Symbiotic Adversarial Learning for Attribute-based Person Search



Yu-Tong Cao*, Jingya Wang*, and Dacheng Tao

UBTECH Sydney AI Centre, The University of Sydney

*Equal contribution

Problem – Attribute-based person search

Query attribute descriptions

- Teenager
- Backpack
- Pants
- Short bottom wear
- Short top wear
- Long hair
- Female
- Top white
- Bottom blue

Ranked retrieval results

Model

Gallery images

Images source: Market-1501 dataset.

Differences with zero-shot learning

1. No class prototypes for unseen classes
2. Large intra-class variations and inter-class similarities

Attribute-based person search (Market-1501)

508 training categories

- No bag
- Long hair
- Female

…

Category: 0

- Handbag
- Long hair
- Female

…

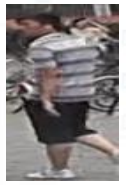
Category: 1

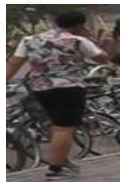
- No bag
- Short hair
- Male

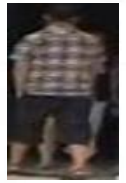
…

Category: 2

~26 images per category







- Teenager
- Short top
- Bottom black

…

Category: 3

Zero-shot learning (AWA2)

40 training categories

- Brown
- Black
- Small

…

Category: Siamese cat

- Orange
- Black
- Big

…

Category: tiger

- Brown
- Yellow
- Big

…

Category: Lion

~609 images per

- Black
- White
- Big

…

Category: giant panda

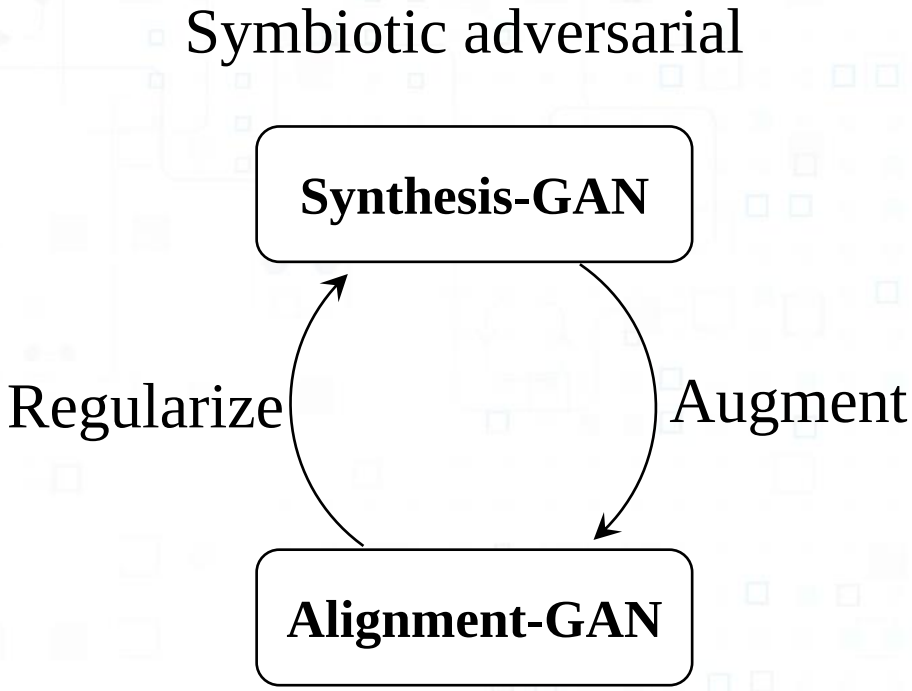
Inter-class similarity

Intra-class variation

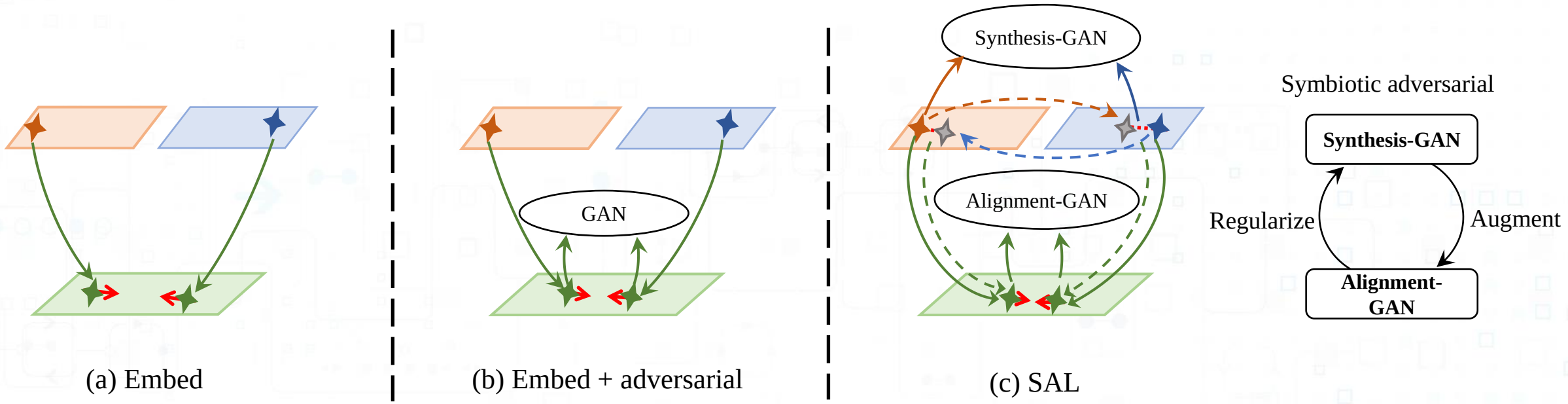
Motivation – Symbiosis

- A close and long-term biological interaction
- Mutualistic symbiosis relationship

Image source: https://icanhas.cheezburger.com/tag/Symbiosis



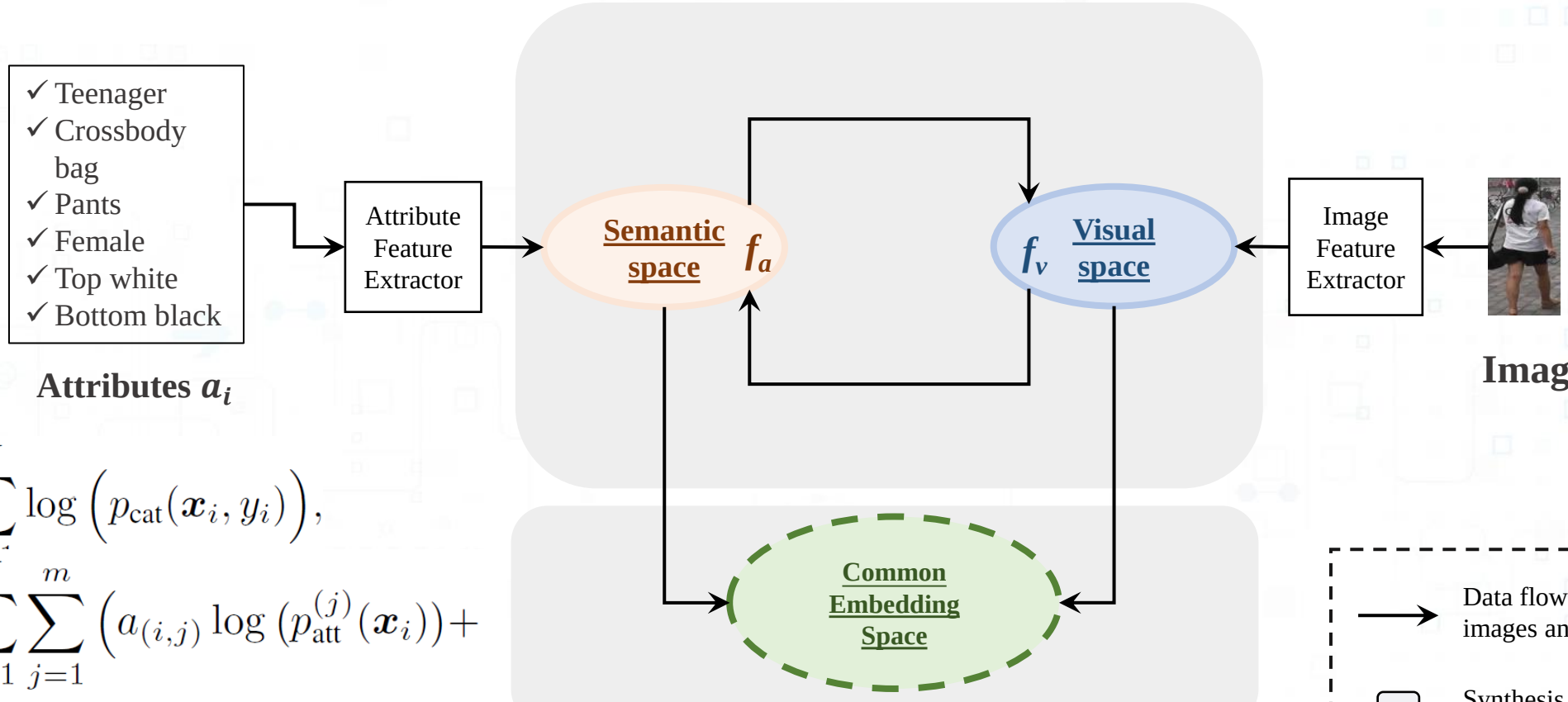
Method – Symbiotic Adversarial Learning



(a) Embed (b) Embed + adversarial (c) SAL

: Real features : Synthetic features : Common space features : Semantic space : Visual space : Common space

Method – Symbiotic Adversarial Learning

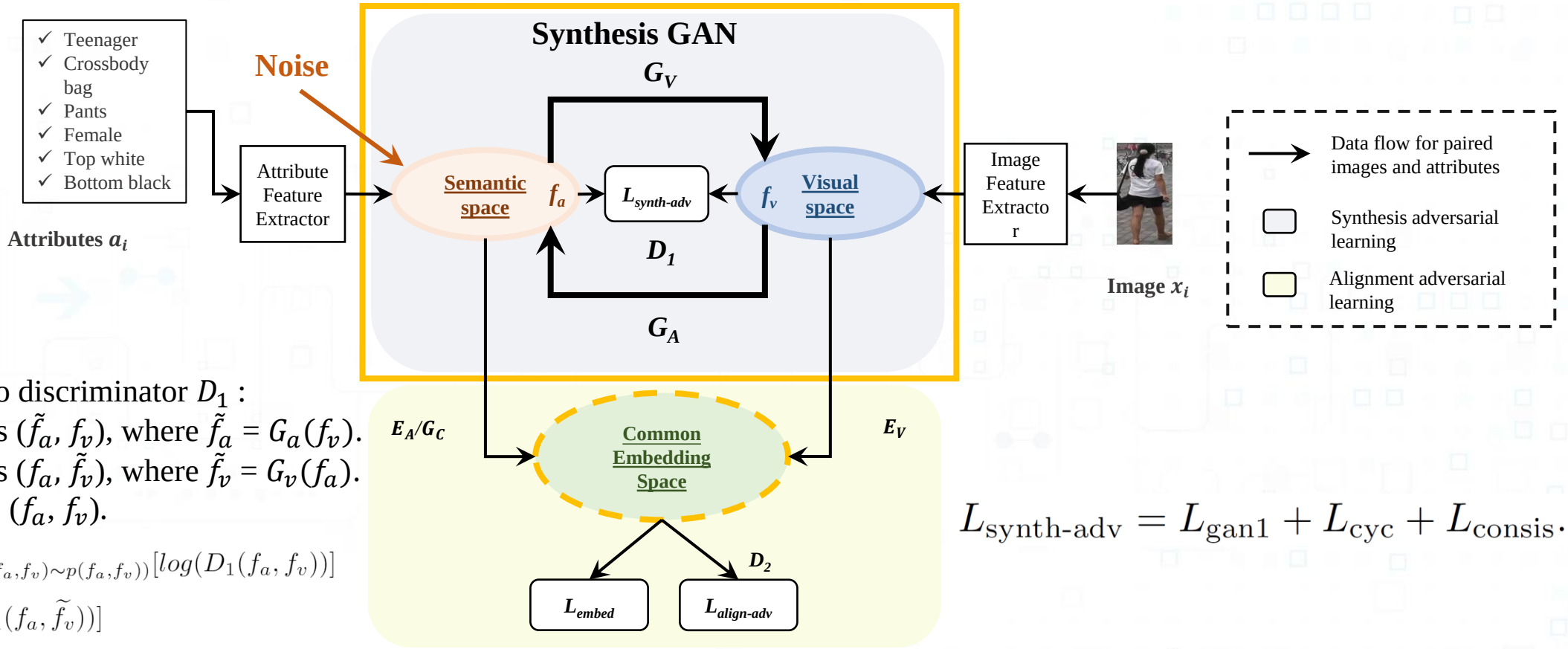


$$L_{\text{cat}} = -\sum_{i=1}^{N} \log\left(p_{\text{cat}}(\boldsymbol{x}_i, y_i)\right),$$

$$L_{\text{att}} = -\sum_{i=1}^{N}\sum_{j=1}^{m}\Big(a_{(i,j)} \log\left(p_{\text{att}}^{(j)}(\boldsymbol{x}_i)\right) + (1 - a_{(i,j)}) \log\left(1 - p_{\text{att}}^{(j)}(\boldsymbol{x}_i)\right)\Big),$$

$$L_{\text{embed}} = L_{\text{cat}} + L_{\text{att}}.$$

Method – Symbiotic Adversarial Learning



Three types of inputs to discriminator D_1 :
(1) The fake input pairs $(\tilde{f}_a, f_v)$, where $\tilde{f}_a = G_a(f_v)$.
(2) The fake input pairs $(f_a, \tilde{f}_v)$, where $\tilde{f}_v = G_v(f_a)$.
(3) The real input pairs (f_a, f_v).

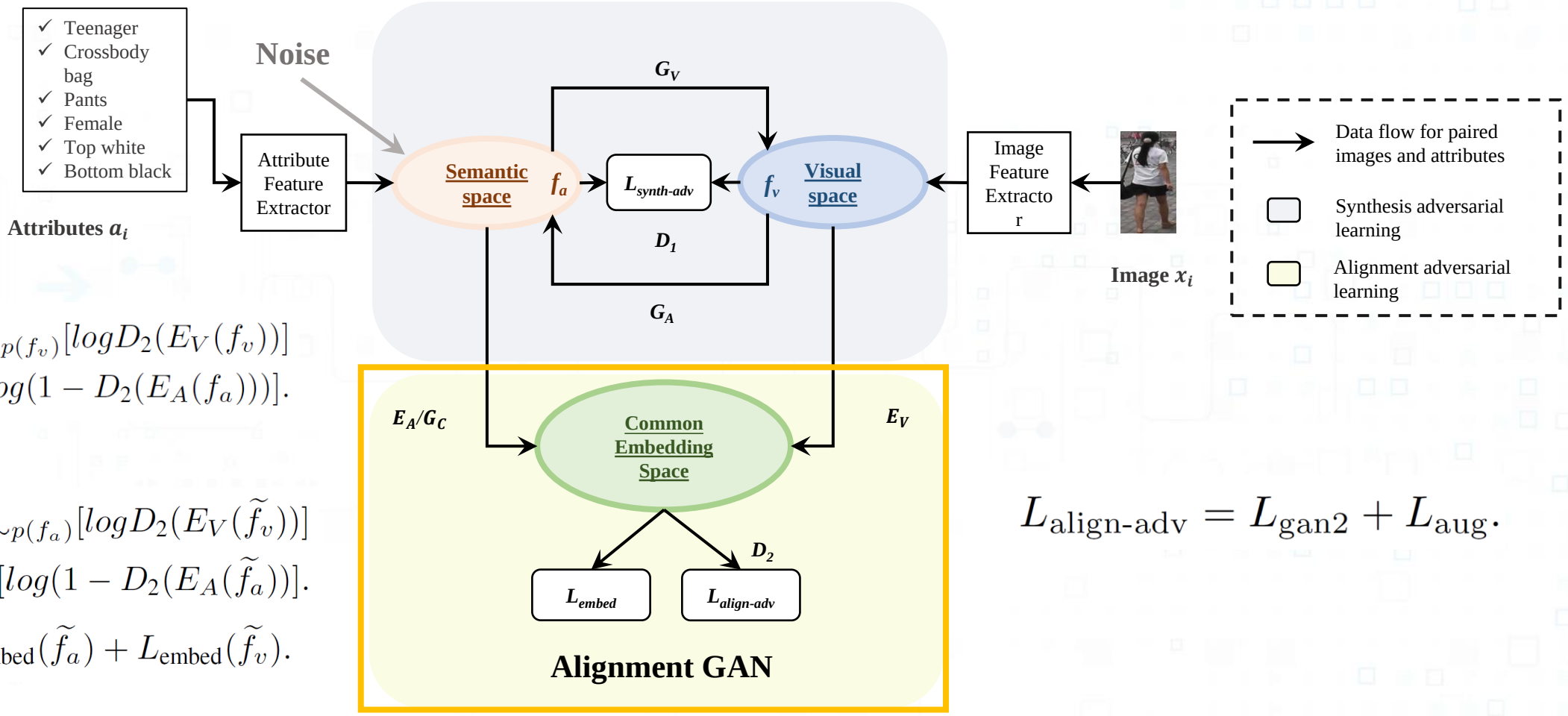
$$L_{\text{gan1}}(G_A, G_V, D_1) = \mathbb{E}_{(f_a,f_v)\sim p(f_a,f_v))}[log(D_1(f_a, f_v))] + \frac{1}{2}\mathbb{E}_{f_a\sim p(f_a)}[log(1 - D_1(f_a, \widetilde{f}_v))] + \frac{1}{2}\mathbb{E}_{f_v\sim p(f_v)}[log(1 - D_1(\widetilde{f}_a, f_v))].$$

$$L_{\text{synth-adv}} = L_{\text{gan1}} + L_{\text{cyc}} + L_{\text{consis}}.$$

$$L_{\text{cyc}}(G_A, G_V) = \mathbb{E}_{f_a\sim p(f_a)}[||G_A(G_V(f_a, z)) - f_a||_2].$$

$$L_{\text{consis}}(G_A, G_V) = \mathbb{E}_{f_v\sim p(f_v)}[||E_A(\widetilde{f}_a) - E_V(f_v)||_2] + \mathbb{E}_{f_a\sim p(f_a)}[||E_V(\widetilde{f}_v) - E_A(f_a)||_2] + \mathbb{E}_{(f_a,f_v)\sim p(f_a,f_v)}[||E_A(\widetilde{f}_a) - E_A(f_a)||_2] + \mathbb{E}_{(f_a,f_v)\sim p(f_a,f_v)}[||E_V(\widetilde{f}_v) - E_V(f_v)||_2],$$

Method – Symbiotic Adversarial Learning



$$L_{\text{gan2}}(G_C, D_2) = \mathbb{E}_{f_v \sim p(f_v)}[logD_2(E_V(f_v))] + \mathbb{E}_{f_a \sim p(f_a)}[log(1 - D_2(E_A(f_a)))].$$

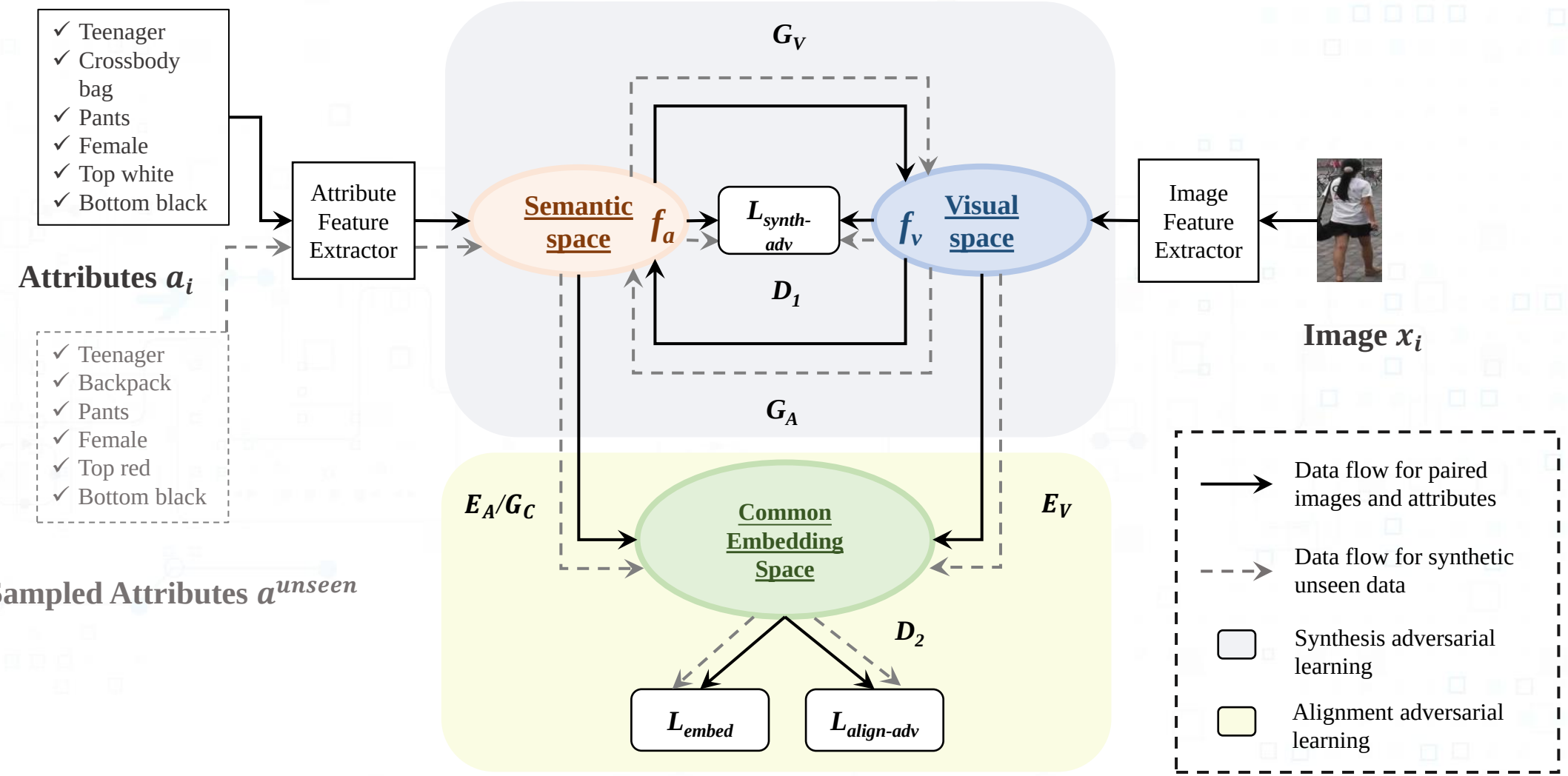
$$L_{\text{aug1}}(G_C, D_2) = \mathbb{E}_{f_a \sim p(f_a)}[logD_2(E_V(\widetilde{f}_v))] + \mathbb{E}_{f_v \sim p(f_v)}[log(1 - D_2(E_A(\widetilde{f}_a)))].$$

$$L_{\text{aug2}}(E_A, E_V) = L_{\text{embed}}(\widetilde{f}_a) + L_{\text{embed}}(\widetilde{f}_v).$$

$$L_{\text{aug}} = L_{\text{aug1}} + L_{\text{aug2}}.$$

$$L_{\text{align-adv}} = L_{\text{gan2}} + L_{\text{aug}}.$$

Method – Symbiotic Adversarial Learning



Results

Table 1. Attribute-based person search performance evaluation. Best results are shown in **bold**. The second-best results are underlined.

Metric (%)		Market-1501 Attributes				PETA			
Model	Reference	mAP	rank1	rank5	rank10	mAP	rank1	rank5	rank10
DeepCCA [1]	ICML'13	17.5	30.0	50.7	58.1	11.5	14.4	20.8	26.3
DeepMAR [23]	ACPR'15	8.9	13.1	24.9	32.9	12.7	17.8	25.6	31.1
DeepCCAE [50]	ICML'15	9.7	8.1	24.0	34.6	14.5	14.2	22.1	30.0
2WayNet [8]	CVPR'17	7.8	11.3	24.4	31.5	15.4	23.7	38.5	41.9
CMCE [24]	ICCV'17	22.8	35.0	51.0	56.5	26.2	31.7	39.2	48.4
ReViSE [41]	ICCV'17	17.7	24.2	45.2	57.6	31.1	30.5	57.0	61.5
MMCC [9]	ECCV'18	22.2	34.9	58.7	70.2	33.9	33.5	57.0	69.0
AAIPR [53]	IJCAI'18	20.7	40.3	49.2	58.6	27.9	39.0	53.6	62.2
AIHM [7]	ICCV'19	24.3	43.3	56.7	64.5	-	-	-	-
SAL (Ours)		**29.8**	**49.0**	**68.6**	**77.5**	**41.2**	**47.0**	**66.5**	**74.0**

Ablation studies

Table 2. Component analysis of SAL on PETA dataset.

Metric (%)	mAP	rank1	rank5	rank10
Embed	31.3	34.0	57.0	64.5
Embed + adv	35.0	37.5	60.5	66.5
Embed + symb-adv	40.6	44.0	64.0	70.5
Embed + symb-adv + unseen(SAL)	41.2	47.0	66.5	74.0

Table 3. Effect of interactions between two GANs on PETA dataset.

Metric (%)	mAP	rank1	rank5	rank10
SAL - L_{aug}	35.4	38.0	60.0	69.0
SAL - L_{consis}	35.2	39.5	56.5	66.0
SAL (Full interaction)	41.2	47.0	66.5	74.0

Table 4. Comparing stage-wise training vs. symbiotic training scheme.

Metric (%)	mAP	rank1	rank5	rank10
SAL w/ stage-wise training	35.0	41.0	58.0	65.0
SAL w/ symbiotic training	41.2	47.0	66.5	74.0

Visualized retrieval results

The green/red border represents correct/wrong selections respectively.

ECCV'20 ONLINE
23-28 AUGUST 2020

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Thank you!

Code at:

https://github.com/ycao5602/SAL