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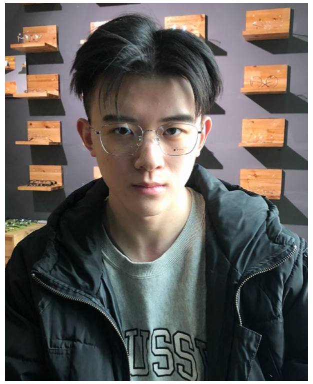
东方理工高等研究院
EASTERN INSTITUTE FOR ADVANCED STUDY

Discrete Point-wise Attack Is Not Enough: Generalized Manifold Adversarial Attack for Face Recognition

Paper Tag: THU-AM-390

Project Page: https://github.com/tokaka22/GMAA


Qian Li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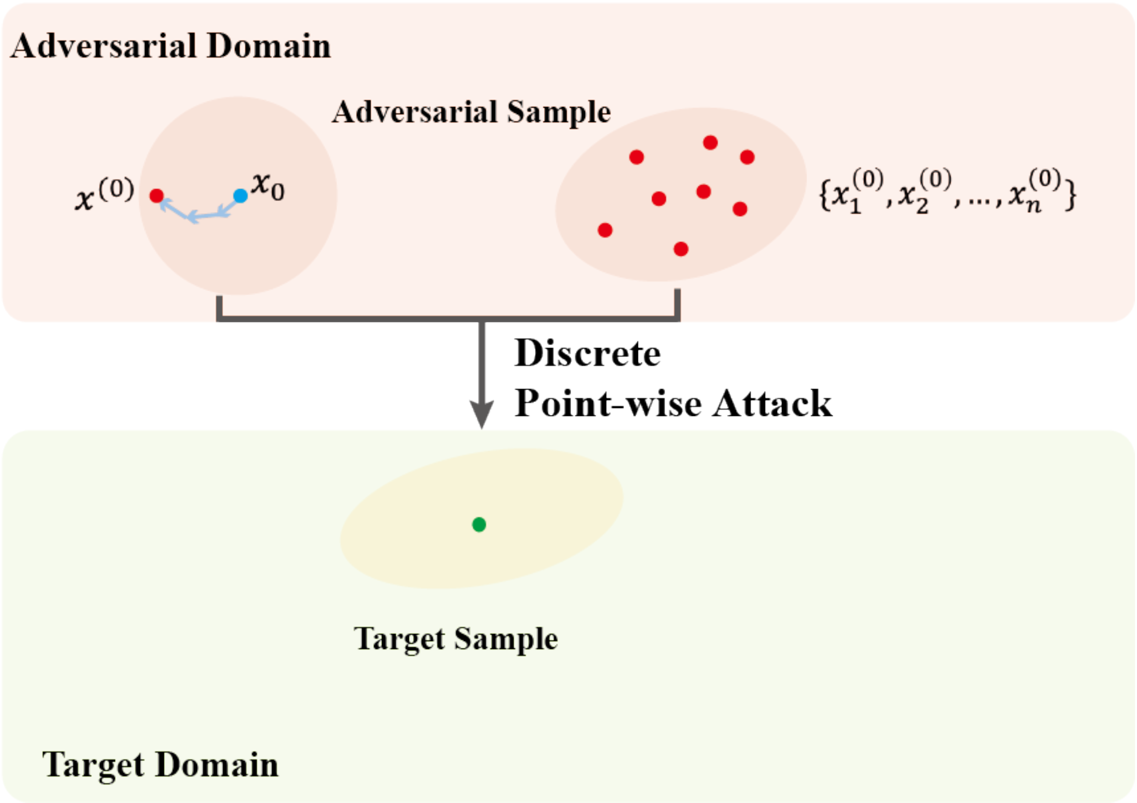
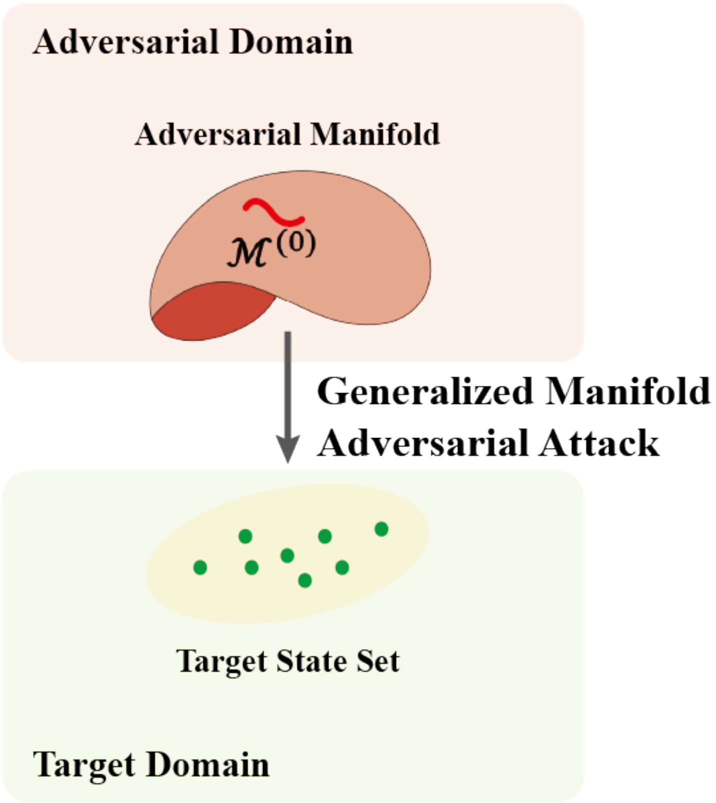
Overview

- We propose a new adversarial attack paradigm **GMAA**.

Discrete Point-wise Attack

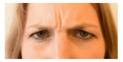


Generalized Manifold Adversarial Attack

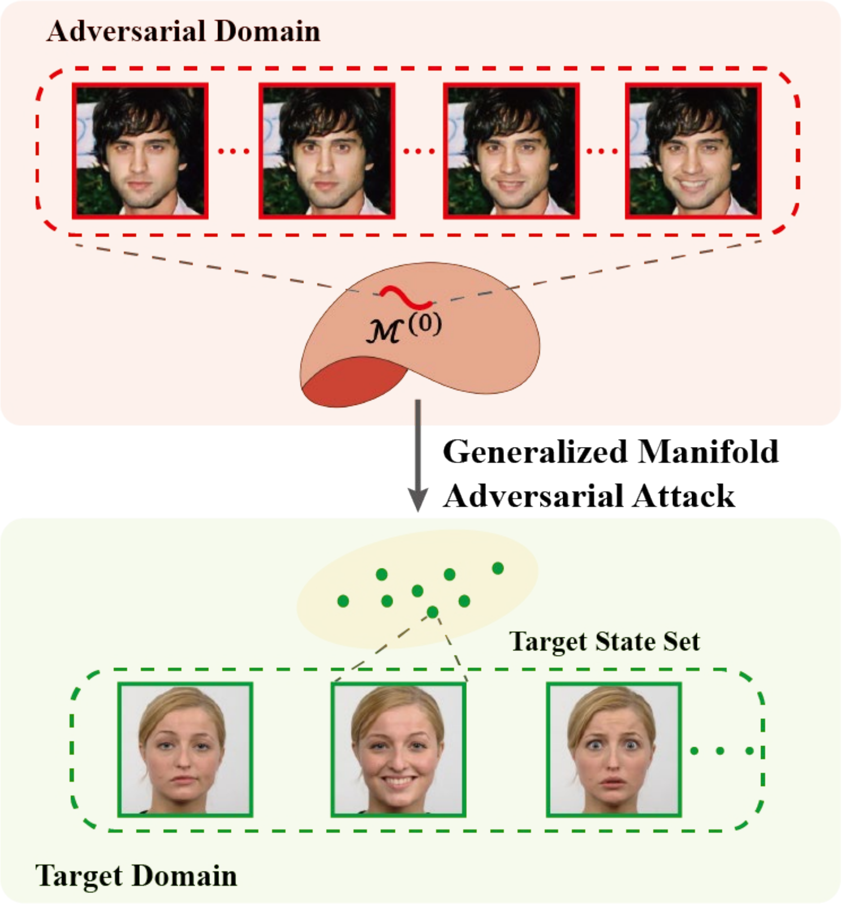


Overview

- We propose a new adversarial attack paradigm **GMAA**.
- We instantiate GMAA in the **face expression state space**.

Action Unit	Description	Facial Muscle	Example
1	Inner Brow Raiser	*Frontalis, pars medialis*	
2	Outer Brow Raiser (unilateral, right side)	*Frontalis, pars lateralis*	
4	Brow Lowerer	*Depressor Glabellae, Depressor Supercilli, Currugator*	
5	Upper Lid Raiser	*Levator palpebrae superioris*	
6	Cheek Raiser	*Orbicularis oculi, pars orbitalis*	
7	Lid Tightener	*Orbicularis oculi, pars palpebralis*	

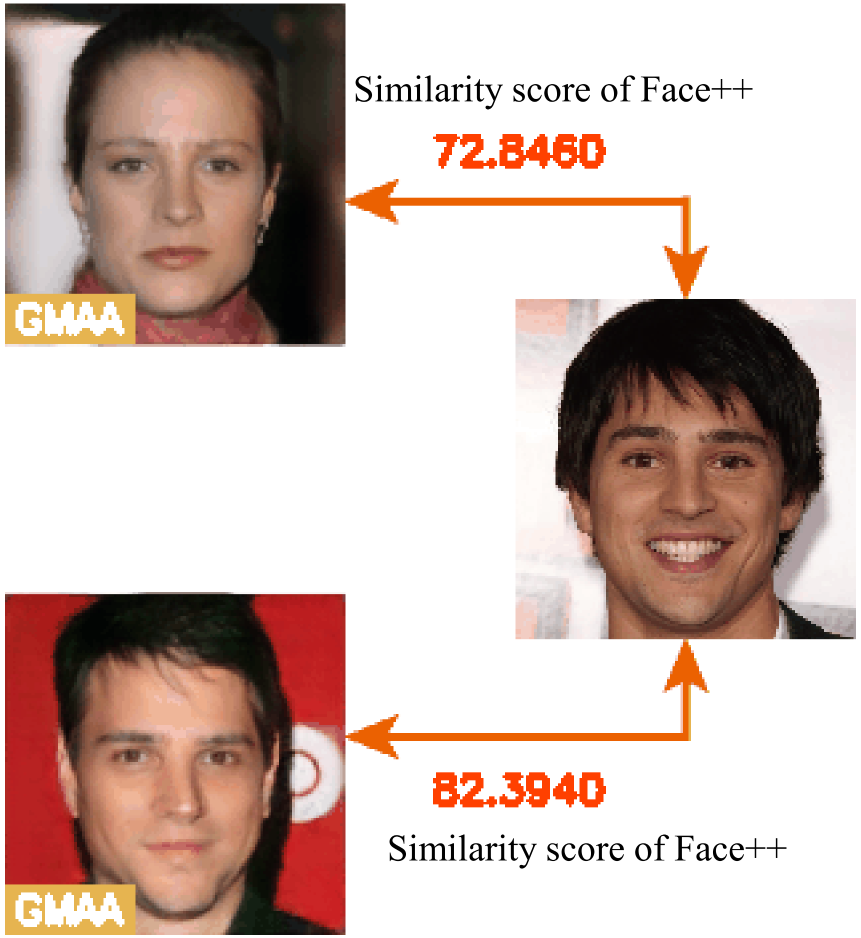
Domain knowledge
AU Vector[1]



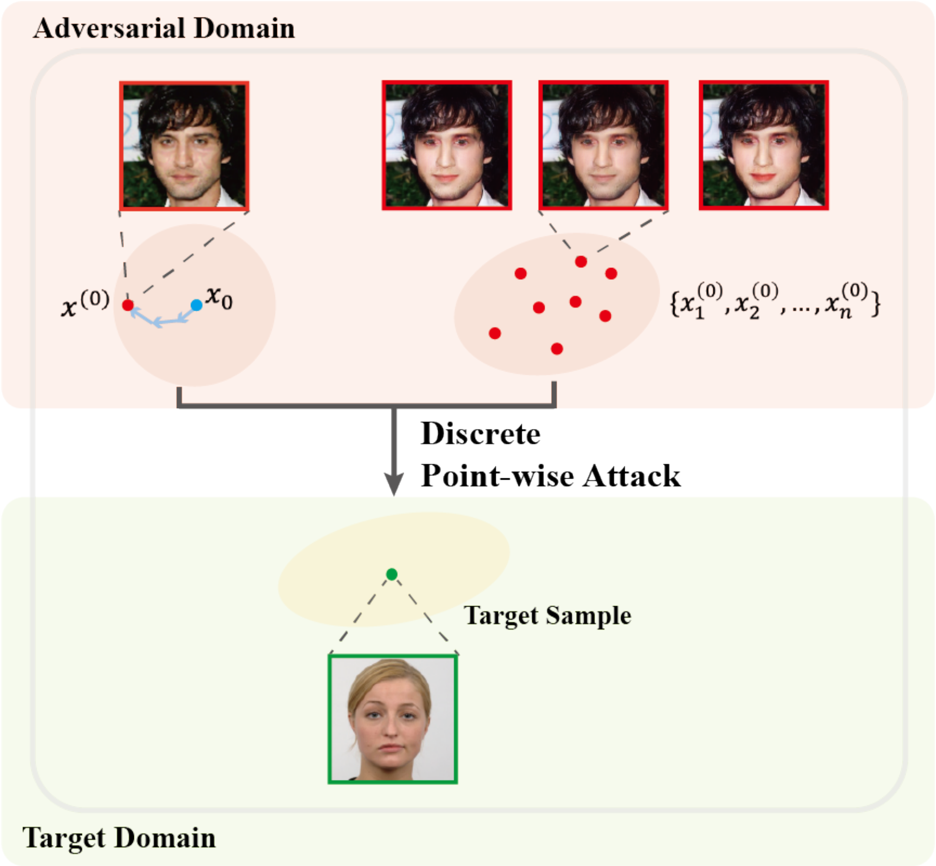
[1] https://imotions.com/blog/learning/research-fundamentals/facial-action-coding-system/

Overview

- We propose a new adversarial attack paradigm **GMAA**.
- We instantiate GMAA in the **face expression state space**.
- Our method has better attack performance and higher visual quality.

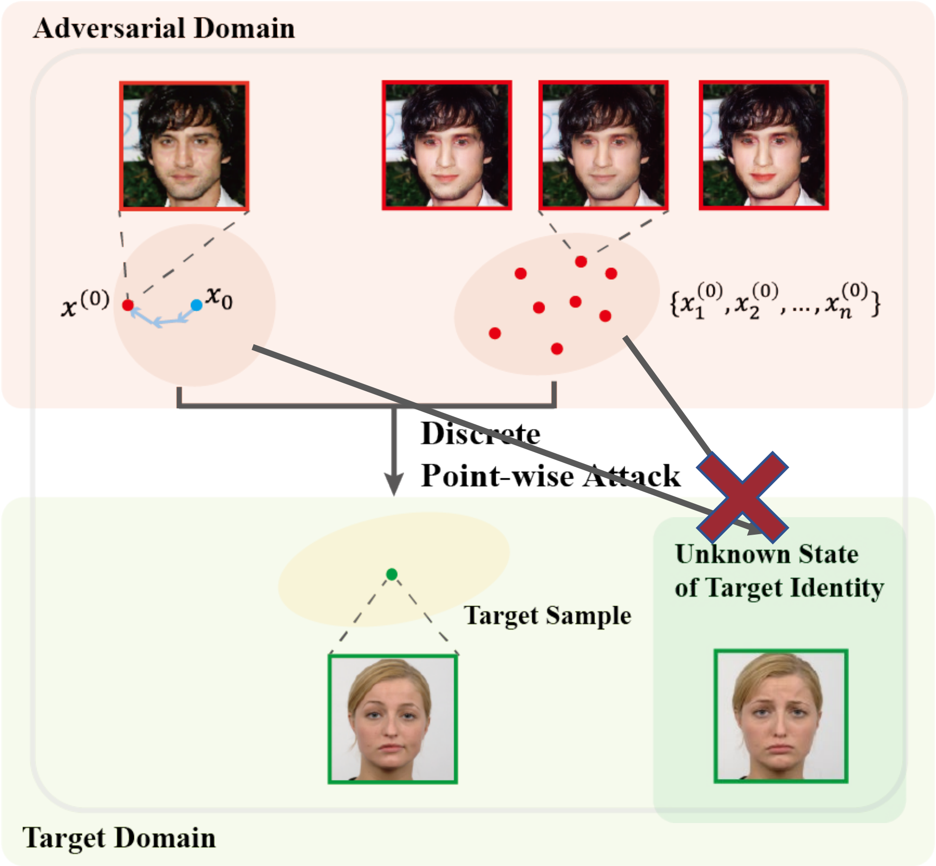


Limitations of previous work



- For the target domain, previous methods tend to attack a single target identity sample.

Limitations of previous work



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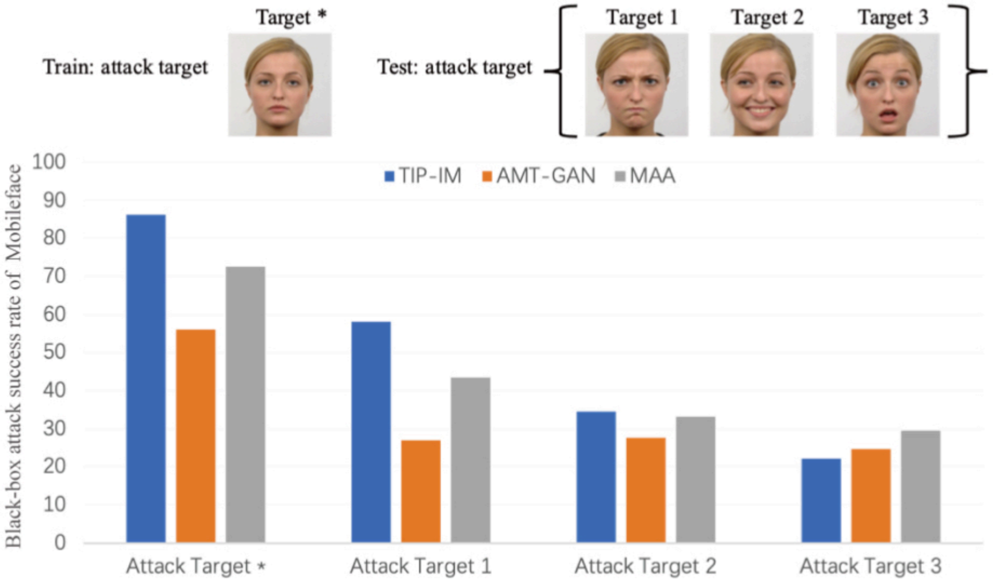
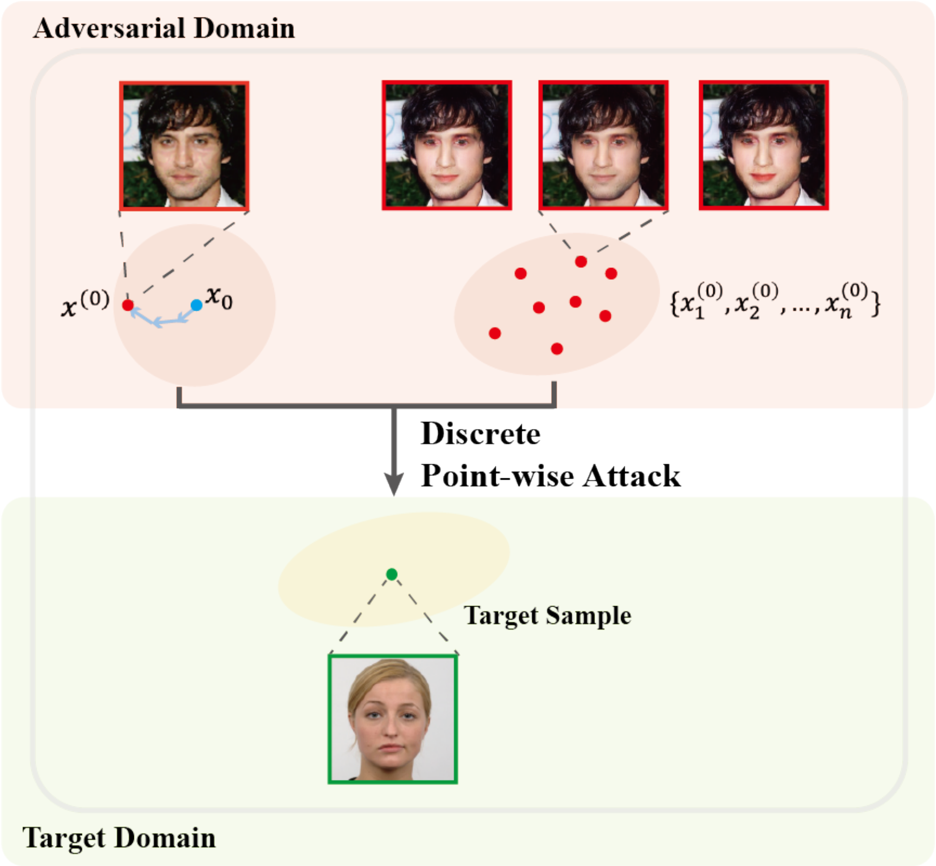


Poor generalization on unknow state target images !

Limitations of previous work



- For the target domain, previous methods tend to attack a single target identity sample.

Poor generalization on unknow state target images !

Generate highly generalizable adversarial examples !

- For the adversarial domain, many methods searching for **discrete adversarial examples** in a hypersphere of the clean sample.

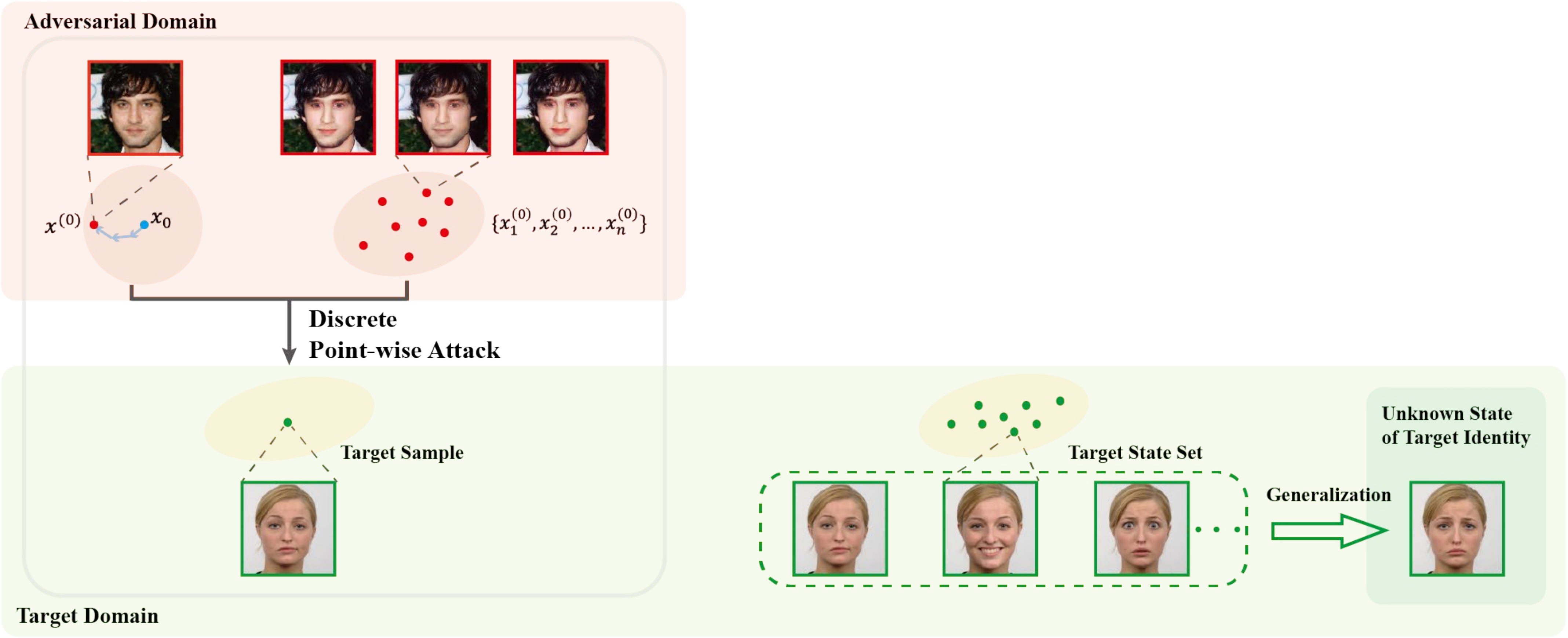
Ignore the continuity of the adversarial domain !

Find a continuous adversarial manifold instead of discrete adversarial examples!

Existing works are not strong enough both in target domain and adversarial domain.

Generalized Manifold Adversarial Attack

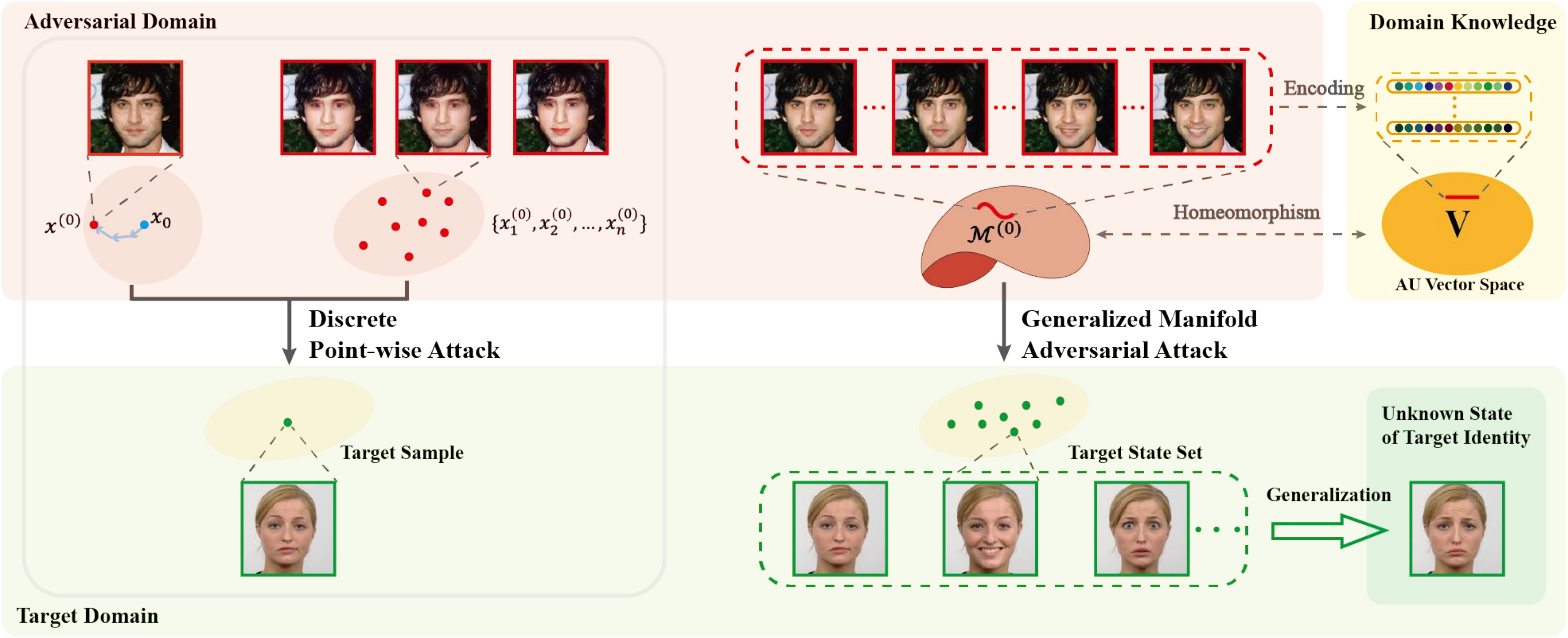
Core idea



- Expand the target domain **from one to many** to encourage a good generalization.

GMAA

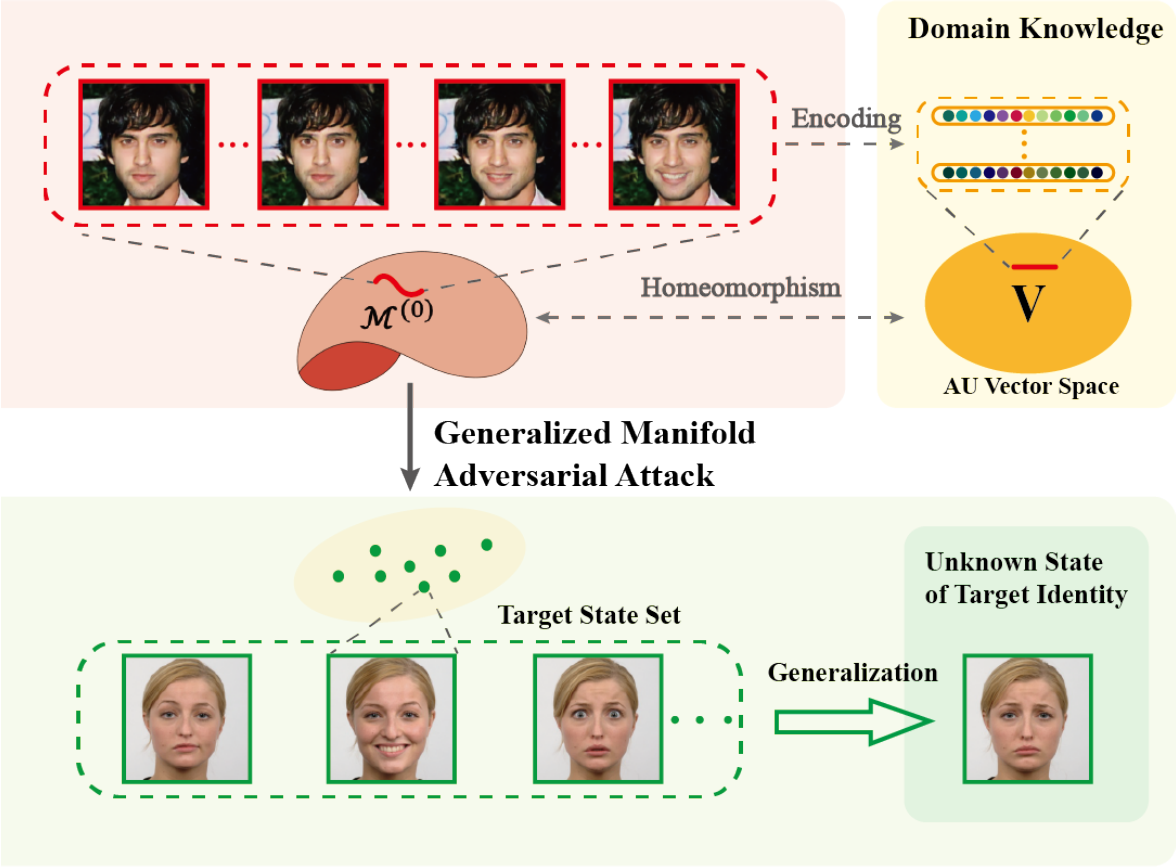
Core idea



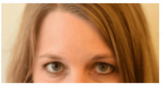
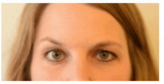
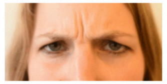
GMAA

- Expand the target domain **from one to many** to encourage a good generalization.
- Expand the adversarial domain **from discrete points to manifold** to strengthen the attack effect.

Core idea



Facial Action Coding System

Action Unit	Description	Facial Muscle	Example
1	Inner Brow Raiser	*Frontalis, pars medialis*	
2	Outer Brow Raiser (unilateral, right side)	*Frontalis, pars lateralis*	
4	Brow Lowerer	*Depressor Glabellae, Depressor Supercilli, Currugator*	
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GMAA

- Expand the target domain **from one to many** to encourage a good generalization.
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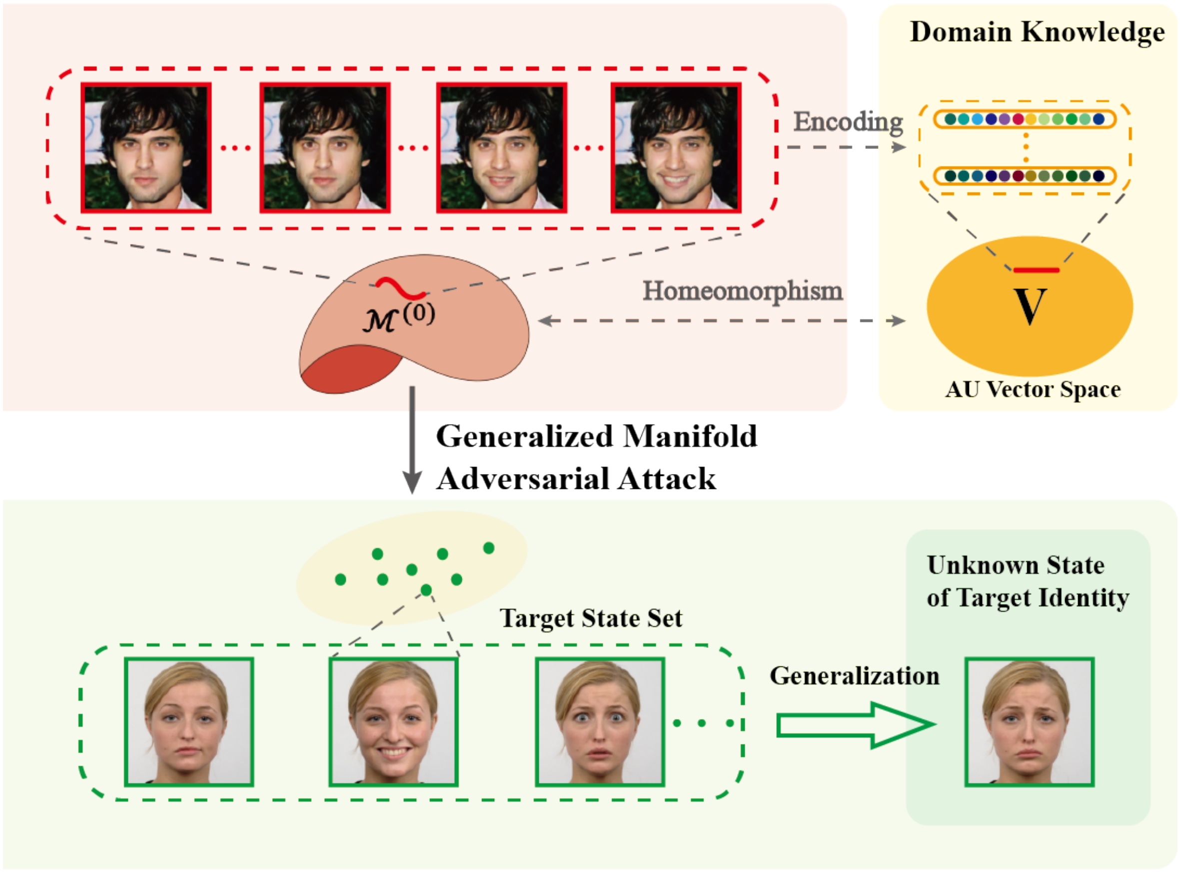

Definition 1. *Let $\boldsymbol{x}_0 \in \mathbb{R}^{3\times H\times W}$, then $\mathcal{M}^0 = G(\boldsymbol{x}_0;\boldsymbol{\theta})$ is a continuous adversarial space if and only if*
(1) $\mathcal{M}^0$ is a subspace of $\mathbb{R}^{3\times H\times W}$.
(2) $\forall \boldsymbol{x}_i^0 \in \mathcal{M}$, $\boldsymbol{x}_i^0$ is an adversarial version of $\boldsymbol{x}_0$.

Theorem 1. *$\mathcal{M}^0$ generated by G_0 is a continuous adversarial manifold, where $G_0 : V \to \mathcal{M}$ is a map when fixed the input $\boldsymbol{x}_0$ in G.*

Remark 1. *Since the $\mathcal{M}^0$ generated by G_0 is a continuous adversarial manifold when fixed the $\boldsymbol{x}_0$, then we can assert over the sample space Ω, the adversarial examples space generated by G constitutes an adversarial fiber bundle.*

Definition 2. *$\mathcal{M}^0$ generated by $\boldsymbol{x}_0 \in \mathbb{R}^{3\times H\times W}$ is a semantic continuous adversarial space if and only if*
(1) $\mathcal{M}^0$ is a continuous adversarial space.
(2) $\forall \boldsymbol{x}_1^0, \boldsymbol{x}_2^0 \in \mathcal{M}^0$, if $\boldsymbol{x}_1^0$ is close to $\boldsymbol{x}_2^0$ on the $\mathcal{M}^0$, then $\boldsymbol{x}_1^0$ and $\boldsymbol{x}_2^0$ satisfy the semantic consistency.

Theorem 2. *$\mathcal{M}^0$ generated by G_0 is a semantic continuous adversarial manifold, where $G_0 : V \to \mathcal{M}$ is a map when fixed the input $\boldsymbol{x}_0$ in G.*

GMAA

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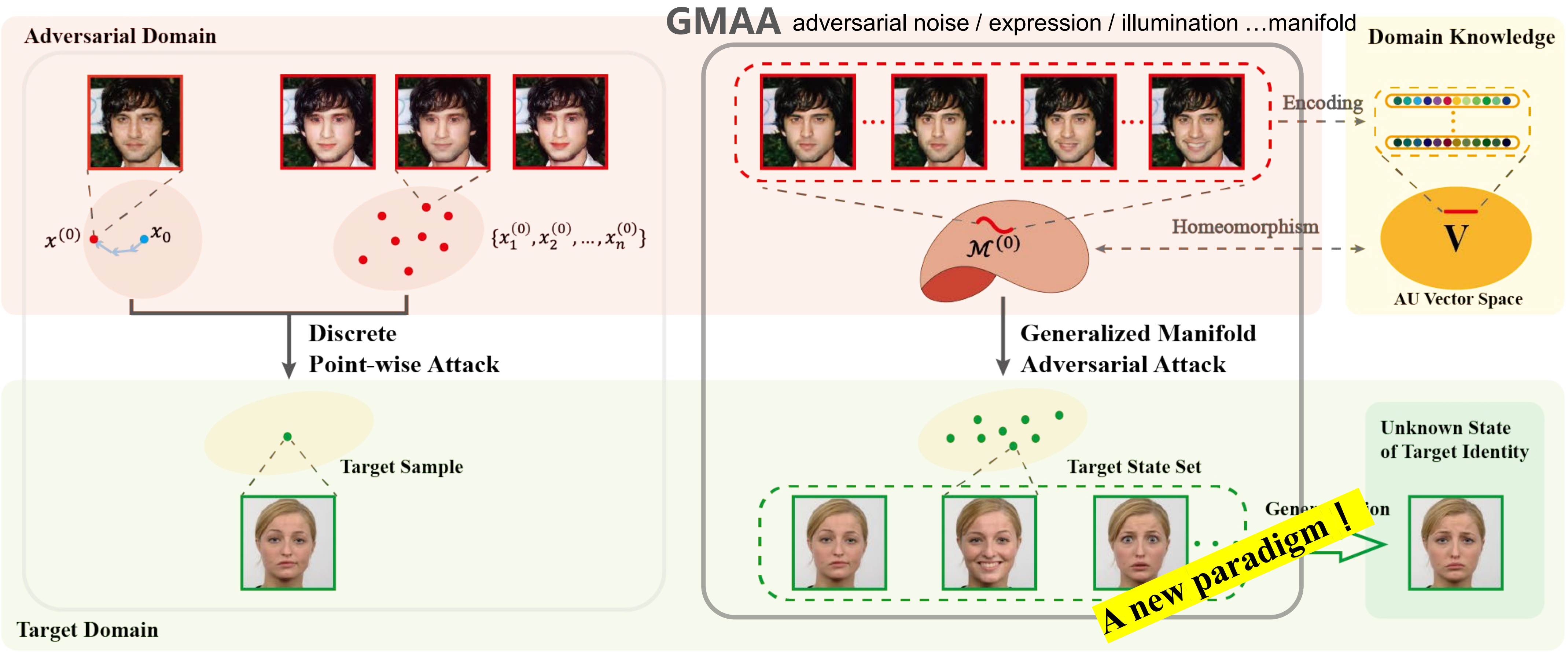
Core idea



GMAA

- Expand the target domain **from one to many** to encourage a good generalization.
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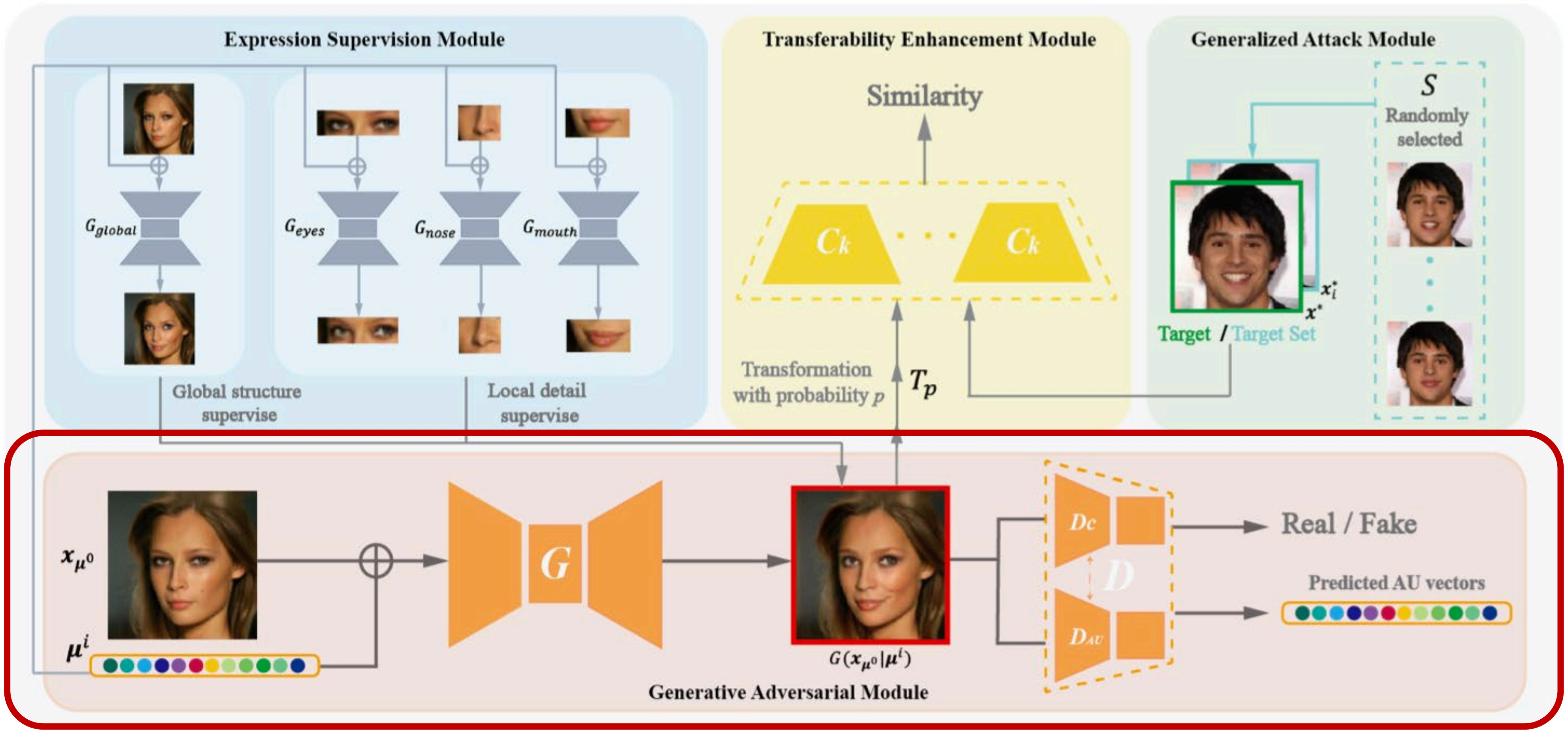
Discrete Point-wise Attack ⇨ Generalized Manifold Adversarial Attack

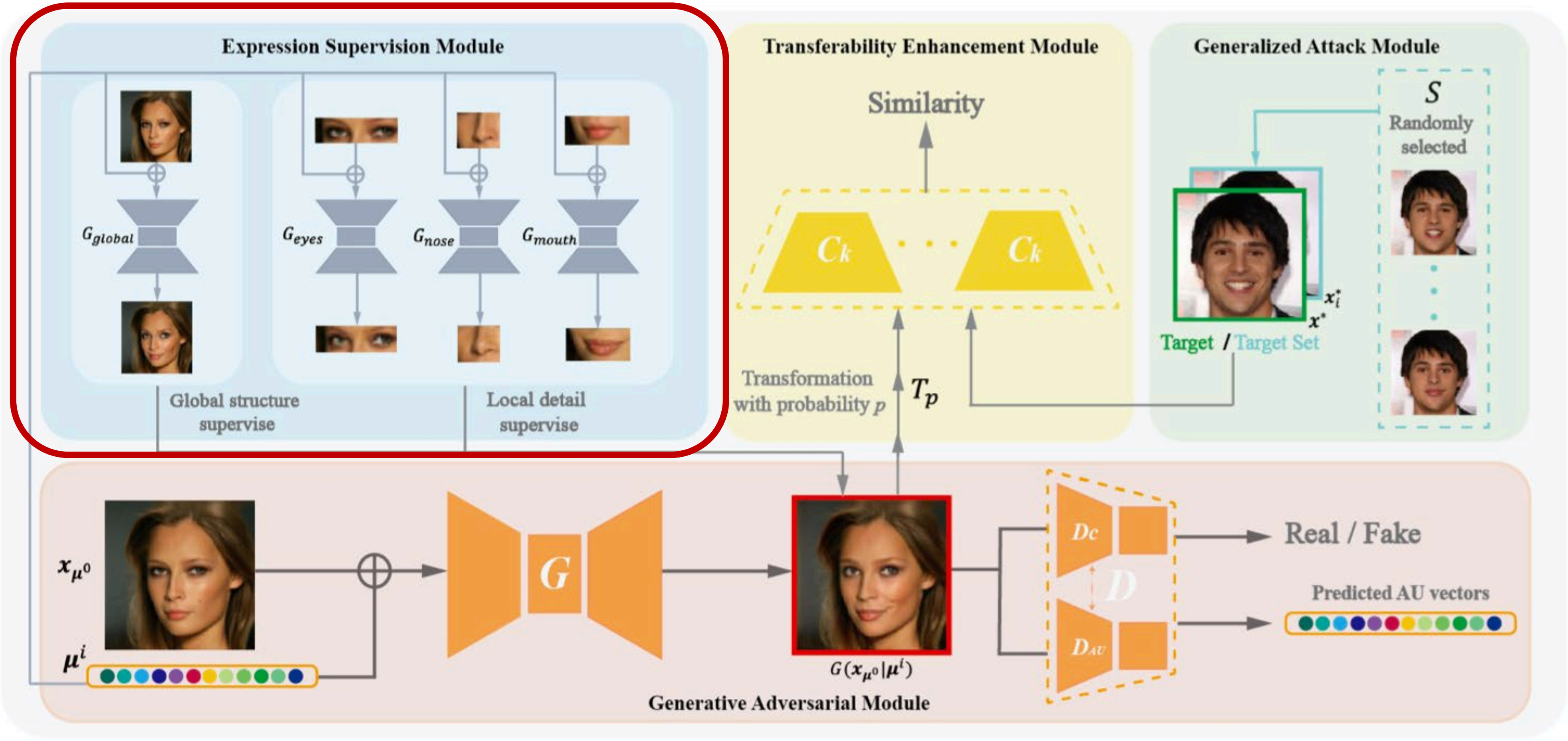
Method



Generative adversarial module

- The generator G produces adversarial example wearing the expression matching to the supplied AU label.
- The discriminator D_c learns to distinguish real images from generated images.
- The AU predictor D_{AU} learns the AU coding rules by real images and their AU labels.

Method

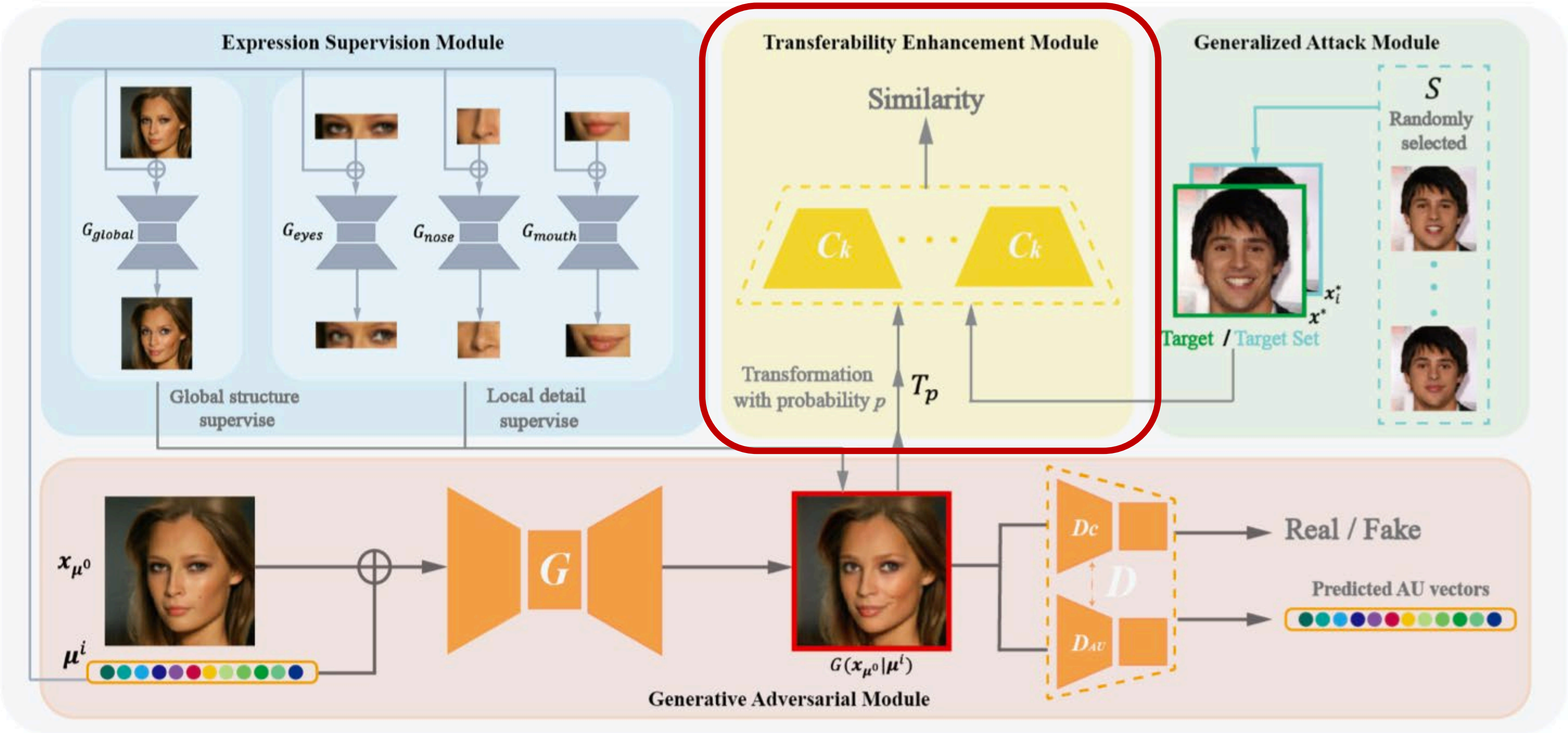


Expression supervision module

- Four pre-trained expression supervision networks protect the visual identity and guide G in expression editing.
- The global branch focuses on structural features of the face, whereas the local branch protects important facial details.
- Each generator has the network structure similar to [2].

[2] Albert Pumarola, Antonio Agudo, Aleix M Martinez, Al- berto Sanfeliu, and Francesc Moreno-Noguer. Ganimation: Anatomically-aware facial animation from a single image. In *Proceedings of the European conference on computer vision (ECCV)*, pages 818–833, 2018.

Method

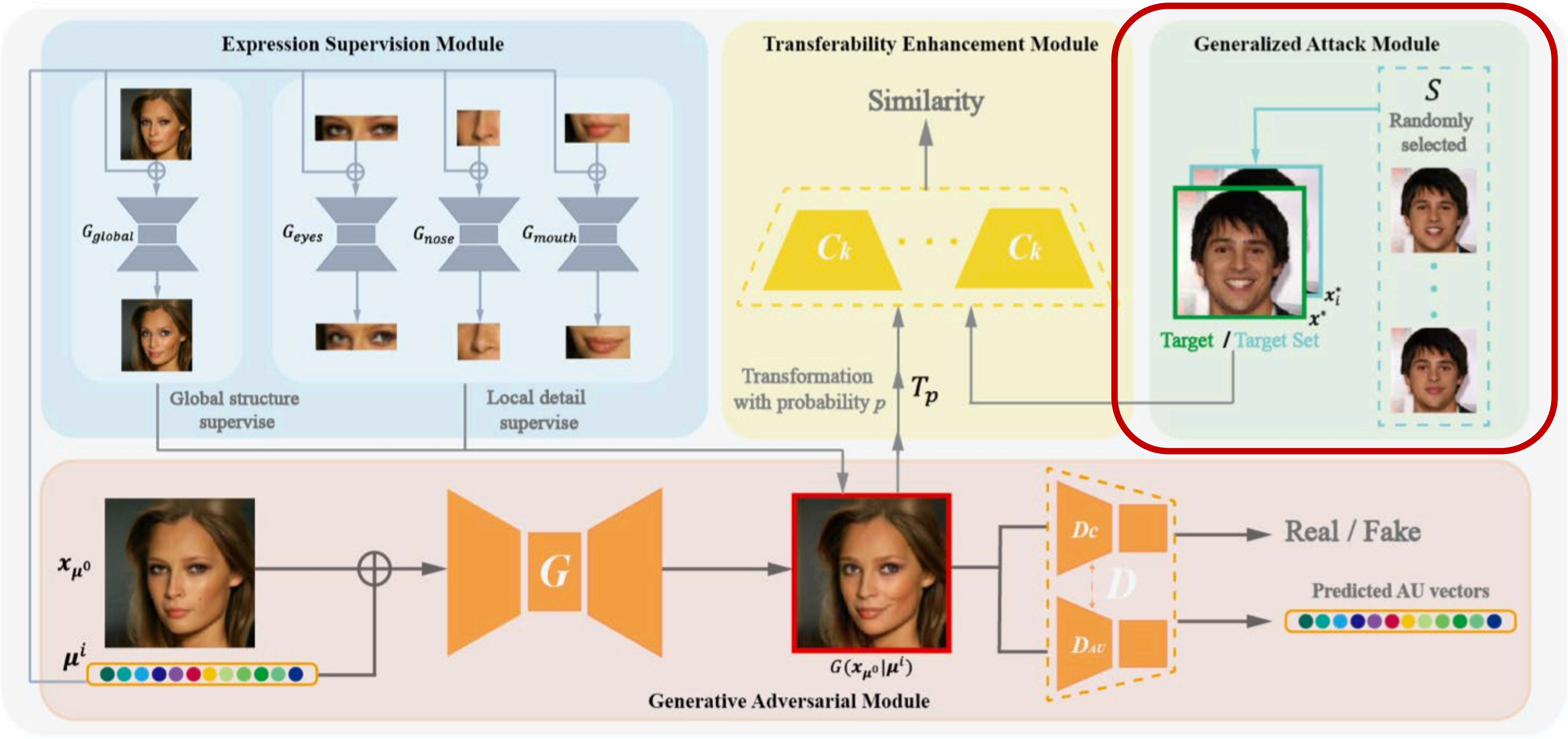


Transferability enhancement module

- To improve the transferability of adversarial examples and the black-box attack success rate, we introduce the transferability enhancement module from [3].
- All baselines are equipped with this module for a fair comparison.

[3] Shengshan Hu, Xiaogeng Liu, Yechao Zhang, Minghui Li, Leo Yu Zhang, Hai Jin, and Libing Wu. Protecting facial privacy: Generating adversarial identity masks via style-robust makeup transfer. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 15014–15023, 2022.

Method



Generalized attack module

- This module intends to raise the attack success rate on the unseen face belonging to the target identity.
- It is a generic module, which can be introduced into other adversarial attack approaches.
- Manifold Adversarial Attack (MAA) means the method without this module, just expand adversarial domain from point to manifold.
- When the model is coupled with this module, we call it G-(method name).

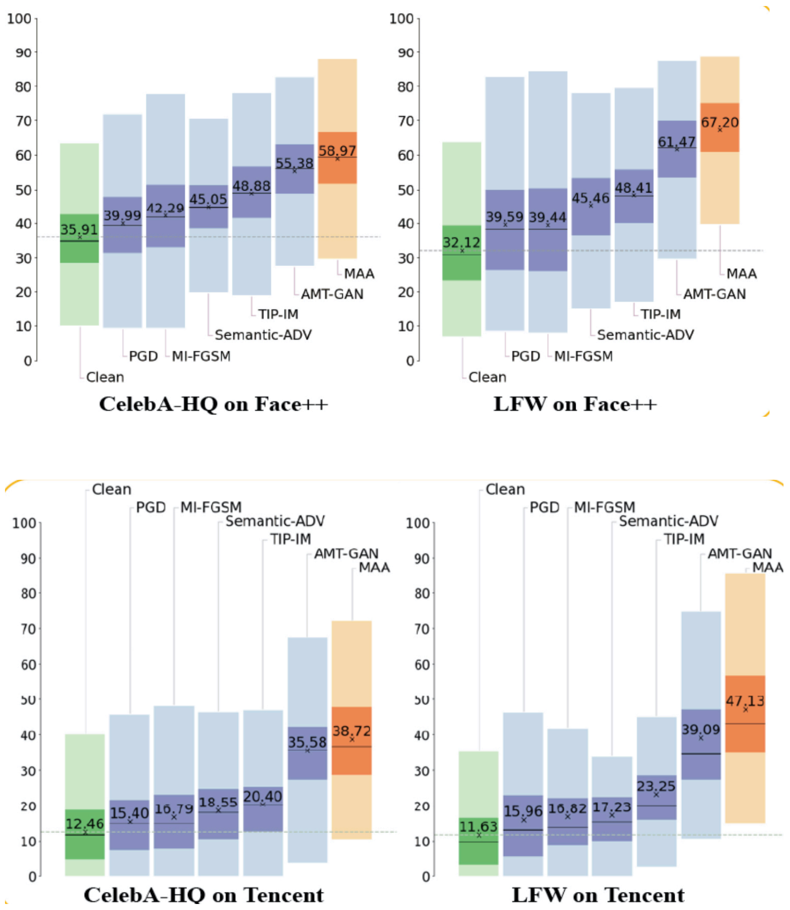
Experiment —— Part 1

- **Black-box attack success rate**

	CelebA-HQ			
	IRSE50	IR152	Facenet	Mobileface
Clean	3.68	3.08	1.31	8.43
PGD [23]	24.20	13.37	5.86	28.72
MI-FGSM [7]	38.90	20.76	9.25	40.48
SemanticAdv [26]	26.53	10.24	7.80	55.32
TIP-IM [34]	44.20	16.09	14.46	**65.36**
AMT-GAN [16]	51.06	15.63	11.63	33.27
MAA	**60.40**	**29.43**	**18.91**	56.13

	LFW			
	IRSE50	IR152	Facenet	Mobileface
Clean	3.20	0.06	0.04	5.00
PGD [23]	31.30	10.20	7.40	33.50
MI-FGSM [7]	38.20	14.20	7.60	39.40
SemanticAdv [26]	33.60	10.40	8.80	37.40
TIP-IM [34]	32.80	15.20	13.00	**79.00**
AMT-GAN [16]	40.72	25.23	13.89	35.67
MAA	**55.80**	**29.20**	**18.00**	60.80

- **Attack performance on commercial API**



CelebA-HQ on Face++ **LFW on Face++**

CelebA-HQ on Tencent **LFW on Tencent**

- **Visual quality**

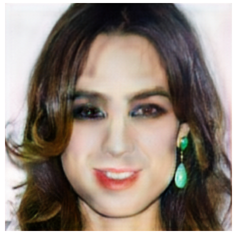
Ours

Target image

Attack Success Rate:100%

Original

TIP-IM
ICCV21



AMT-GAN
CVPR22

Experiment —— Part 2

- **Ablation studies of generalized attack module**

  ——Attack real state set

Targe set $S = \{$  $\cdots \}$

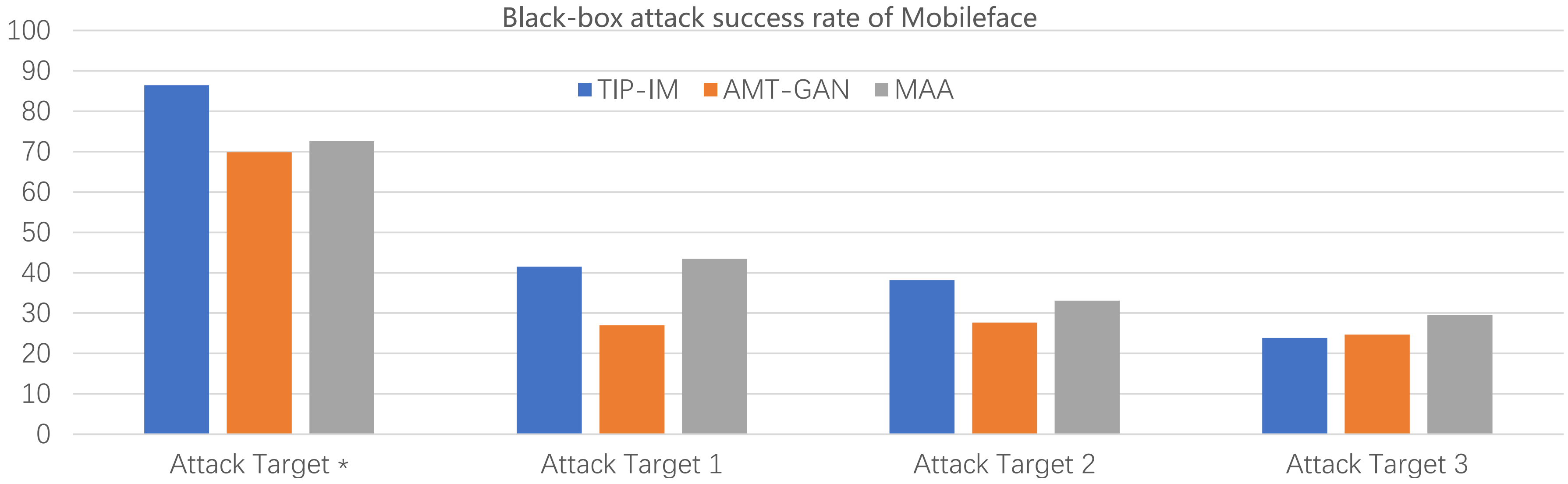
1 2 3

Targe * 

Case 0

Train: attack target *

Test: attack target *\1\2\3



Experiment —— Part 2

- **Ablation studies of generalized attack module**

  ——Attack real state set

Targe set $S = \{$  1 2 3 $\cdots \}$

Targe * 

Case 0

Train: attack target *

Test: attack target *\1\2\3

Case 1

Train: attack target $S/\{1\}$

Test : attack target 1

Case 2

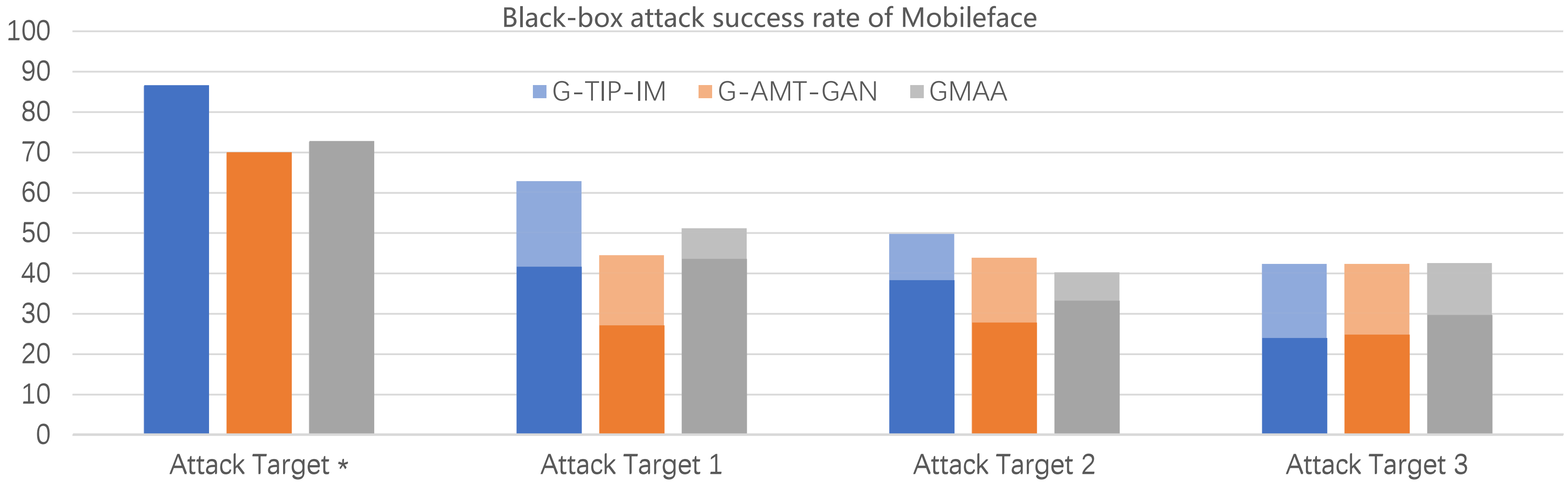
Train: attack target $S/\{2\}$

Test: attack target 2

Case 3

Train: attack target $S/\{3\}$

Test: attack target 3



Experiment —— Part 2

- **Ablation studies of generalized attack module**

  ——Attack real state set

Targe set $S = \{$


1


2


3

$\cdots \}$

Targe *

Case 0

Train: attack target *

Test: attack target *\1\2\3

Case 1

Train: attack target $S/\{1\}$

Test : attack target 1

Case 2

Train: attack target $S/\{2\}$

Test: attack target 2

Case 3

Train: attack target $S/\{3\}$

Test: attack target 3

	Target*		**Target 1**		**Target 2**		**Target 3**	
	Facenet	Mobileface	Facenet	Mobileface	Facenet	Mobileface	Facenet	Mobileface
TIP-IM [34] / **G-TIP-IM**	17.68	86.33	4.54 / **7.62**	58.03 / **70.93**	10.75 / **20.42**	34.42 / **49.20**	11.93 / **19.41**	22.21 / **42.43**
AMT-GAN [16] / **G-AMT-GAN**	16.12	55.95	8.22 / **13.23**	26.99 / **47.14**	9.78 / **17.12**	27.67 / **43.93**	10.91 / **16.16**	24.69 / **42.37**
MAA / **GMAA**	25.22	72.62	11.43 / **17.84**	43.44 / **67.50**	13.30 / **21.71**	33.08 / **41.24**	12.64 / **19.15**	29.56 / **47.21**

Experiment —— Part 2

- **Ablation studies of generalized attack module**

  ——Attack synthesized state set

Generated targe set $S = \{$

$\cdots \}$

	Facenet	Mobileface
TIP-IM [34] / **G-TIP-IM**	5.80 / **9.50**	17.20 / **23.5**
AMT-GAN [16] / **G-AMT-GAN**	4.04 / **8.27**	9.82 / **12.45**
MAA / **GMAA**	6.60 / **10.60**	13.50 / **21.60**

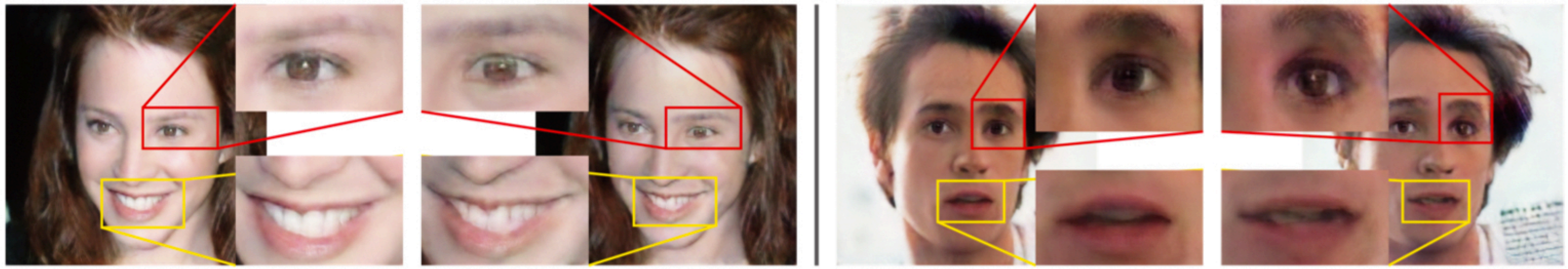
Experiment —— Part 3

- **Other Ablation studies**

—— Ablation studies of D_{AU}

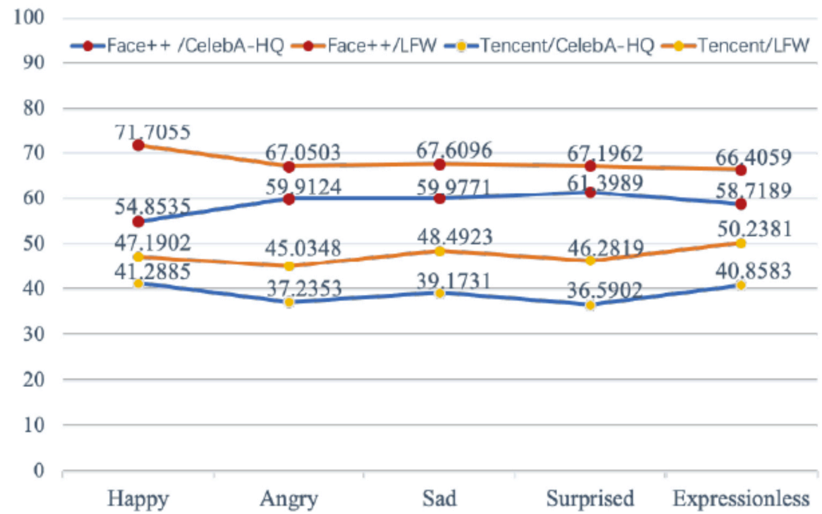
	Without D_{AU}	Without local editors	Original
MSE	0.5549	0.6283	**0.3582**

—— Ablation studies of local editors



with local editors **without local editors** **with local editors** **without local editors**

—— Ablation studies of different expressions



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