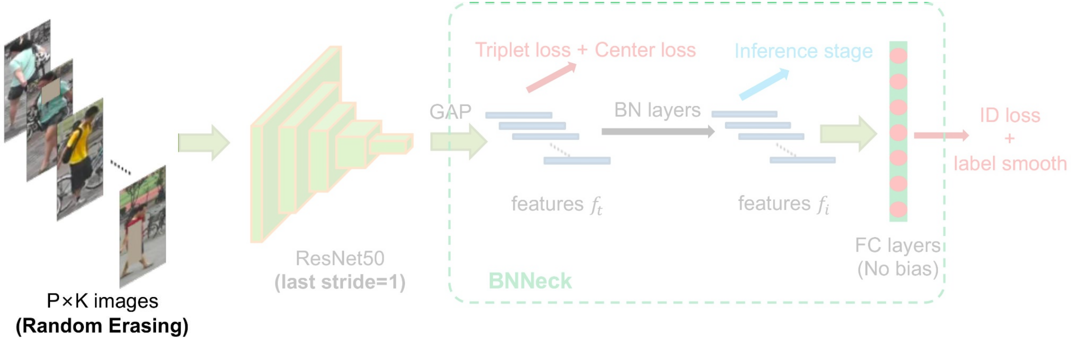

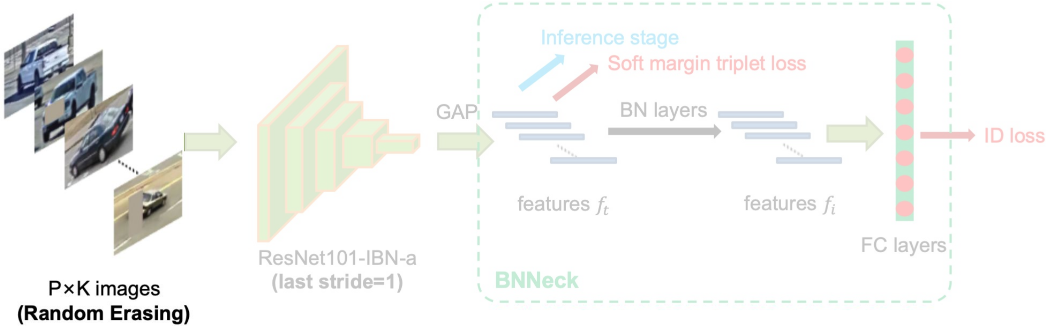

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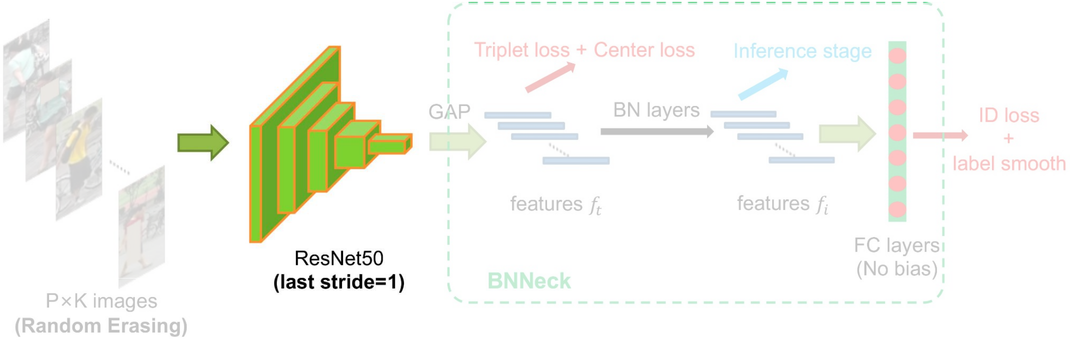

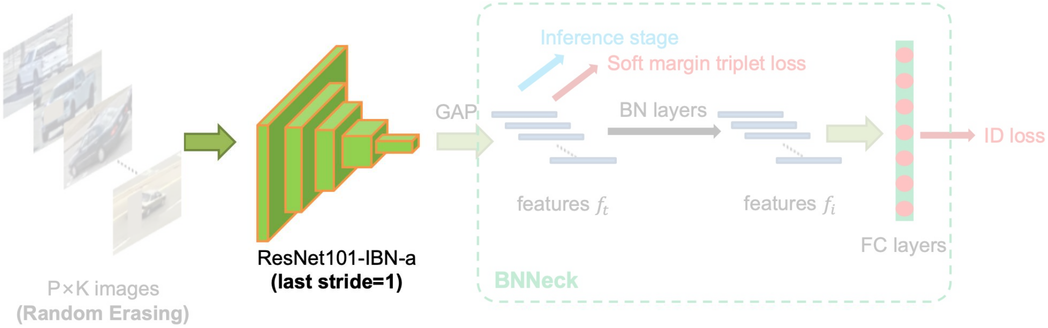

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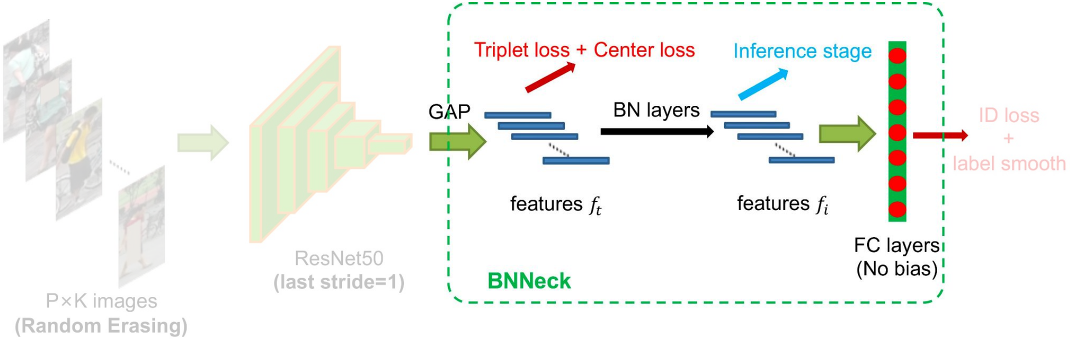

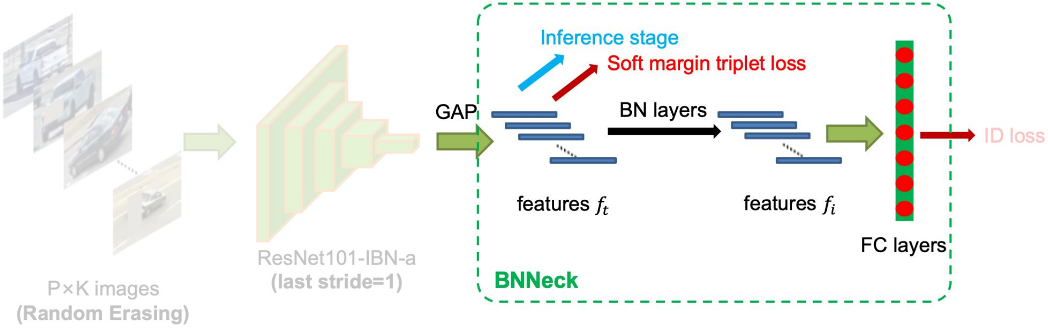

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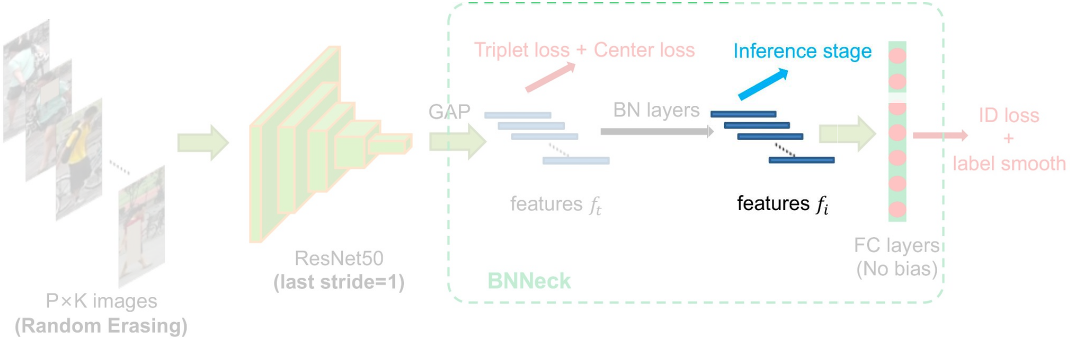

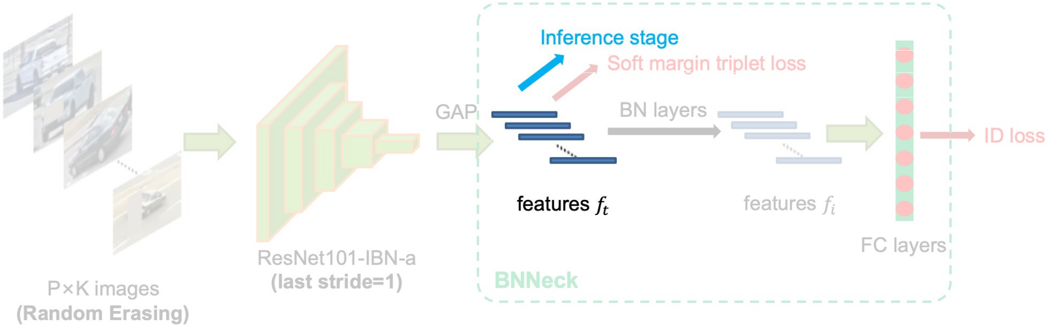

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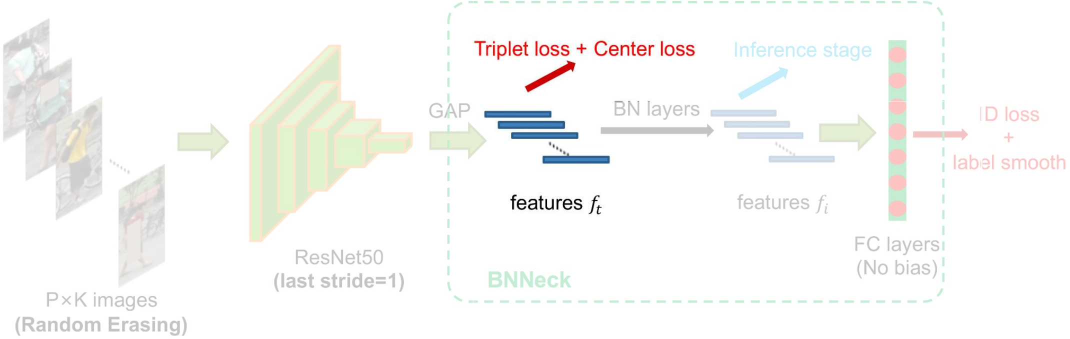

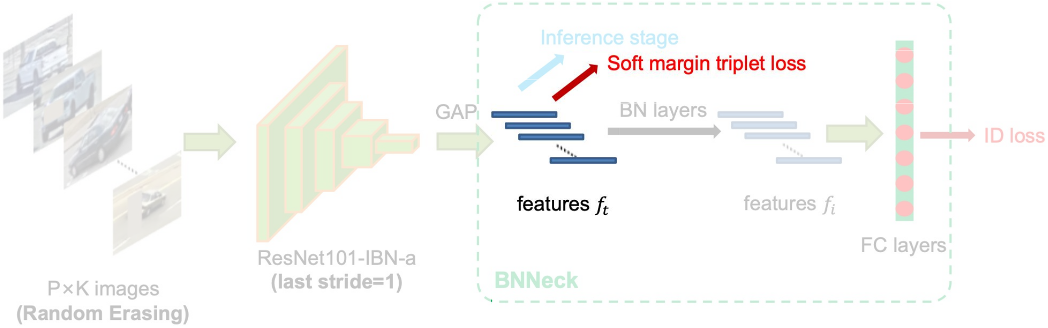

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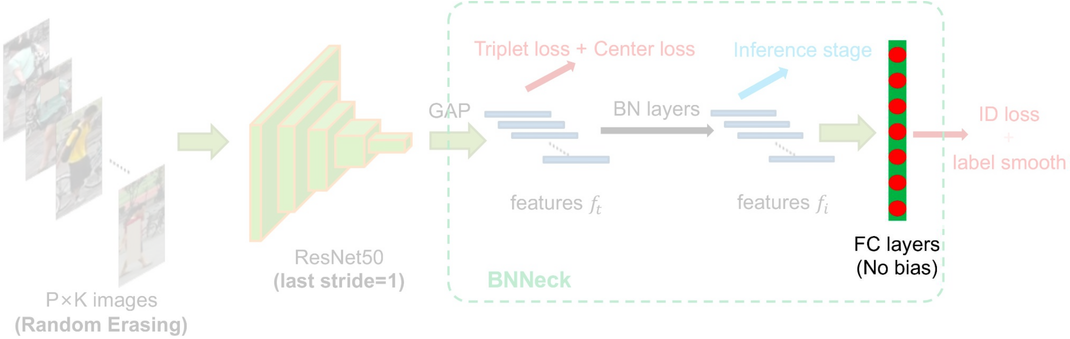

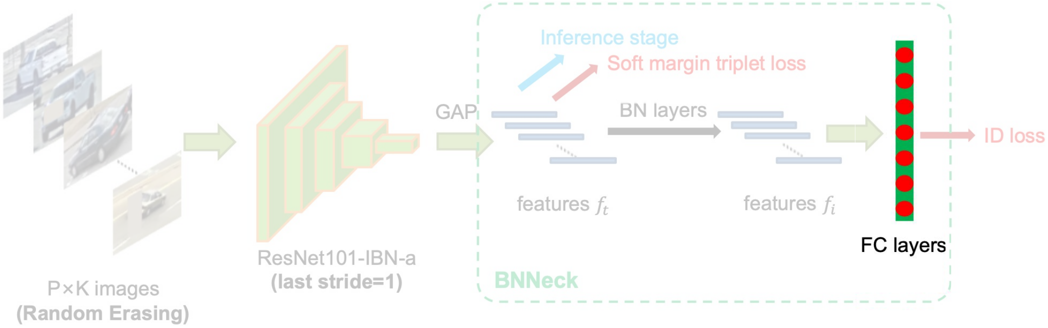

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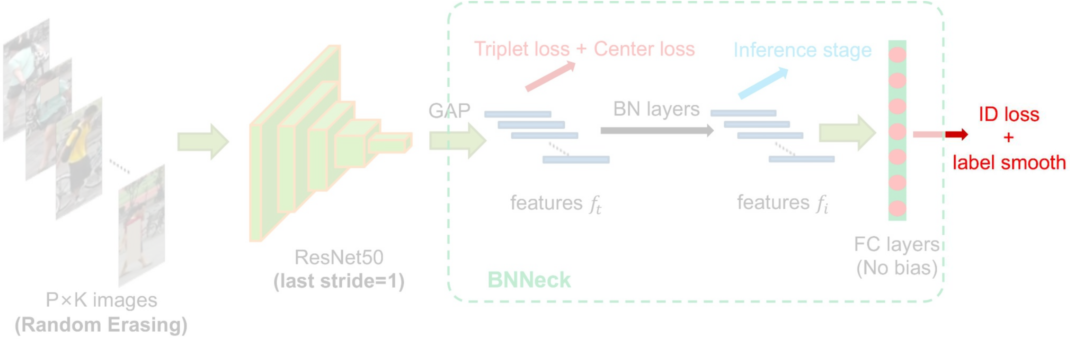

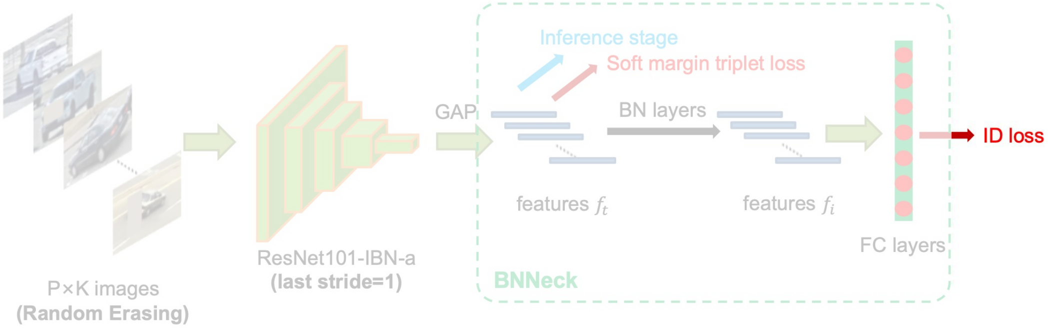

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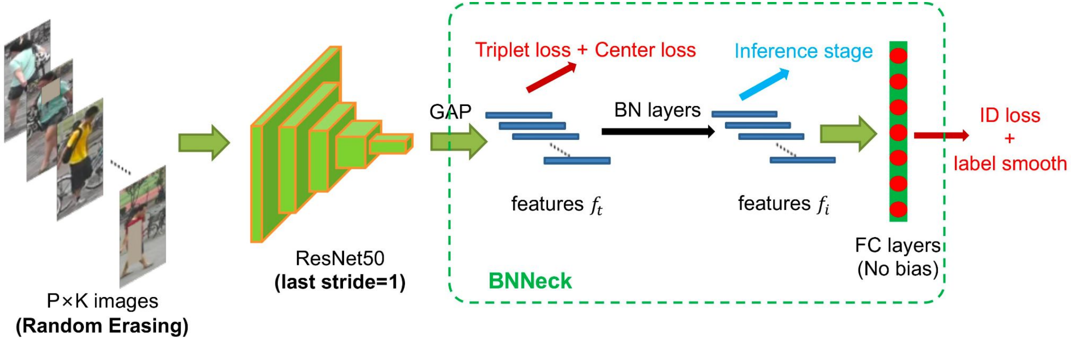

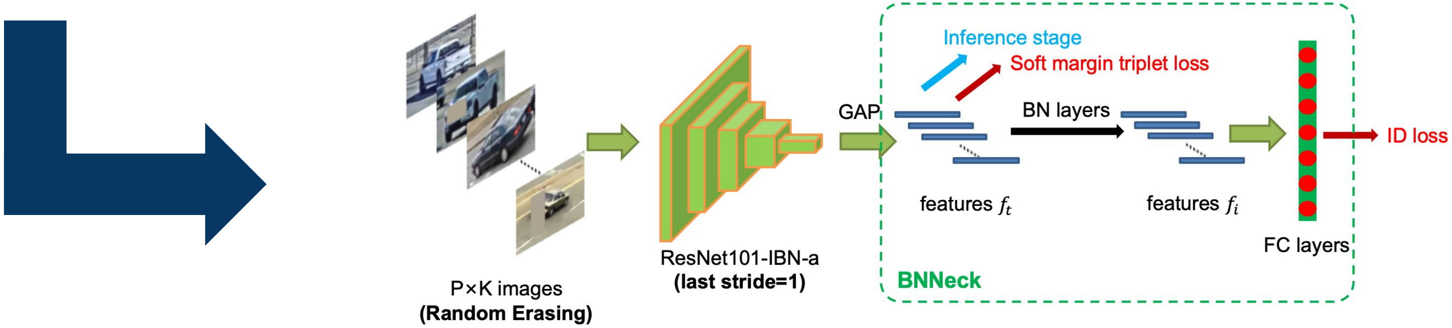

Project Status

Demos and further works

Preliminary results

Train	Test	Train Time	Rank-1	Rank-5	Rank-10	mAP
Market	Market	3h 25m	88.89 %	95.19 %	97.62 %	72.92 %
	Duke		34.06 %	49.64 %	55.83 %	18.28 %
Duke	Market	4h 10m	43.85 %	63.06 %	70.33 %	18.88 %
	Duke		79.30 %	89.09 %	92.05 %	61.45 %

Tests are made on an Azure VM provided by Microsoft with a Nvidia K80 12 Gb GPU

github.com/layumi/Person_reID_baseline_pytorch

Demo | Market trained

Market

Duke

Demo | Duke trained

Duke

Market

Further works

Person Re-ID		Vehicles Re-ID
BoT-BS	→	Multi-Domain Learning and Identity Mining for Vehicle Re-Identification
NFormer	→	?

References

1. He, T., Zhang, Z., Zhang, H., Zhang, Z., Xie, J., & Li, M. (2018). Bag of Tricks for Image Classification with Convolutional Neural Networks. arXiv. https://doi.org/10.48550/arXiv.1812.01187
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