Clothing-Change Feature Augmentation for Person Re-Identification

Ke Han, Shaogang Gong, Yan Huang, Liang Wang, Tieniu Tan

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Presenter: Li Shangze

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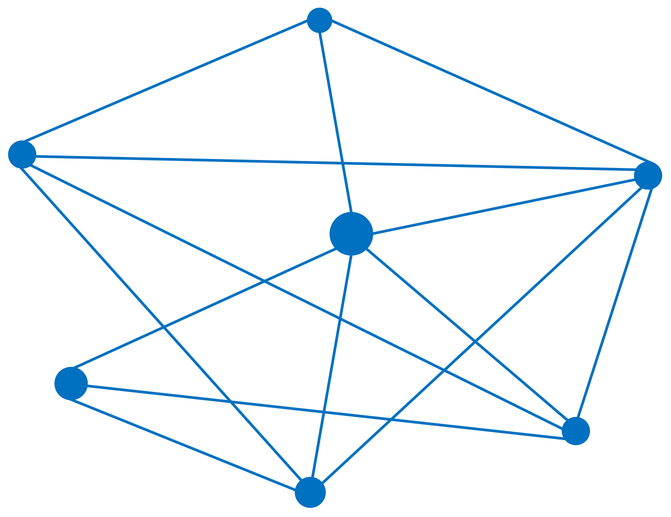
Overview

Background

Contribution



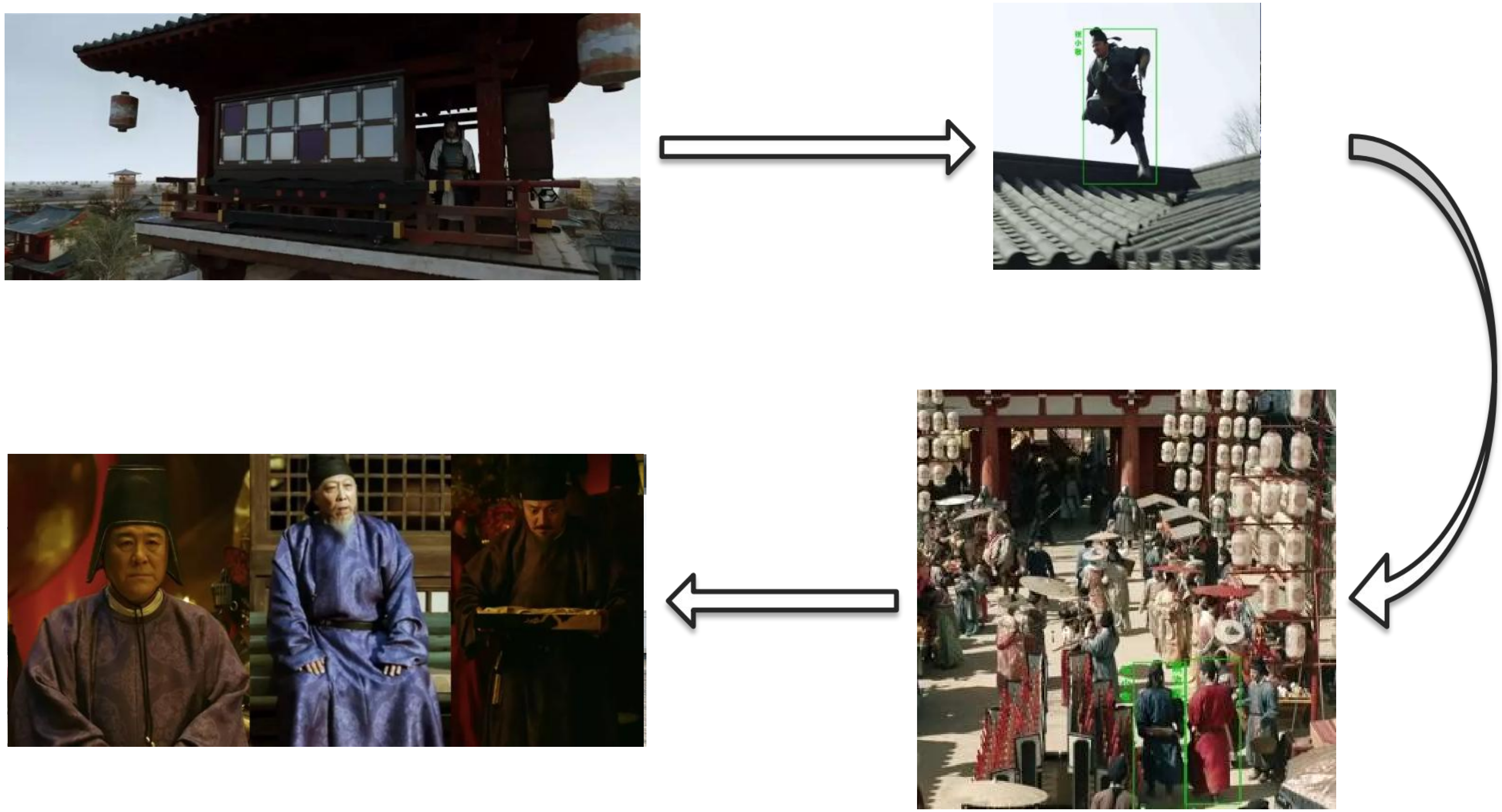
Motivation

Experiment

Method

Background

What is Person Re-identification?



Background

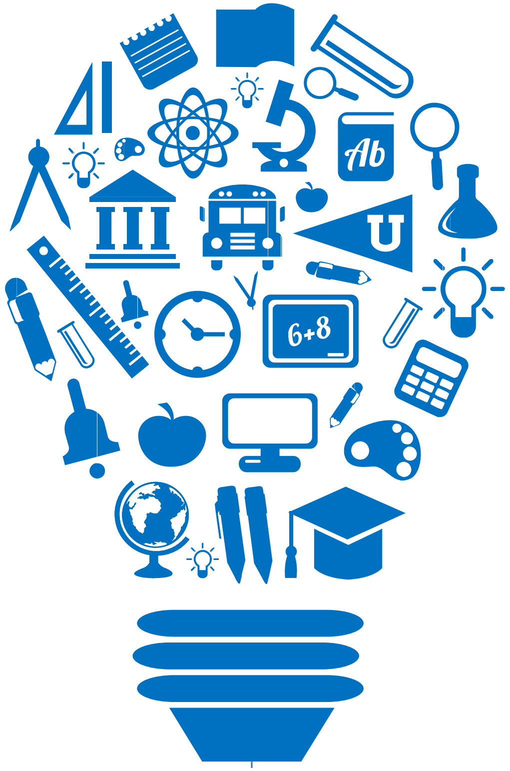
- **One-modality based methods**

  learn clothing-independent representations solely from RGB images

- **Multi-modality based methods**

  exploit other auxiliary information to help capture clothing-independent information

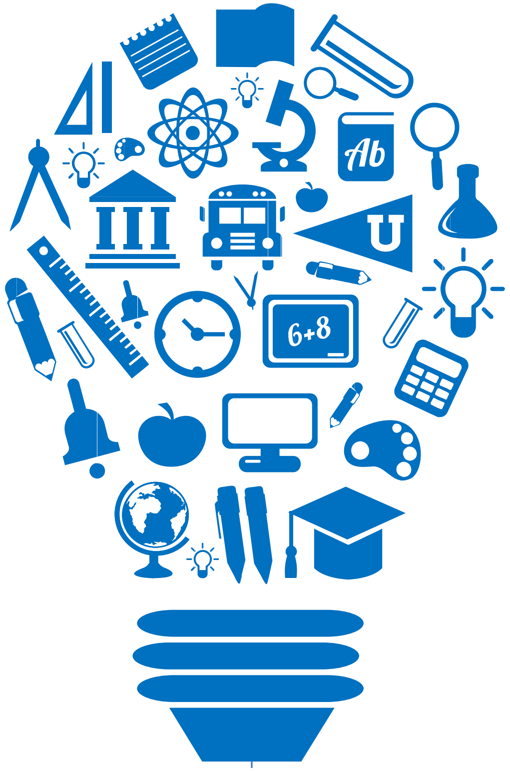
Background



Problem 1

Existing methods’ robustness to clothing variations is limited by the quite limited number and diversity of clothing in training data.

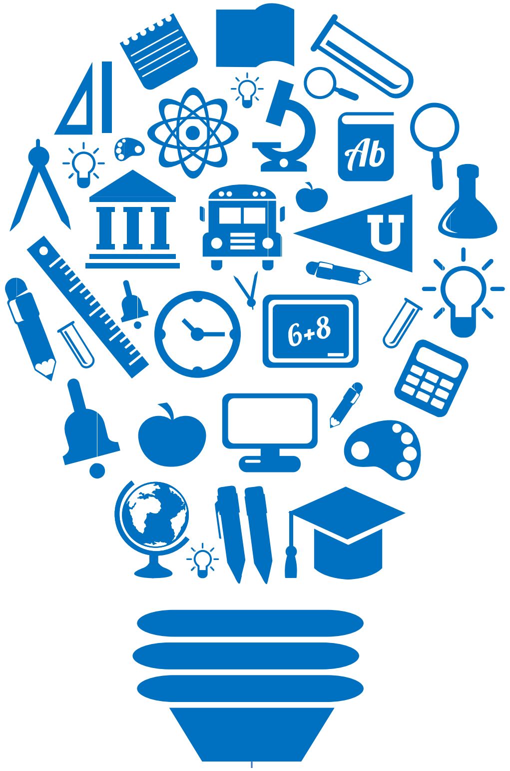
Background



Problem 2

Direct data augmentation in the image space dramatically increases computational time and storage space, and its effectiveness on model generalization is also not directly measurable.

Background

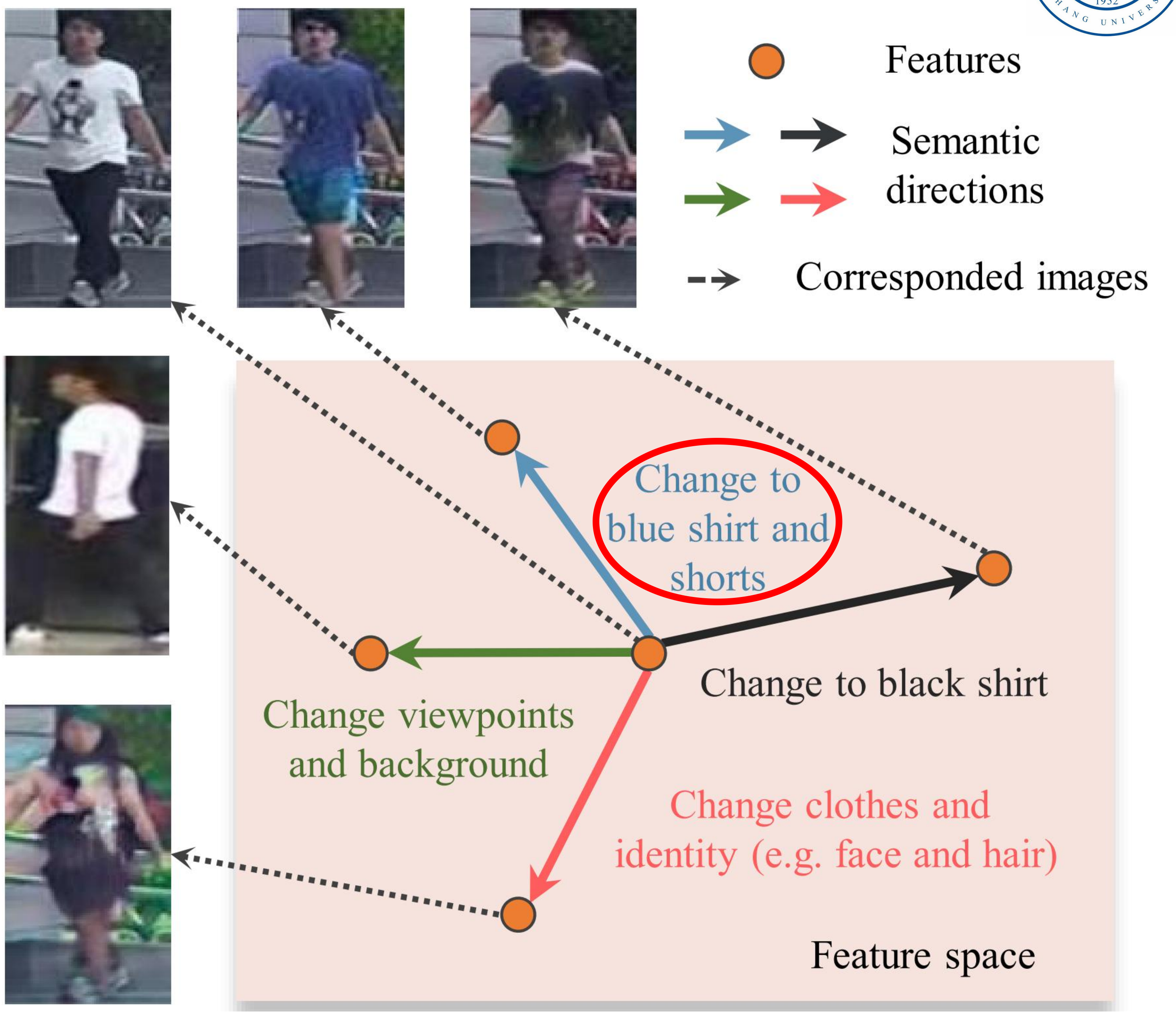


Problem 3

Due to the complexity of image synthesis, current generative Re-ID methods typically only model the exchange of clothes between two persons, and cannot generate plausible new clothes to expand the clothing-change library more freely.

Motivation

There exist many semantic directions in the deep feature space. Transforming a feature representation along specific directions can result in a representation corresponding to another image data sample of different semantics.



Motivation

Resolution

propose a Clothing-Change Feature Augmentation (CCFA) model for CC Re-ID by augmenting implicitly clothing-change data in the feature space

Aim

explore the plausible feature distribution expansion that reflects meaningful clothing colour and texture variations on a person's appearance

Advantages

- computationally more efficient
- expand significantly more new clothes that do not exist in the dataset

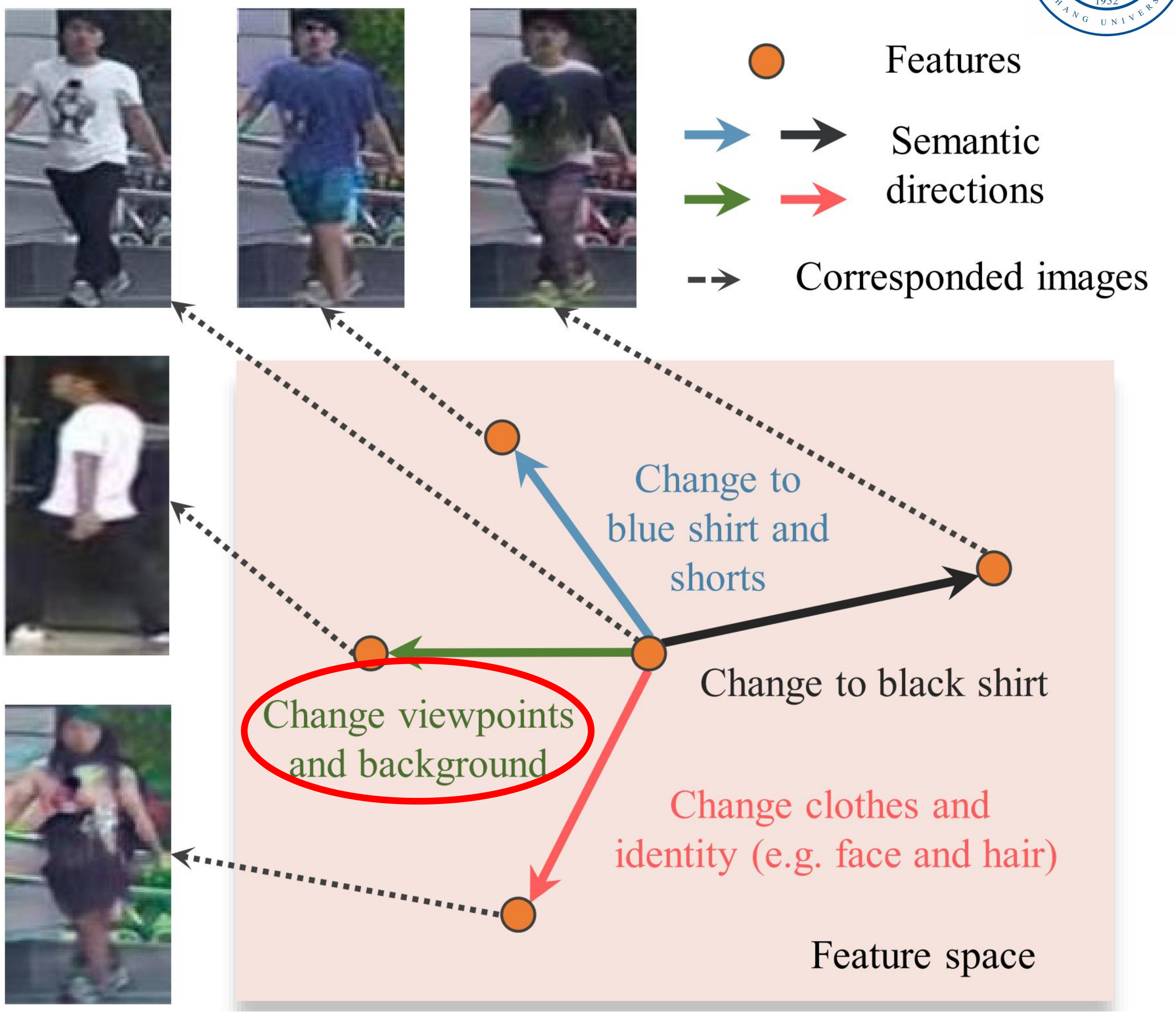
Motivation

Challenge

Many semantic directions of feature expansion are irrelevant to clothing and are semantically meaningless.

Target

Find out meaningful directions in order to maximise the diversity of clothing-change to benefit training.



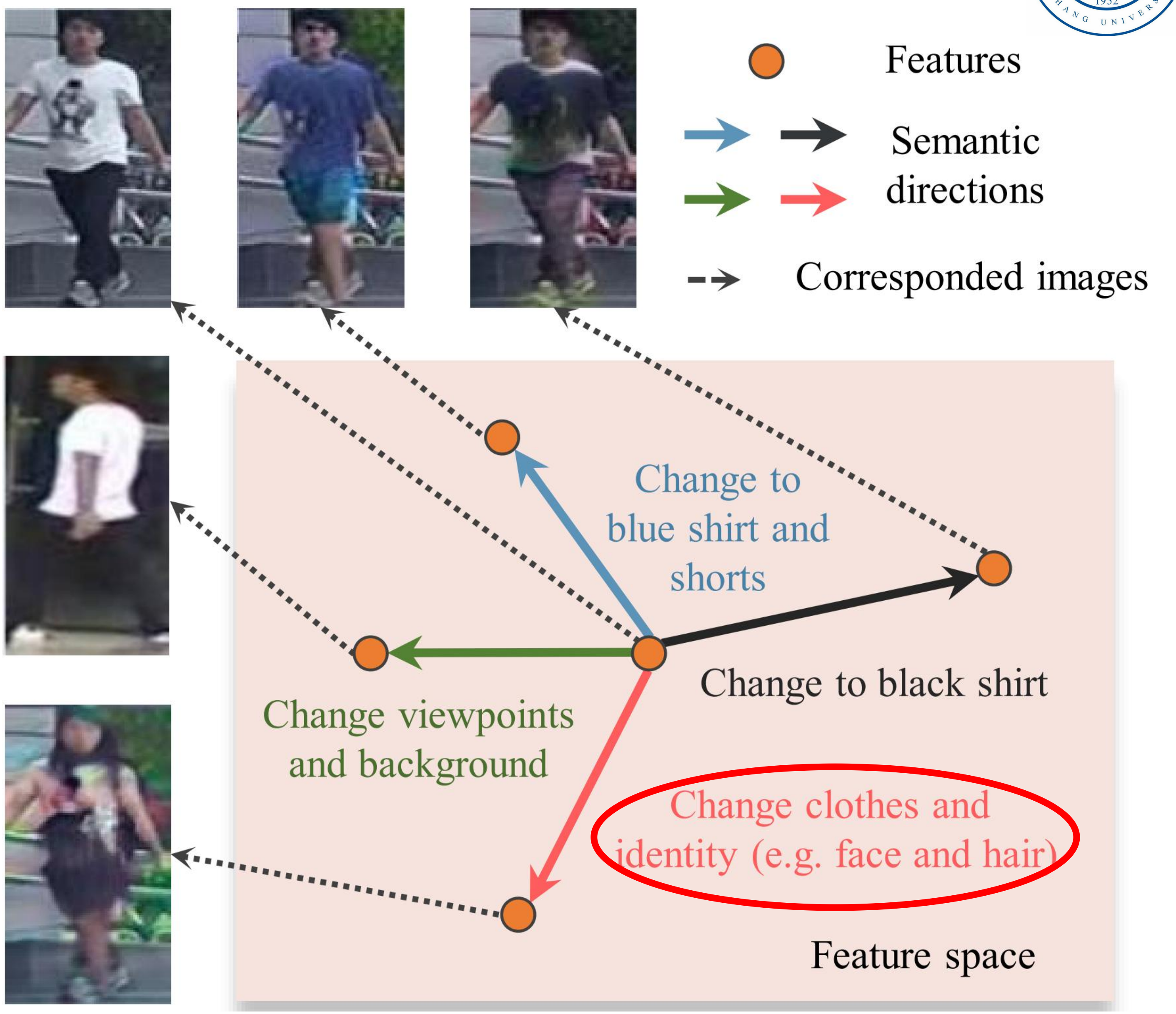
Motivation

Challenge

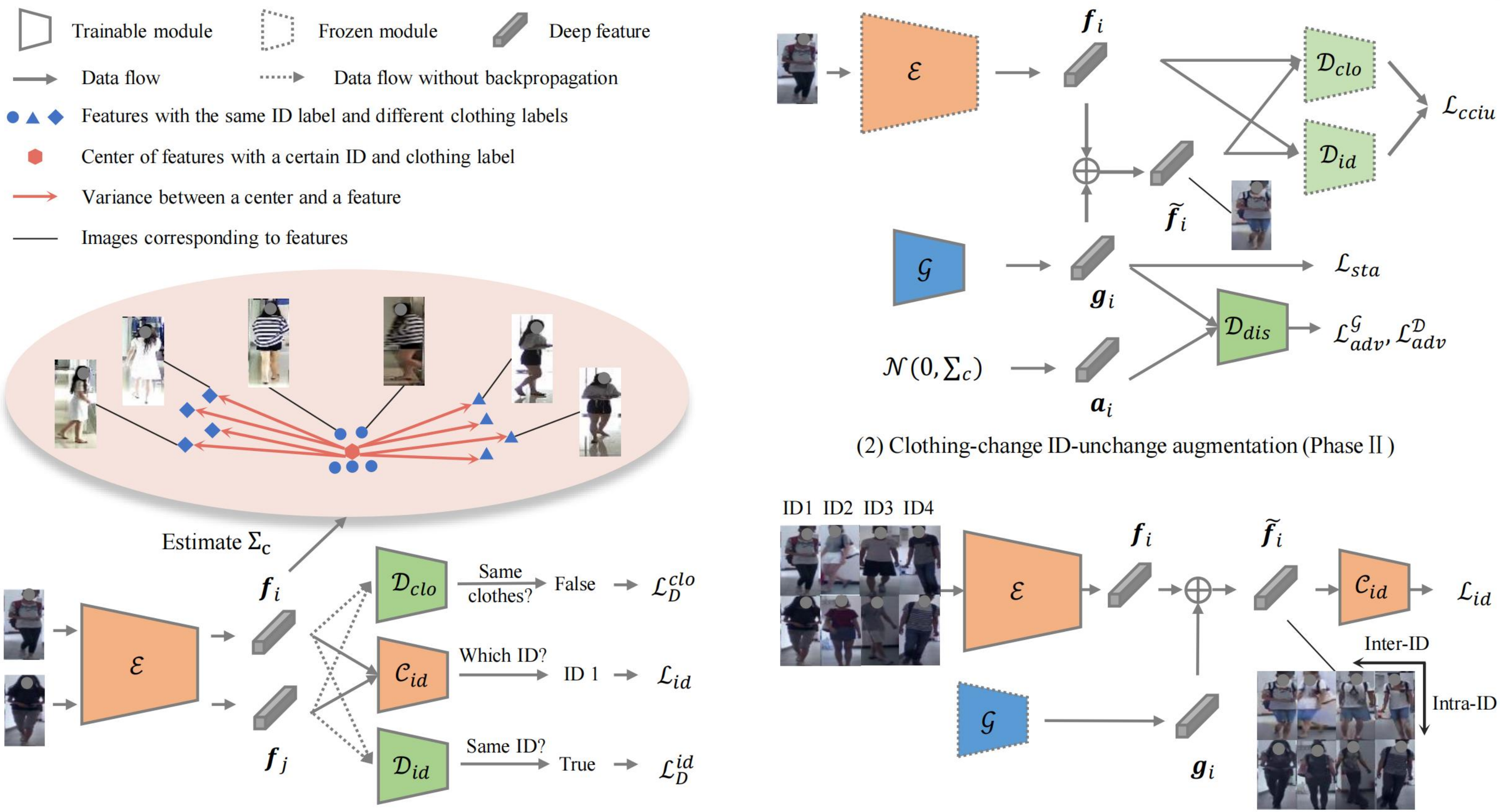
Changing clothes may damage the identity property, i.e. person-specific unique characteristics.

Target

Maintain a person's intrinsic identity property to make meaningful clothing-change augmentation.



Method



(1) Clothing-change covariance estimation (Phase Ⅰ)

(2) Clothing-change ID-unchange augmentation (Phase Ⅱ)

(3) Training with the ID-correlated augmentation strategy (Phase Ⅲ)

Method

➤ Phase I

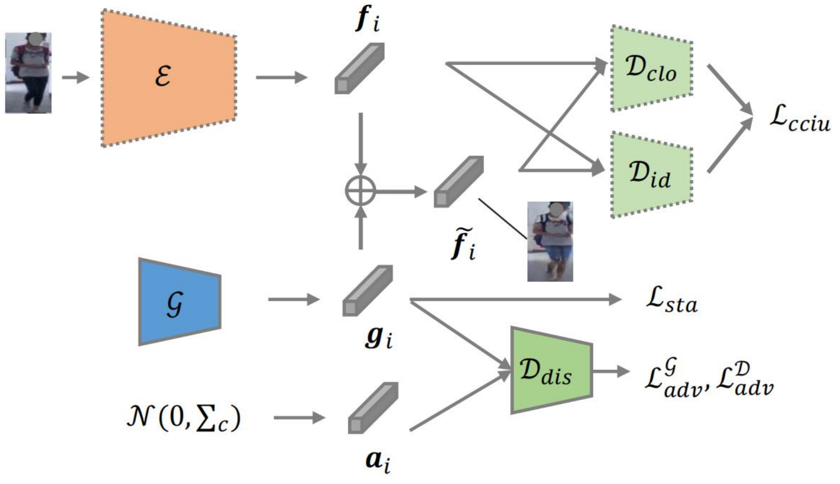
a clothing-change covariance estimation method

➤ Phase II

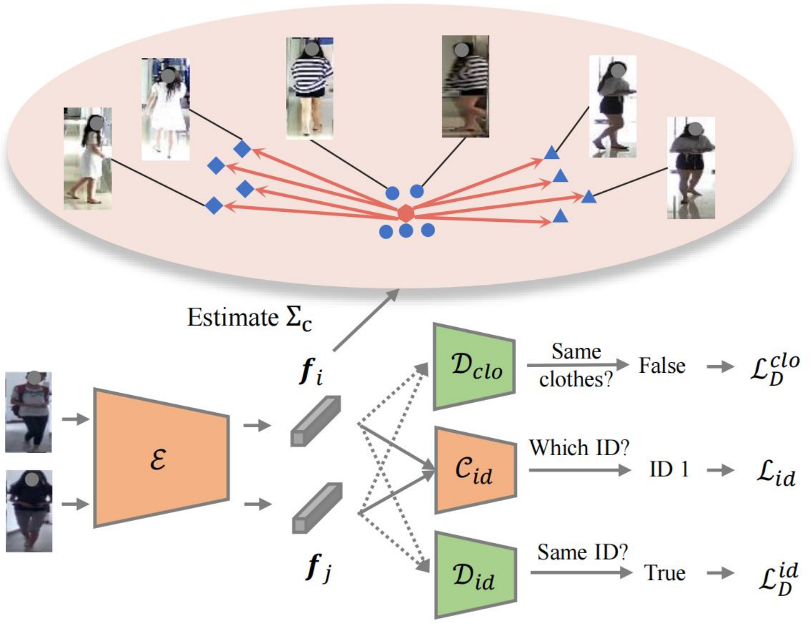
an augmentation generator

➤ Phase III

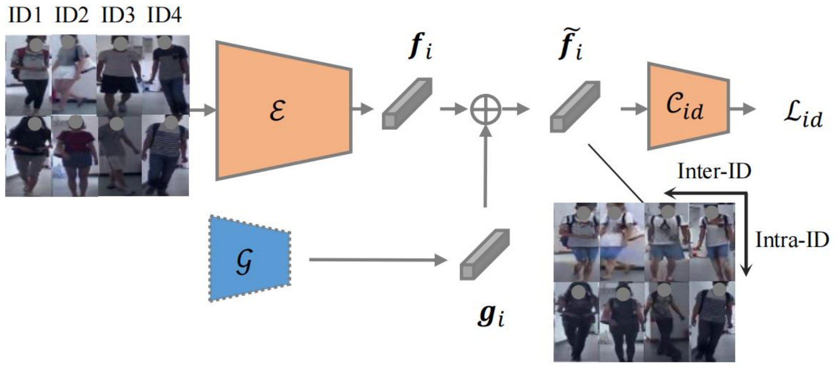
an ID-correlated augmentation strategy



(2) Clothing-change ID-unchange augmentation (Phase II)



(1) Clothing-change covariance estimation (Phase Ⅰ)



(3) Training with the ID-correlated augmentation strategy (Phase III)

Method

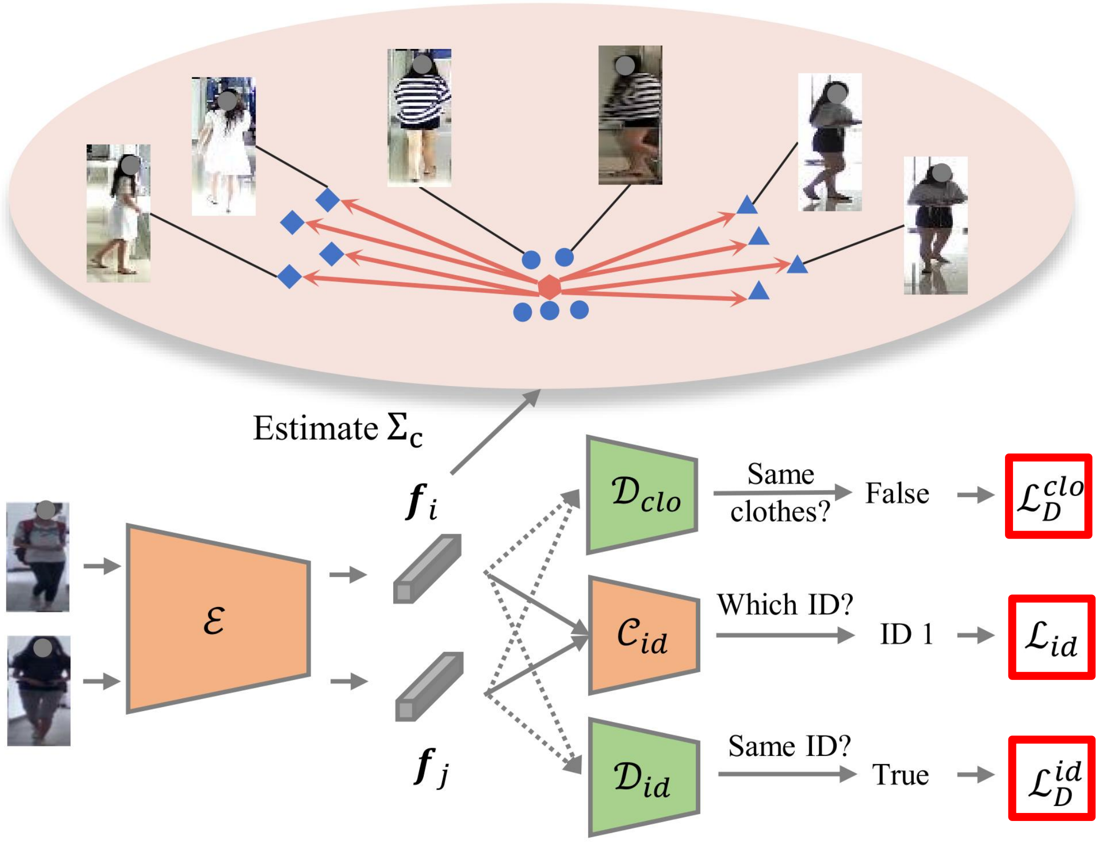
➢ What is **Feature Augmentation?**

$$\mathcal{S} = \{(\boldsymbol{x}_i, y_i, c_i)\}_{i=1}^{N} \qquad \boldsymbol{f}_i = \mathcal{E}(\boldsymbol{x}_i)$$

$$\tilde{\boldsymbol{f}}_i = \boldsymbol{f}_i + \lambda \cdot \boldsymbol{a}_i, where\ \ \boldsymbol{a}_i \sim \mathcal{N}(0, \Sigma_c)$$

covariance vector $(\sigma_1^2, \cdots, \sigma_n^2)$

$$(\Sigma_c')_t = \mathbb{E}[((\boldsymbol{\mu}_t)_{y_i}^{c_i} - \boldsymbol{f}_{y_i}^{c_j})^2]\ \ (i \neq j)$$



(1) Clothing-change covariance estimation (Phase Ⅰ)

$$\mathcal{L}_D^{clo} = -\mathbb{E}[\mathbb{1} \cdot \log(\mathcal{D}_{clo}(\boldsymbol{f}_i, \boldsymbol{f}_j)) + (1 - \mathbb{1}) \cdot \log(1 - \mathcal{D}_{clo}(\boldsymbol{f}_i, \boldsymbol{f}_j))]$$

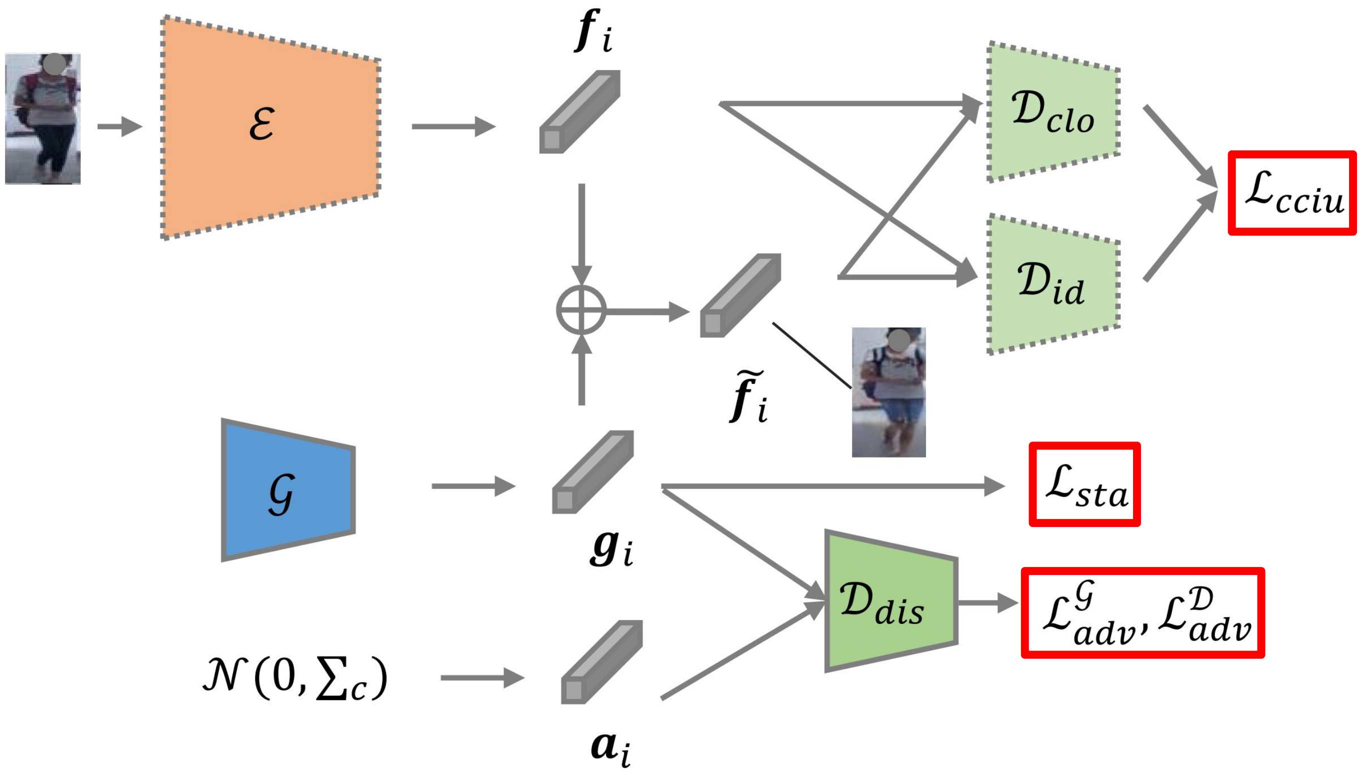
$$\mathcal{L}_{id} = \mathcal{L}_{ce} + \alpha \cdot \mathcal{L}_{tri}$$

$$\mathcal{L}_D^{id} = -\mathbb{E}[\mathbb{1} \cdot \log(\mathcal{D}_{id}(\boldsymbol{f}_i, \boldsymbol{f}_j)) + (1 - \mathbb{1}) \cdot \log(1 - \mathcal{D}_{id}(\boldsymbol{f}_i, \boldsymbol{f}_j))]$$

Method

Criteria

- the clothing information is changed
- the identity property is not changed



(2) Clothing-change ID-unchange augmentation (Phase II)

Total loss

$$\mathcal{L}_{\mathcal{G}} = \mathcal{L}_{adv}^{\mathcal{G}} + \gamma_1 \cdot \mathcal{L}_{sta} + \gamma_2 \cdot \mathcal{L}_{cciu}$$

maximise clothing-change

minimise identity-change

$$\mathcal{L}_{cciu} = -\mathbb{E}[\log(1 - \mathcal{D}_{clo}(\boldsymbol{f}_i, \tilde{\boldsymbol{f}}_i)) + \log(\mathcal{D}_{id}(\boldsymbol{f}_i, \tilde{\boldsymbol{f}}_i)]$$

$$\mathcal{L}_{sta} = \|\mathbb{E}[\boldsymbol{g}_i]\|_1 + \|\mathbb{E}[(\mathbb{E}[\boldsymbol{g}_i] - \boldsymbol{g}_i)^2] - \Sigma_c\|_1$$

$$\mathcal{L}_{adv}^{\mathcal{D}} = -\mathbb{E}[\log(\mathcal{D}_{dis}(\boldsymbol{a}_i)) + \log(1 - \mathcal{D}_{dis}(\boldsymbol{g}_i))]$$

$$\mathcal{L}_{adv}^{\mathcal{G}} = \mathbb{E}[-\log(\mathcal{D}_{dis}(\boldsymbol{g}_i))]$$

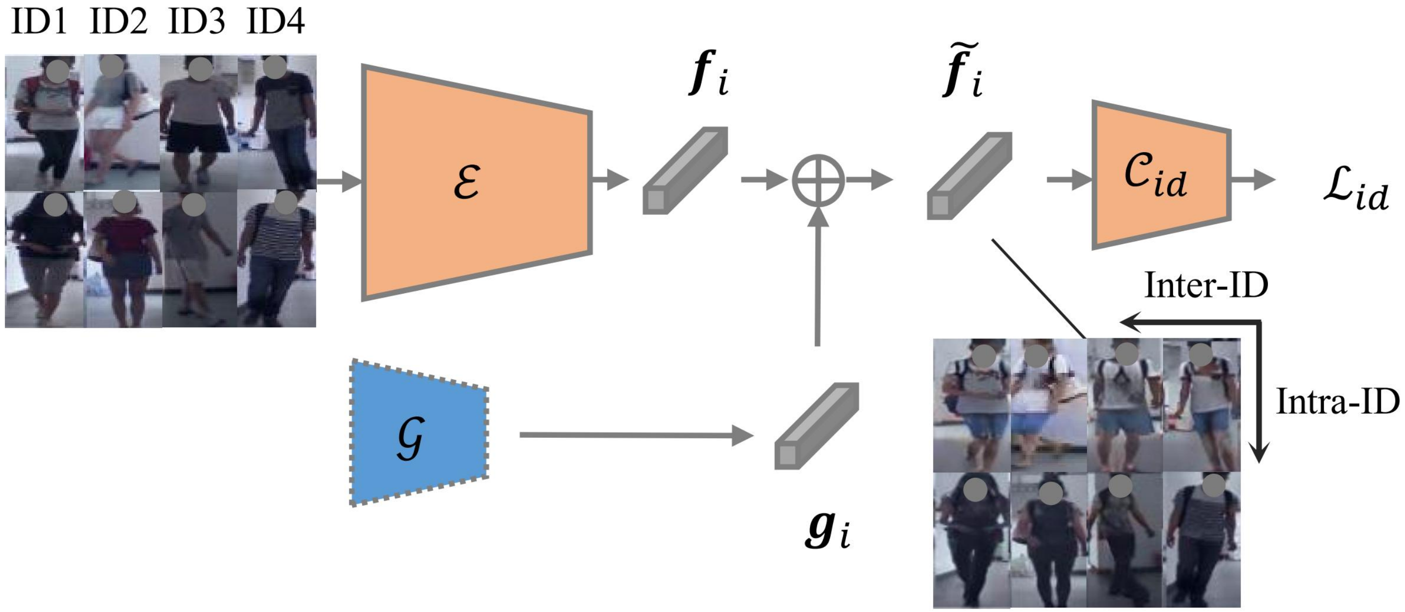
Method

➤ ID-correlated augmentation strategy

(1) $\boldsymbol{f}_i$ (2) $\tilde{\boldsymbol{f}}_i$ with ID-uncorrelated augmentation (3) $\tilde{\boldsymbol{f}}_i$ with ID-correlated augmentation

Resolution

- different augmentation on the same person
- the same augmentation on different persons



(3) Training with the ID-correlated augmentation strategy (Phase III)

Consequence

- the intra-ID clothing variations are increased
- the inter-ID clothing variations are reduced

Method

Algorithm 1 Training procedure of the CCFA model

Input: $M \cdot J$ images, where M and J are the numbers of persons and images per person in a mini-batch.

for *each mini-batch* **do**
    Extract features by $\mathcal{E}$.
    if ***Phase I*** **then**
        Estimate covariance vector Σ_c via Eq. (2).
        Optimise $\mathcal{E}$ and $\mathcal{C}_{id}$ via Eq. (3), $\mathcal{D}_{clo}$ via Eq. (4), and $\mathcal{D}_{id}$ via Eq. (5).
    else if ***Phase II*** **then**
        Freeze $\mathcal{E}$, $\mathcal{D}_{clo}$ and $\mathcal{D}_{id}$.
        Optimise $\mathcal{G}$ via Eq. (10) and $\mathcal{D}_{dis}$ via Eq. (7).
    else if ***Phase III*** **then**
        Freeze $\mathcal{G}$.
        for j in range(J) **do**
            $\mathcal{G}$ generates a random augmentation vector $\boldsymbol{g}_j$.
            Perform ID-correlated augmentation:
            $\tilde{\boldsymbol{f}}_{1j} = \boldsymbol{f}_{1j} + \lambda \cdot \boldsymbol{g}_j, \cdots, \tilde{\boldsymbol{f}}_{Mj} = \boldsymbol{f}_{Mj} + \lambda \cdot \boldsymbol{g}_j$,
            where $\boldsymbol{f}_{mj}$ is the feature vector of the j-th sample of the m-th person in a mini-batch, and $\tilde{\boldsymbol{f}}_{mj}$ is the augmented feature vector.
        end
        Optimise $\mathcal{E}$ and $\mathcal{C}_{id}$ via Eq. (3).

end

Experiment

Method Type	Method	Modality	PRCC [39]				LTCC [25]			
			CC Mode		SC Mode		CC Mode		General Mode	
			mAP	Rank 1	mAP	Rank 1	mAP	Rank 1	mAP	Rank 1
Feature Augmentation	SFA [19]	RGB	47.8	49.6	94.8	98.3	11.8	34.8	33.6	61.7
	IDSA [37]	RGB	49.1	50.2	95.6	98.6	12.2	34.2	33.9	64.6
CC Re-ID	CESD [25]	RGB+pose	-	-	-	-	12.4	26.1	34.3	71.4
	SPT+ASE [39]	Sketch	-	34.4	-	64.2	-	-	-	-
	3DSL [2]	RGB+pose+sil.+3D	51.3	-	-	-	14.8	31.2	-	-
	FSAM [13]	RGB+pose+sil.	-	54.5	-	98.8	16.2	38.5	35.4	73.2
	SPS [27]	RGB+parsing	<u>57.2</u>	**62.8**	96.7	99.5	16.7	<u>42.1</u>	37.6	70.9
	RCSANet [15]	RGB	50.2	48.6	97.2	**100**	-	-	-	-
	GI-ReID [17]	RGB+sil.	37.5	-	-	-	10.4	23.7	29.4	63.2
	CAL [7]	RGB	55.8	55.2	**99.8**	**100**	<u>18.0</u>	40.1	<u>40.8</u>	<u>74.2</u>
	CCFA (Phase I)	RGB	47.5	48.1	95.3	98.0	11.4	33.8	30.6	65.7
	CCFA (Phase III)	RGB	**58.4**	<u>61.2</u>	<u>98.7</u>	<u>99.6</u>	**22.1**	**45.3**	**42.5**	**75.8**

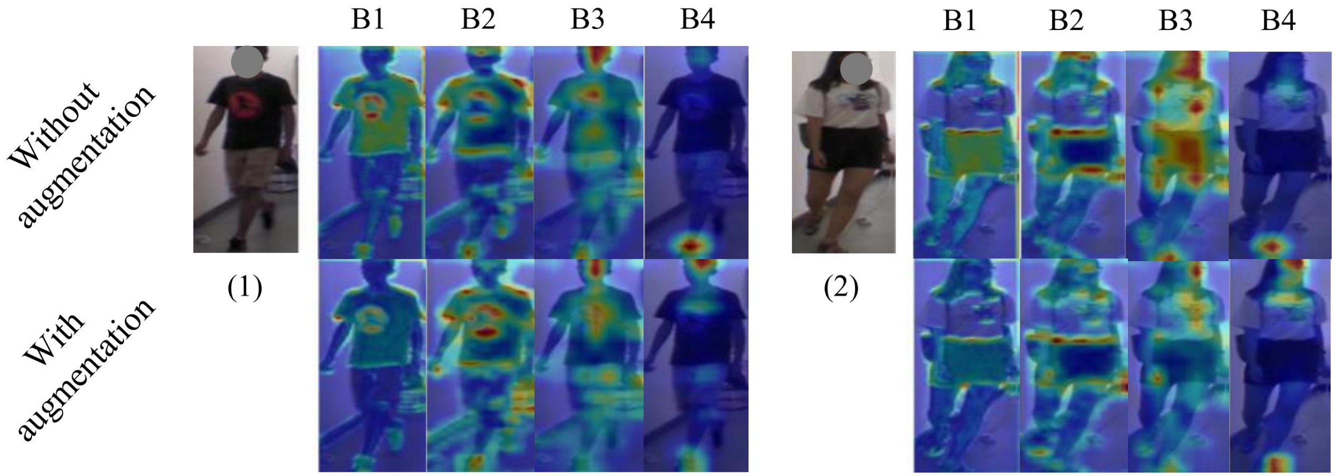
Other methods

- only learn representations from existing data
- need auxiliary training data of other modalities

This method

- synthesize abundant meaningful new clothing variations
- only use RGB images, free of estimation errors

Experiment

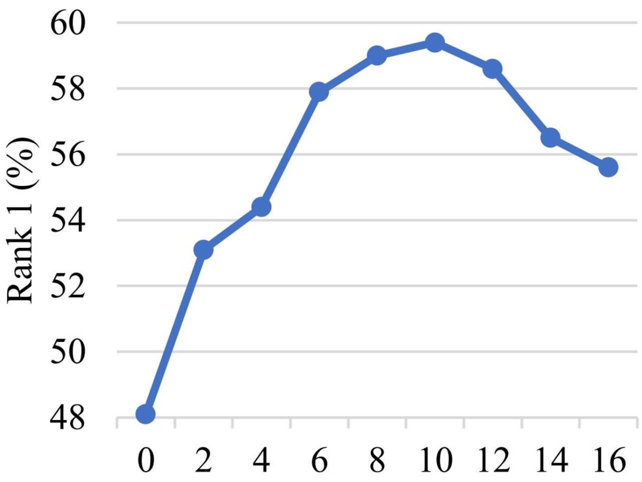


Augmentation Generation	CC Mode	SC Mode
Baseline (w/o augmentation)	48.1	98.0
With $\mathcal{N}(0, \Sigma_c)$	57.6	99.2
With $\mathcal{G}$ (ours)	**61.2**	**99.6**

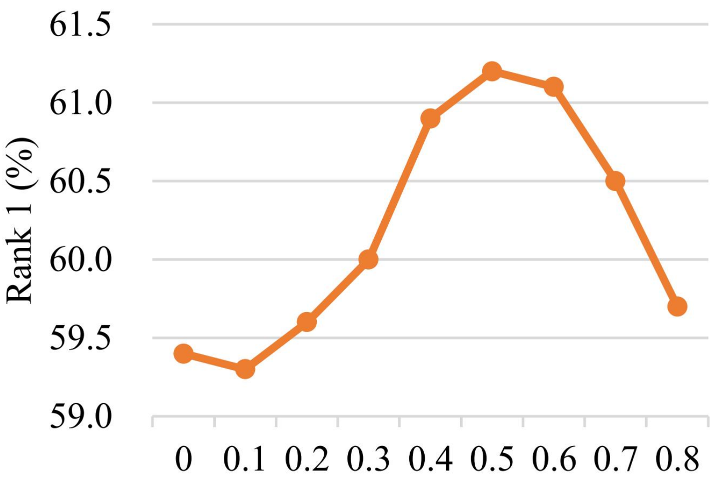
Augmentation Strategy	CC Mode	SC Mode
Baseline	48.1	98.0
ID-uncorrelated	55.5	98.6
ID-correlated (ours)	**61.2**	**99.6**

Experiment

$\mathcal{L}_{cciu}$	$\mathcal{L}_{sta}$	$\mathcal{L}_{adv}^{\mathcal{G}}$	$\mathcal{L}_{adv}^{\mathcal{D}}$	CC Mode	SC Mode
✗	✔	✔	✔	57.0	99.1
Use $\mathcal{D}_{clo}$ term only	✔	✔	✔	59.3	99.5
Use $\mathcal{D}_{id}$ term only	✔	✔	✔	58.4	99.2
✔	✗	✔	✔	56.7	96.3
✔	✔	✗	✔	37.4	71.7
✔	✔	✔	✗	44.5	82.5
✔	✔	✗	✗	49.7	92.3
✔	✔	✔	✔	**61.2**	**99.6**



(1) c (b=0)



(2) b (c=10)

Contribution

Implicitly augment clothing-change data in the feature space, by maximising clothing-change whilst minimising identity-change for person features.

Present a clothing-change covariance estimation method to formulate clothing-change semantic directions of feature distribution expansion, and introduce an augmentation generator to implement the clothing-change ID-unchange augmentation.

An ID-correlated augmentation strategy is proposed to increase intra-ID clothing variations and simultaneously to reduce inter-ID clothing variations, explicitly enforcing the Re-ID model to explore clothing independent information more fully.

Thank you for watching!