FACE PAPERS SUMMARY

CVPR, ECCV, ICCV, AAAI

- 염지현 -

목차

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2. Attentional Feature-Pair Relation Networks for Accurate Face Recognition
3. Attribute-Enhanced Face Recognition With Neural Tensor Fusion Networks
4. Attribute-Guided Face Generation Using Conditional CycleGAN
5. CAFE-GAN: Arbitrary Face Attribute Editing with Complementary Attention Feature
6. CONFIG: Controllable Neural Face Image Generation
7. Consistent Instance False Positive Improves Fairness in Face Recognition
8. Decorrelated Adversarial Learning for Age-Invariant Face Recognition
9. Discovering Fair Representations in the Data Domain
10. Domain Balancing: Face Recognition on Long-Tailed Domains
11. Fair Attribute Classification Through Latent Space De-Biasing

Anti-Makeup: Learning A Bi-Level Adversarial Network for Makeup-Invariant Face Verification

Li, Yi, et al. "Anti-makeup: Learning a bi-level adversarial network for makeup-invariant face verification." *Proceedings of the AAAI Conference on Artificial Intelligence*. Vol. 32. No. 1. 2018.

- 제목: Anti-Makeup: Learning A Bi-Level Adversarial Network for Makeup-Invariant Face Verification → 안티 메이크업: 메이크업 불변 얼굴 검증을 위한 BLAN 학습

- 해결하고자 하는 문제: 메이크업한 얼굴과 메이크업 하지 않은 얼굴 간의 불일치 문제

- 해결 방법
  - BLAN(bi-level adversarial network) 도입하여 메이크업 불변 얼굴 인증 문제 해결
    - 메이크업 얼굴 이미지와 메이크업 하지 않은 얼굴 이미지(메이크업 이미지로부터 생성) 사용
    - 적대적 네트워크 사용(메이크업 하지 않은 얼굴 재구성 네트워크 + 신원 정보 보존 네트워크)

- 구조: GAN

Anti-Makeup: Learning A Bi-Level Adversarial Network for Makeup-Invariant Face Verification

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화장 얼굴

생성한 화장하지 않은 얼굴

GT (화장하지 않은 얼굴)

한계: 남자 얼굴에서는 부자연스러움

Anti-Makeup: Learning A Bi-Level Adversarial Network for Makeup-Invariant Face Verification

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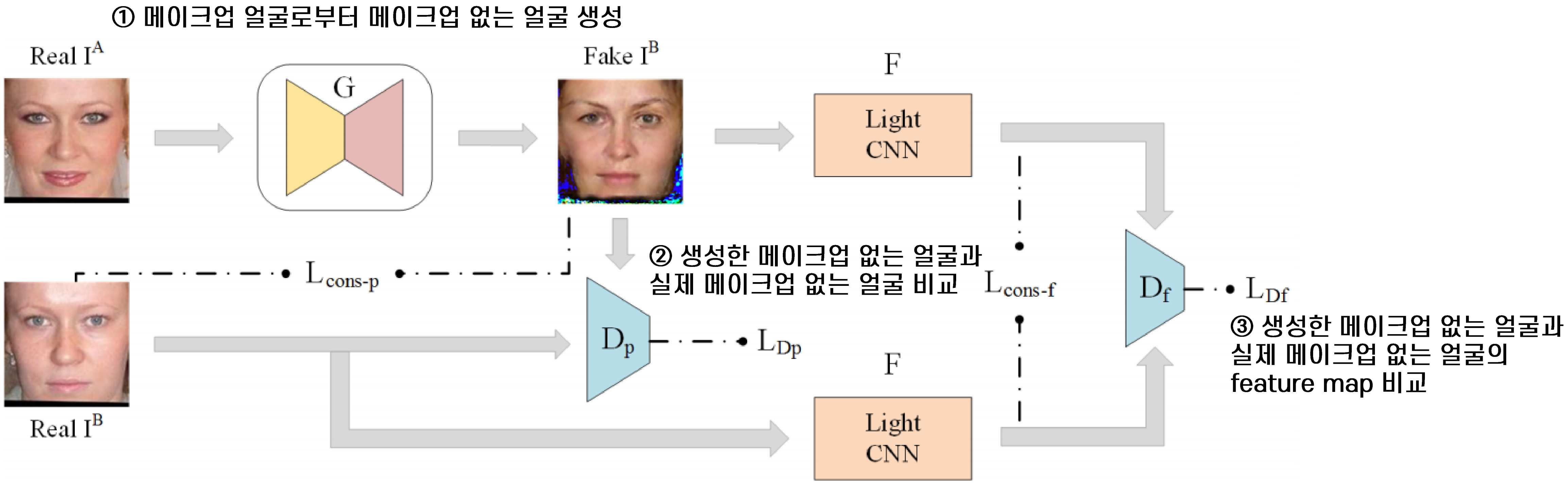

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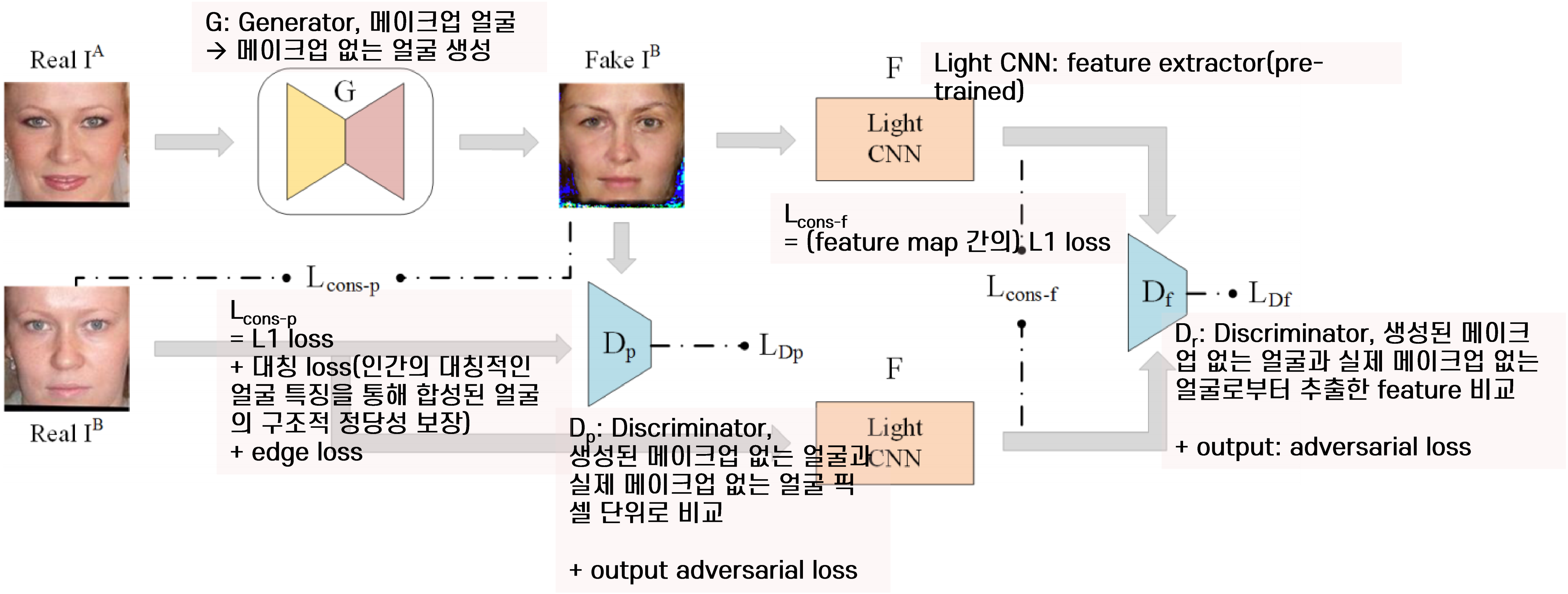

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- Similarity metric: cosine distance

Table 1: Rank-1 accuracy (%) on three makeup datasets.

Dataset	Method	Accuracy
Dataset 1	(Guo, Wen, and Yan 2014)	80.5
	(Sun et al. 2017)	82.4
	VGG	89.4
	Light CNN	92.4
	BLAN	94.8
Dataset 2	(Sun et al. 2017)	68.0
	VGG	86.0
	Light CNN	91.5
	BLAN	92.3
FAM	(Nguyen and Bai 2010)	59.6
	(Hu et al. 2013)	62.4
	VGG	81.6
	Light CNN	86.3
	BLAN	88.1

Attentional Feature-Pair Relation Networks for Accurate Face Recognition

Kang, Bong-Nam, et al. "Attentional feature-pair relation networks for accurate face recognition." Proceedings of ICCV. 2019.

- 제목: Attentional Feature-Pair Relation Networks for Accurate Face Recognition
  → 정확한 얼굴 인식을 위한 Attentional Feature-Pair Relation Networks

- 해결하고자 하는 문제: 얼굴의 포즈, 표정, 조명의 급격한 변화로 인한 얼굴 인식 실패 문제

- 해결 방법
  - AFRN(Attentional Feature-pair Relation Network)
    - 얼굴 이미지를 9x9 local 블록으로 구역 나누기
    - 나눈 구역에서 중요하지 않은 부분에는 낮은 점수를 주고 점수에 따라 가중치 부여
    - 가중치 기반 Top-K 구역을 선택 후 나머지(무관한 부분) 삭제
    - Top-K 구역에 bilinear attention network 사용하여 joint feature-pair relation 추출
  - 해당 모델을 통해 얼굴이 비슷하게 생긴 서로 다른 사람을 구분할 때 "비뚤어진 코" 특징으로 구분할 수 있게 됨

- 구조: Encoder

Attentional Feature-Pair Relation Networks for Accurate Face Recognition

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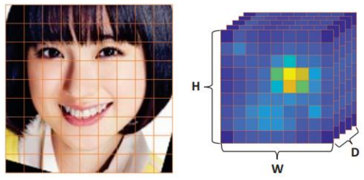

(a) (b)

9x9 local 영역으로 나눈 후 activation map 출력
→ 중요한 부분과 덜 중요한 부분 확인 가능

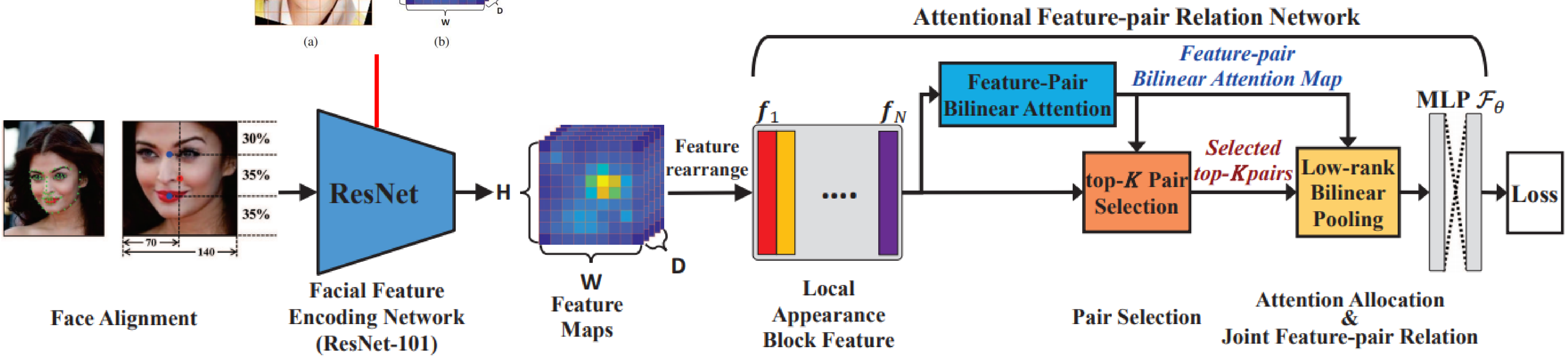

Figure 1. Working principle of the proposed Attentional Feature-pair Relation Network.

Attentional Feature-Pair Relation Networks for Accurate Face Recognition

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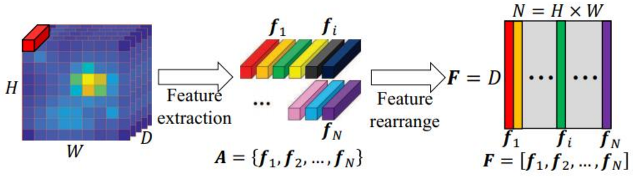
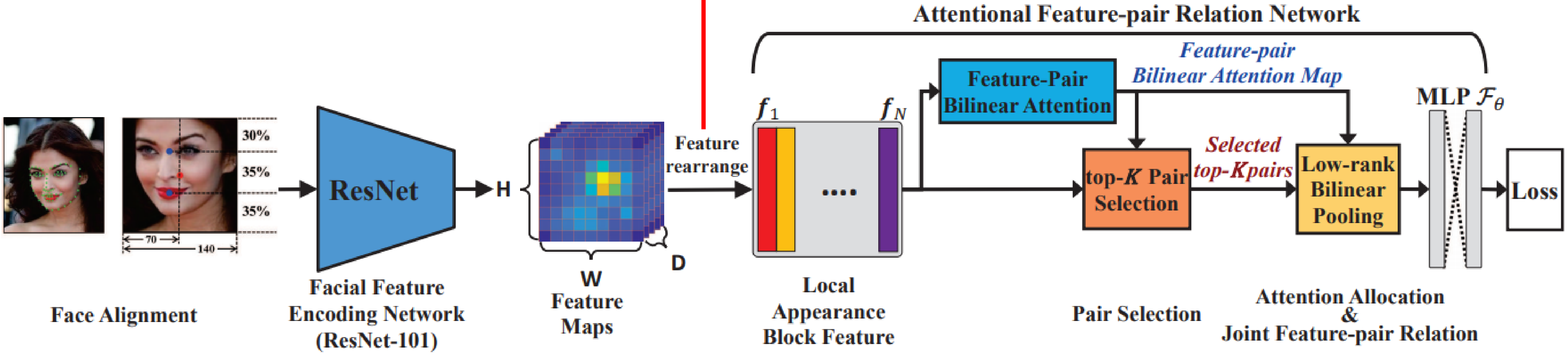


Figure 3. Facial feature rearrangement.

Feature rearrange
: feature map을 pixel별로, 채널 별로
나누어 한 줄로 펴서 재정렬



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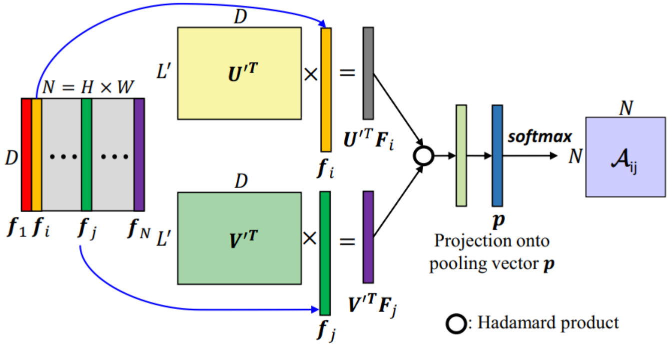
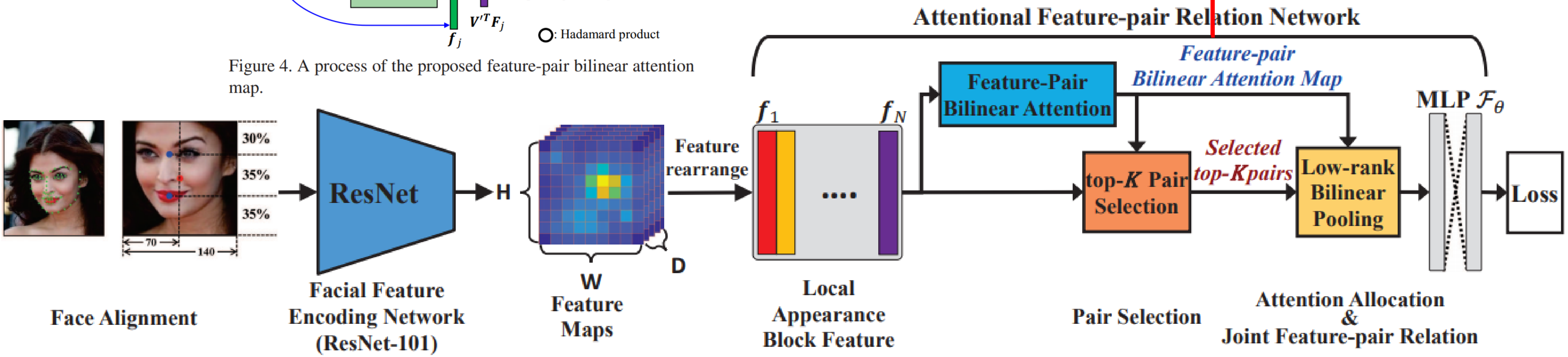


Figure 4. A process of the proposed feature-pair bilinear attention map.

Feature-Pair Bilinear Attention Map
: Local Appearance Block Feature 간의 관계성을 담은 map 출력



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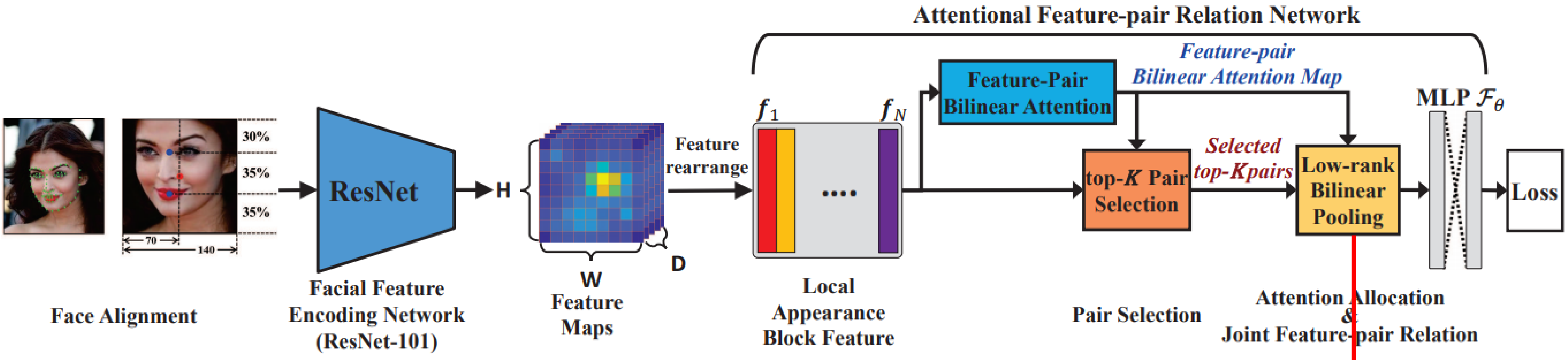

Figure 1. Working principle of the proposed Attentional Feature-pair Relation Network.

Joint feature-pair relation
: local appearance block features에 대한 joint feature-pair relation 추출

- Joint 의미 파악 X
- LABF 간의 연결 관계를 하나의 식으로 추출하는 것이 아닌가 추측

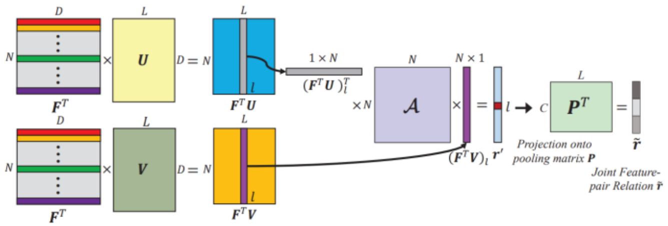

Figure 5. The joint feature-pair relation.

Attentional Feature-Pair Relation Networks for Accurate Face Recognition

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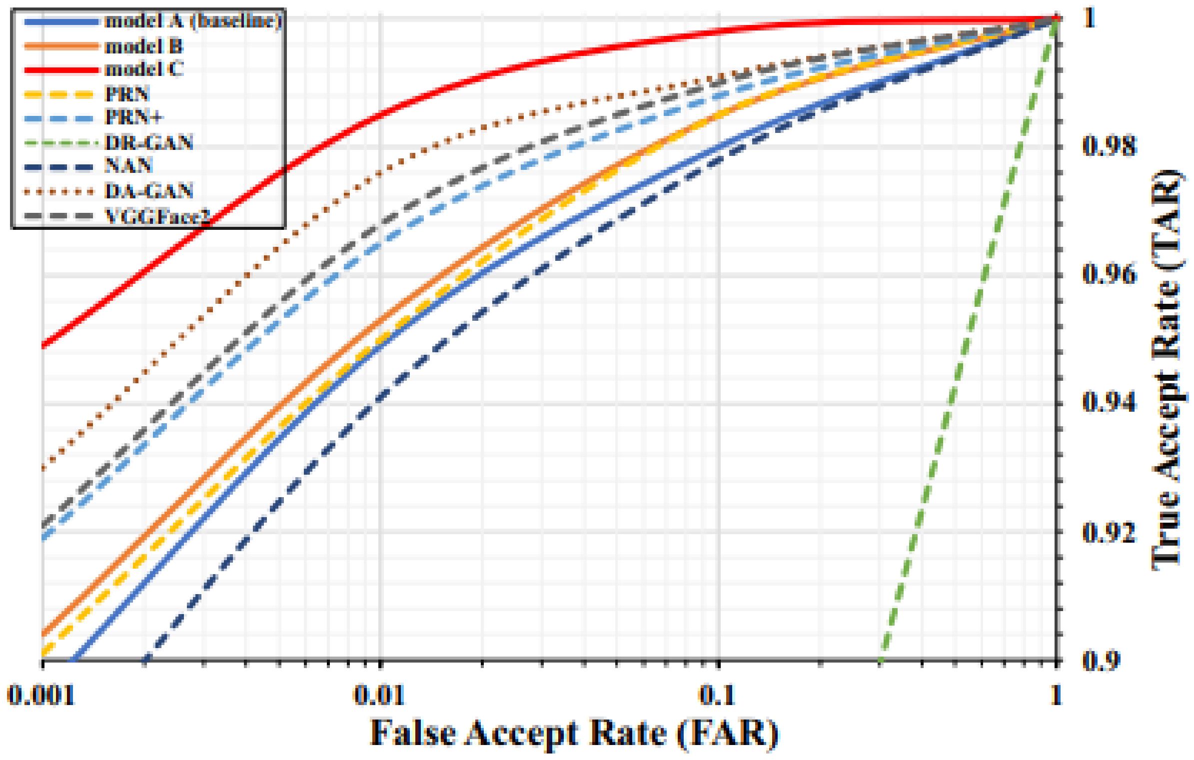
모델 A: 구조 맨 앞 ResNet만 있는 모델
모델 B: feature-pair selection layer가 없는 AFRN
모델 C: feature-pair selection layer가 있는 AFRN



(a) ROC

Attribute-Enhanced Face Recognition With Neural Tensor Fusion Networks

Hu, Guosheng, et al. "Attribute-enhanced face recognition with neural tensor fusion networks." Proceedings of ICCV. 2017.

- 제목: Attribute-Enhanced Face Recognition With Neural Tensor Fusion Networks
  → Neural Tensor Fusion Network를 사용한 attribute-enhanced 얼굴 인식

- 해결하고자 하는 문제: 얼굴의 포즈 변경과 같은 개인 내 변화에 대한 불변성에 있어 한계
  (예: 눈썹 두께, 성별 등)

- 해결 방법
  - FRF(Face Recognition feature)와 FAF(face attribute feature)의 융합
    - FRF: 매우 차별적이지만 덜 강력함, → LeanFace를 통해 사람 간 미묘한 차이 포착
    - FAF: 매우 강력하지만 덜 차별적, 얼굴 속성 feature → AttNet을 통해 얼굴 속성 감지

- 구조: CNN

Attribute-Enhanced Face Recognition With Neural Tensor Fusion Networks

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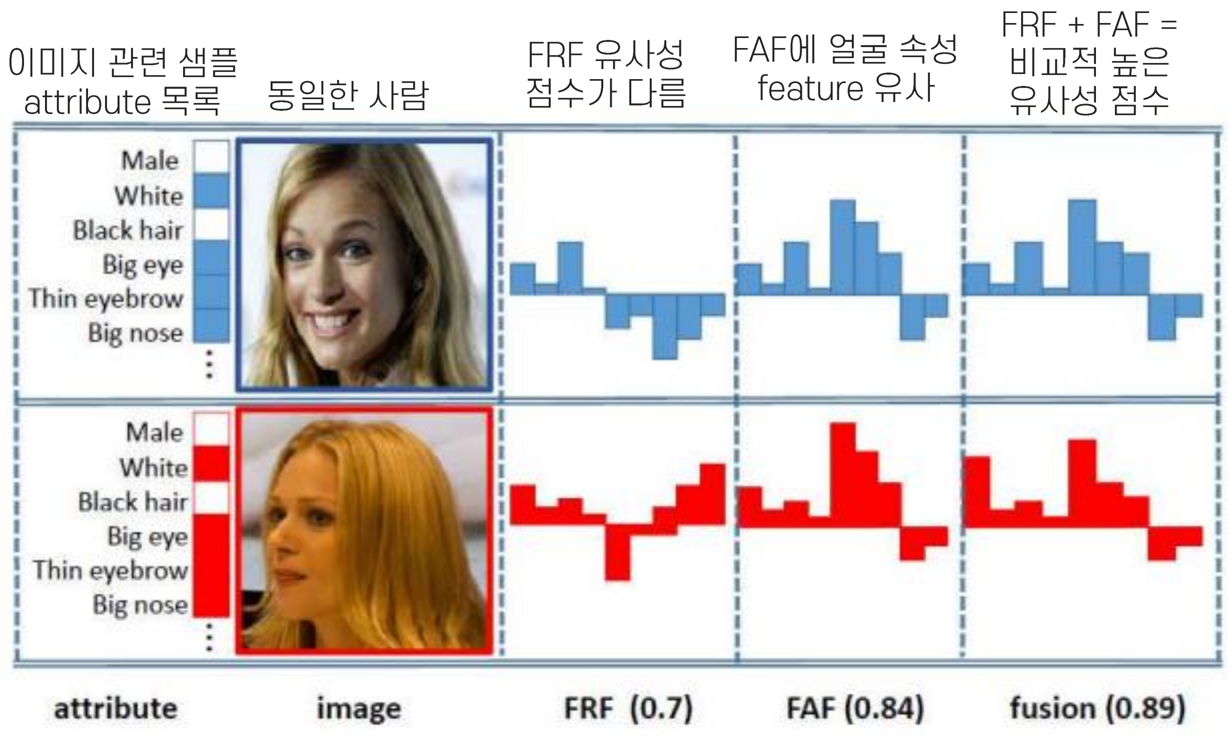

Attribute-Enhanced Face Recognition With Neural Tensor Fusion Networks

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GTNN(Gated two-stream neural network)
- 텐서를 융합하여 인식을 수행하는 neural network
- 2개의 입력 스트림 사용
- 신원 예측 neural netework로 사용

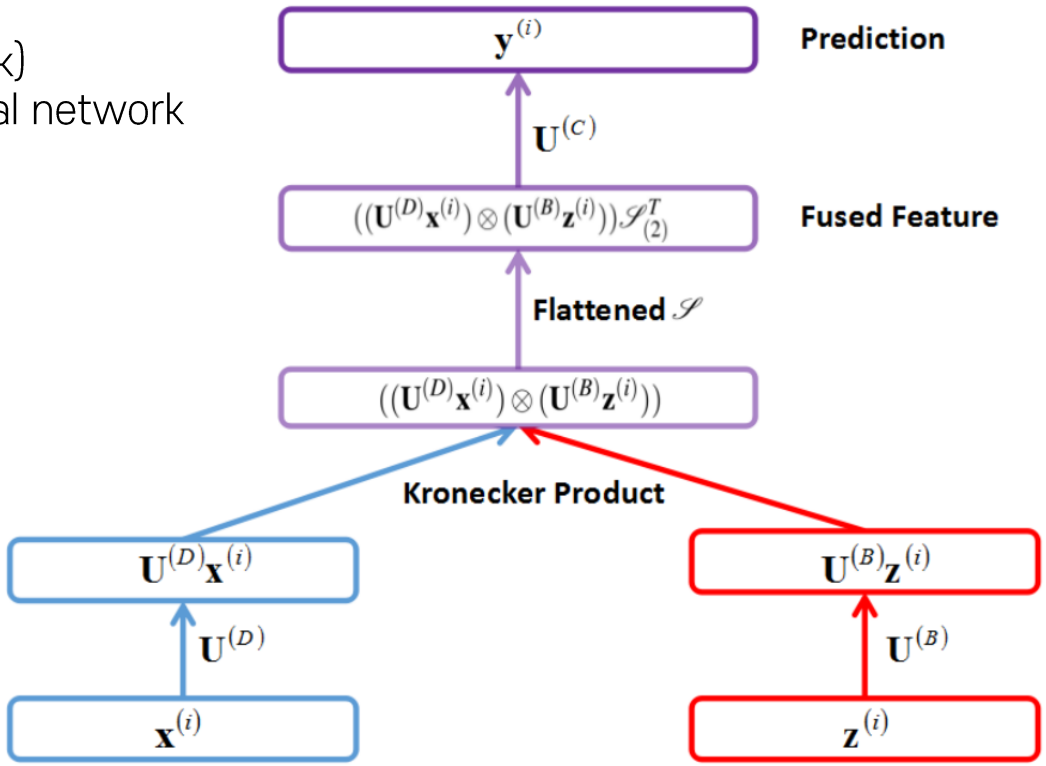

Figure 2: Gated two-stream neural network to implement low-rank tensor-based fusion. The architecture computes Eq. (7), with the Tucker decomposition in Eq. (4). The network is identity-supervised at train time, and feature in the fusion layer used as representation for verification.

Attribute-Enhanced Face Recognition With Neural Tensor Fusion Networks

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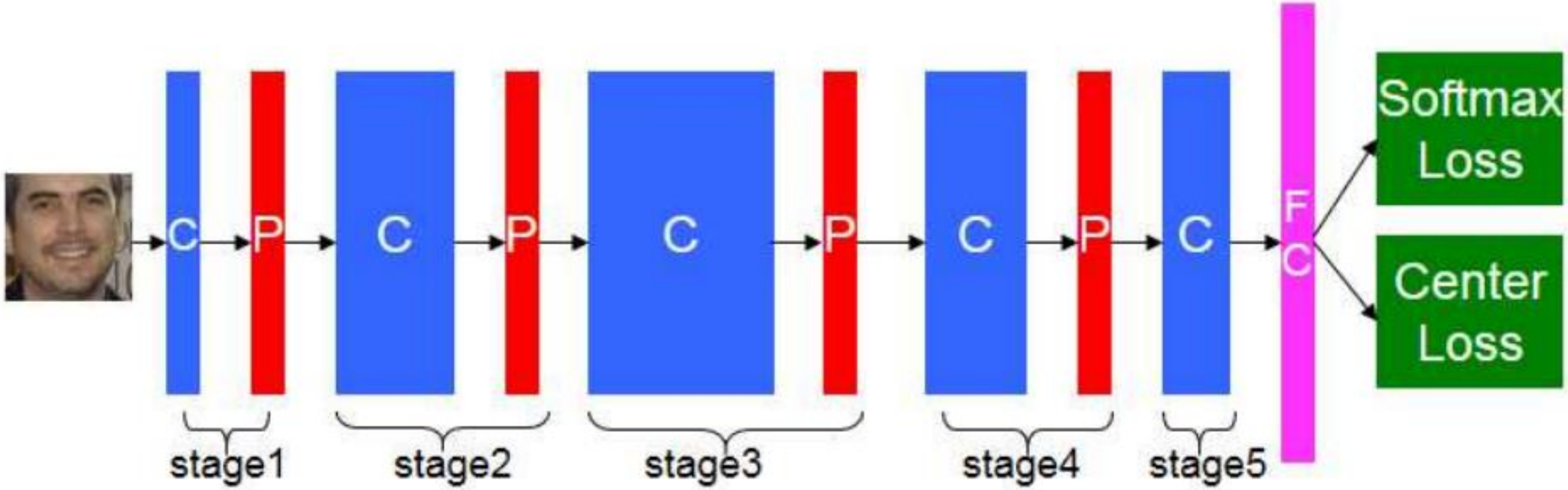
LeanFace
- 얼굴 인식 CNN
- GTNN 텐서 융합 시 FRF를 추출해주는 network
- 연구자들이 자체 제작한 모델

+) center loss: intra class 사이 간격을 좁혀주는 loss(예: 안경 쓴 지현, 화장한 지현 사이의 간격을 좁혀주는 loss)



Attribute-Enhanced Face Recognition With Neural Tensor Fusion Networks

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Table 2: Face recognition rate (%) on different poses on Multi-PIE

Method	-90°	-75°	-60°	(-45°, 45°)	+60°	+75°	+90°
SPAE [14]		-		91.4		-	
RL [59]		-		98.3		-	
MvDN [15]		-		99.3		-	
U3DMM [11]		-		97.8		-	
E3DMM [58]		-		98.6		-	
LBP	1.3	2.3	1.7	43.0	0.7	0.3	0.7
LeanFace	72.0	94.3	99.0	100	98.3	89.0	61.0
AttNet	6.0	9.7	11.7	56.1	11.3	8.0	5.0
GTNN (LBP, AttNet)	**16.3**	**14.3**	**15.0**	**69.3**	**6.7**	**4.3**	**3.3**
GTNN (LeanFace, AttNet)	**78.3**	**97.3**	**99.7**	**100**	**98.0**	**94.3**	**68.0**

GTNN을 활용한 모델에서 얼굴 인식 feature를 추출해주는 LeanFace와 얼굴 속성을 추출해주는 기존 연구인 AttNet을 조합한 모델이 가장 높은 성능을 보임

Attribute-Guided Face Generation Using Conditional CycleGAN

Lu, Yongyi, Yu-Wing Tai, and Chi-Keung Tang. "Attribute-guided face generation using conditional cyclegan." Proceedings of the European conference on computer vision (ECCV). 2018.

- 제목: Attribute-Guided Face Generation Using Conditional CycleGAN
  → Conditional CycleGAN을 사용한 Attribute-Guided 얼굴 생성

- 해결하고자 하는 문제: 사용자가 제공한 속성을 기반으로 얼굴 생성하기

- 해결 방법
  - Conditional CycleGAN 기반의 Attribute Guided Face Generation
  - 논문에서 제시한 모델 기반 응용 프로그램 세 가지
    - 신원 보존 얼굴 초해상도
    - 얼굴 스와핑
    - 정면 얼굴 생성

- 구조: GAN

Attribute-Guided Face Generation Using Conditional CycleGAN

Lu, Yongyi, Yu-Wing Tai, and Chi-Keung Tang. "Attribute-guided face generation using conditional cyclegan." Proceedings of the European conference on computer vision (ECCV). 2018.

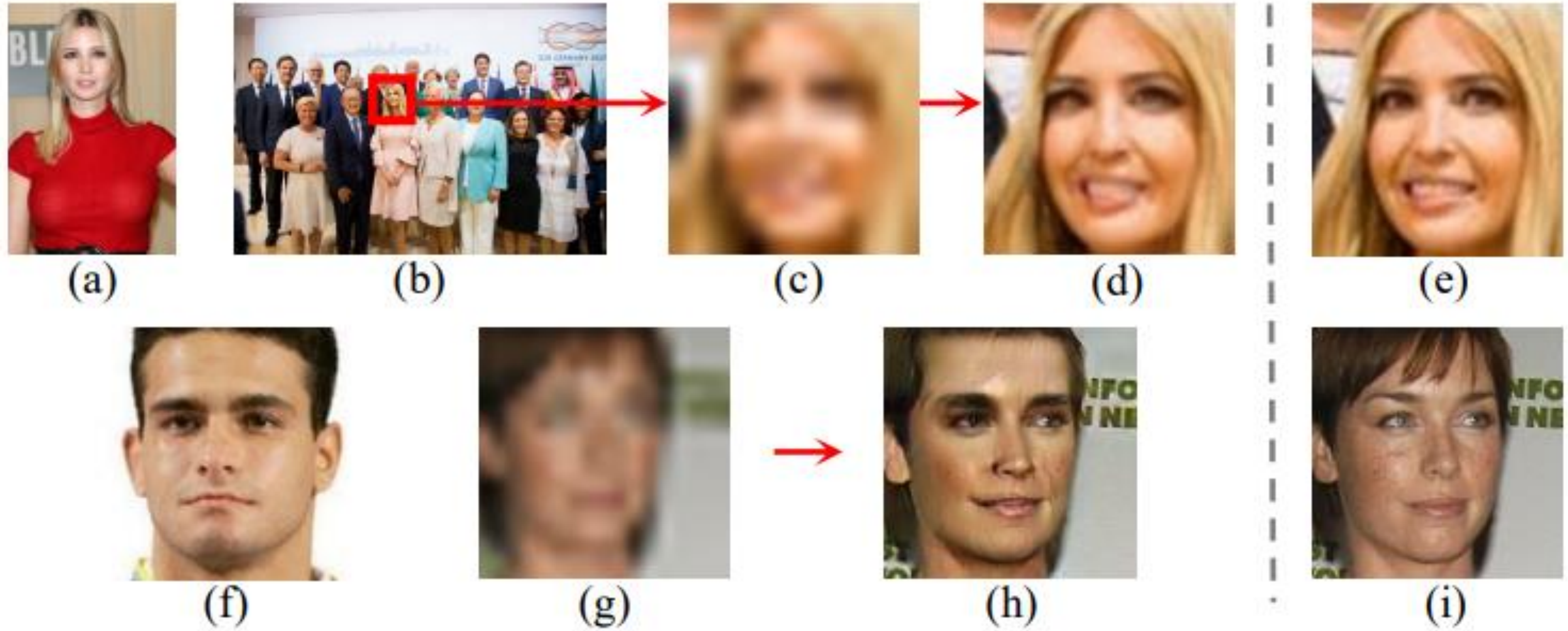
입력 속성: Identity

입력 사진

(b)에서 crop 한
저해상도 이미지

(a) + (c) 한
고해상도 이미지

GT



입력 속성: Identity

(f)와 신원이 다른
저해상도 이미지

(f) + (g) 한
고해상도 이미지

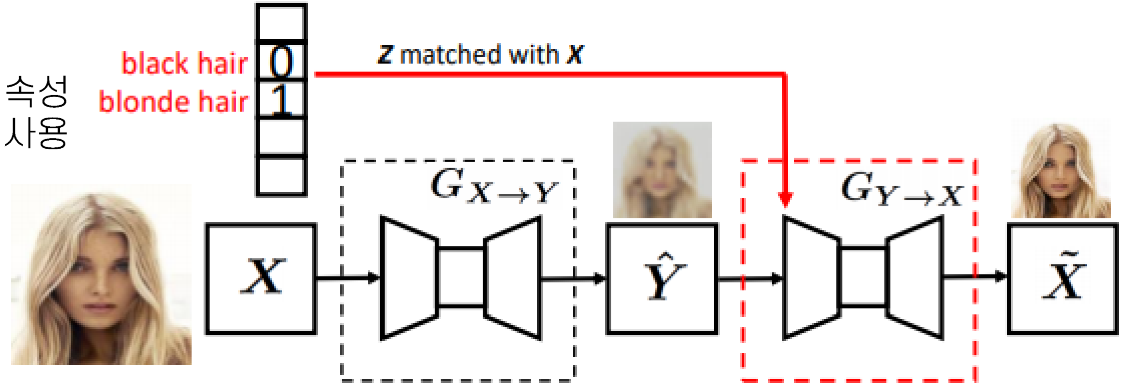
(g)의 GT

Attribute-Guided Face Generation Using Conditional CycleGAN

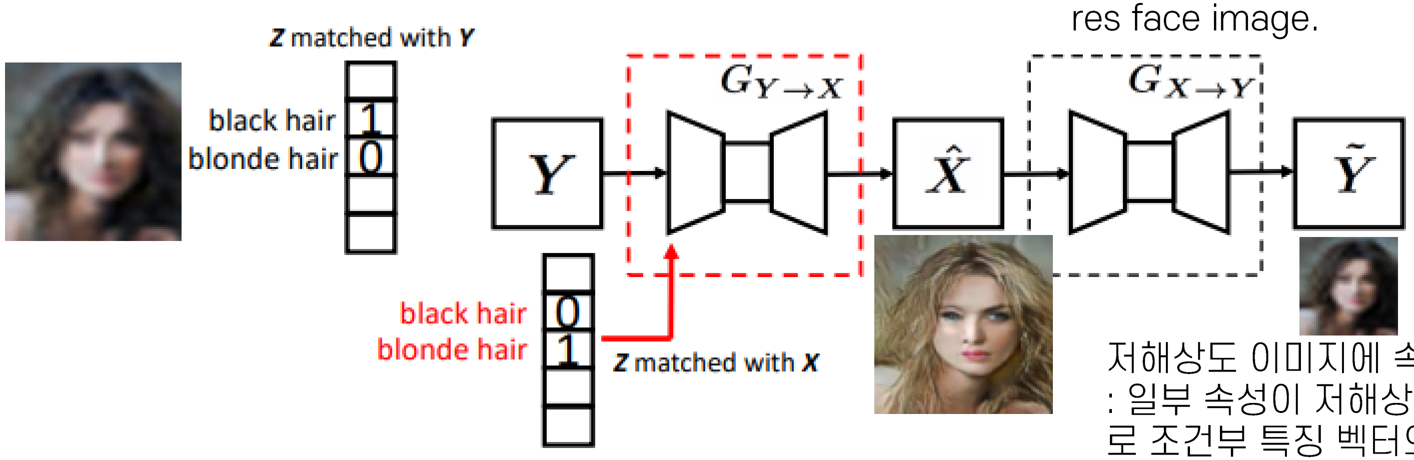
Lu, Yongyi, Yu-Wing Tai, and Chi-Keung Tang. "Attribute-guided face generation using conditional cyclegan." Proceedings of the European conference on computer vision (ECCV). 2018.

- Attribute-guided face generation을 위한 Condition CycleAGAN

Attribute vector
: 입력 이미지인 고해상도의 속성과 동일한 조건부 특징 벡터 사용



If the conditional feature vector always receives the correct attributes, the generator network would learn to skip the information in the conditional feature vector since some of the attributes can be found in the low-res face image.



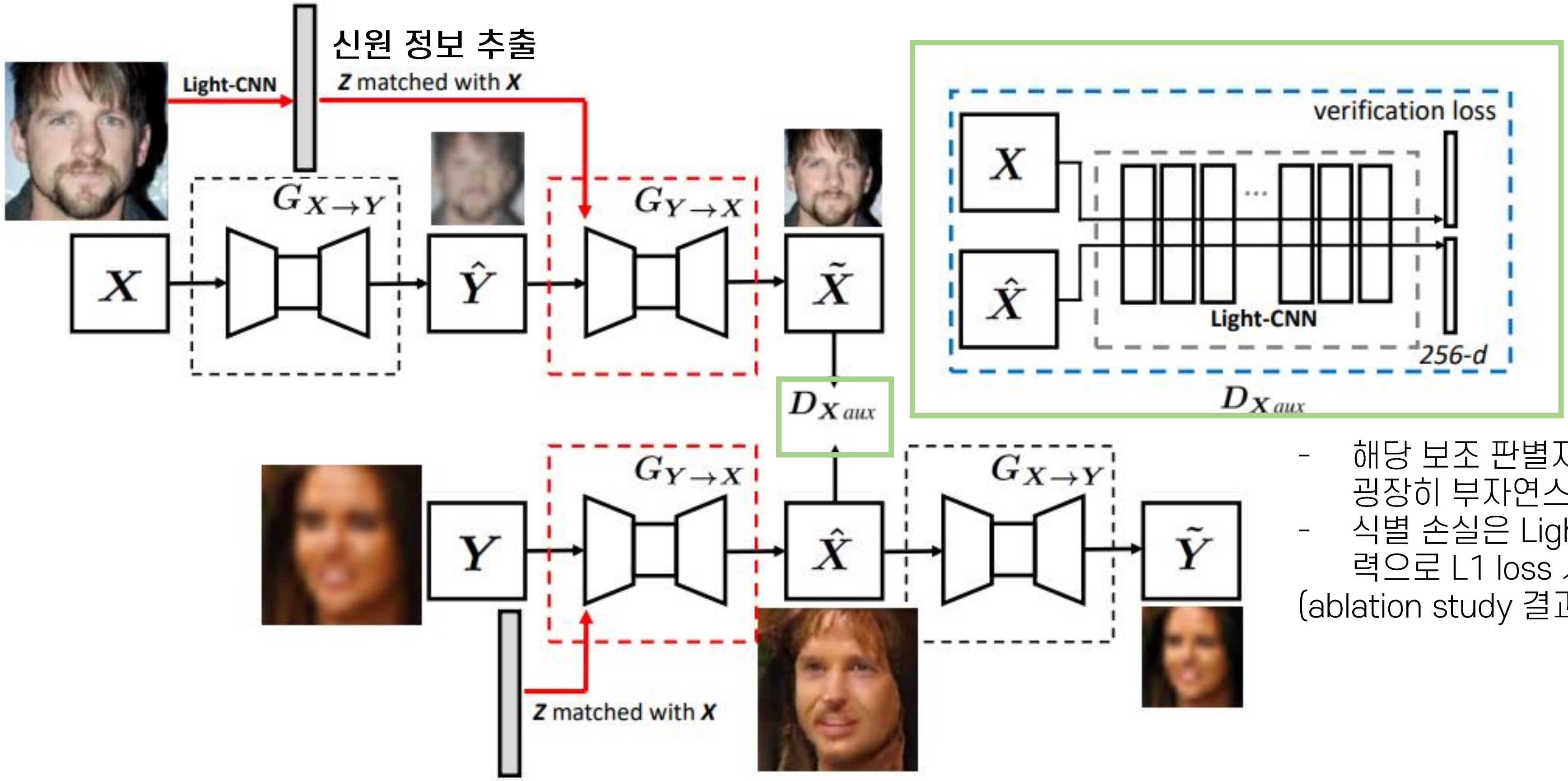
저해상도 이미지에 속성 특징이 전달되지 않은 이유
: 일부 속성이 저해상도 얼굴 이미지에서 찾을 수 있으므로 조건부 특징 벡터의 정보를 건너뛰는 학습을 한다.

* Discriminator 존재(본 구조에서는 단순화를 위해 생략)

Attribute-Guided Face Generation Using Conditional CycleGAN

Lu, Yongyi, Yu-Wing Tai, and Chi-Keung Tang. "Attribute-guided face generation using conditional cyclegan." Proceedings of the European conference on computer vision (ECCV). 2018.

- Identity-guided face generation을 위한 Condition CycleAGAN



- 해당 보조 판별자가 없을 시에 결과가 굉장히 부자연스러움
- 식별 손실은 Light-CNN의 결과를 입력으로 L1 loss 사용

(ablation study 결과 x)

* Discriminator 존재(본 구조에서는 단순화를 위해 생략)

Attribute-Guided Face Generation Using Conditional CycleGAN

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속성 변경

Fig. 6. Attribute-guided face generation. We flip one attribute label for each generated high-res face images, given the low-res face inputs. The 10 labels are: Bald, Bangs, Blond_Hair, Gray_Hair, Bushy_Eyebrows, Eyeglasses, Male, Pale_Skin, Smiling, Wearing_Hat.

Attribute-Guided Face Generation Using Conditional CycleGAN

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저해상도 이미지 + 저해상도 이미지 신원 = 고해상도 이미지

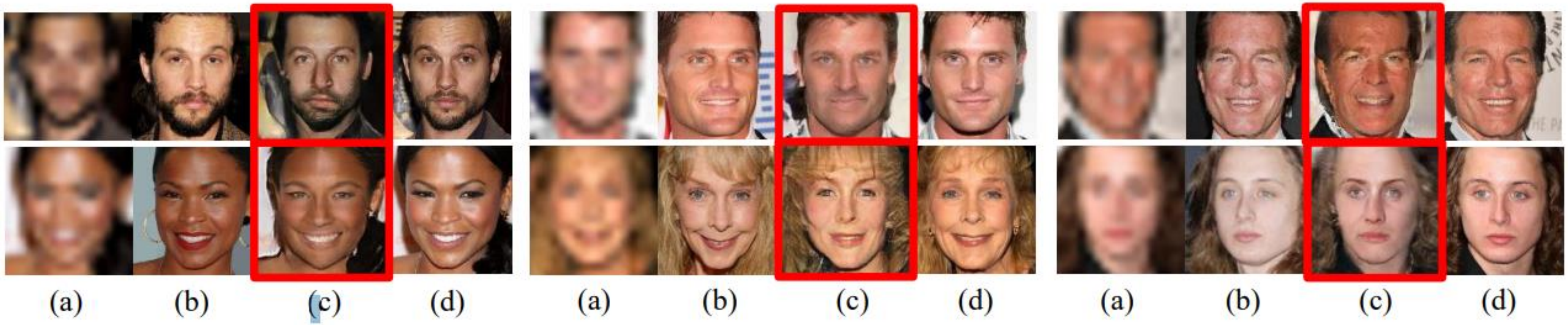
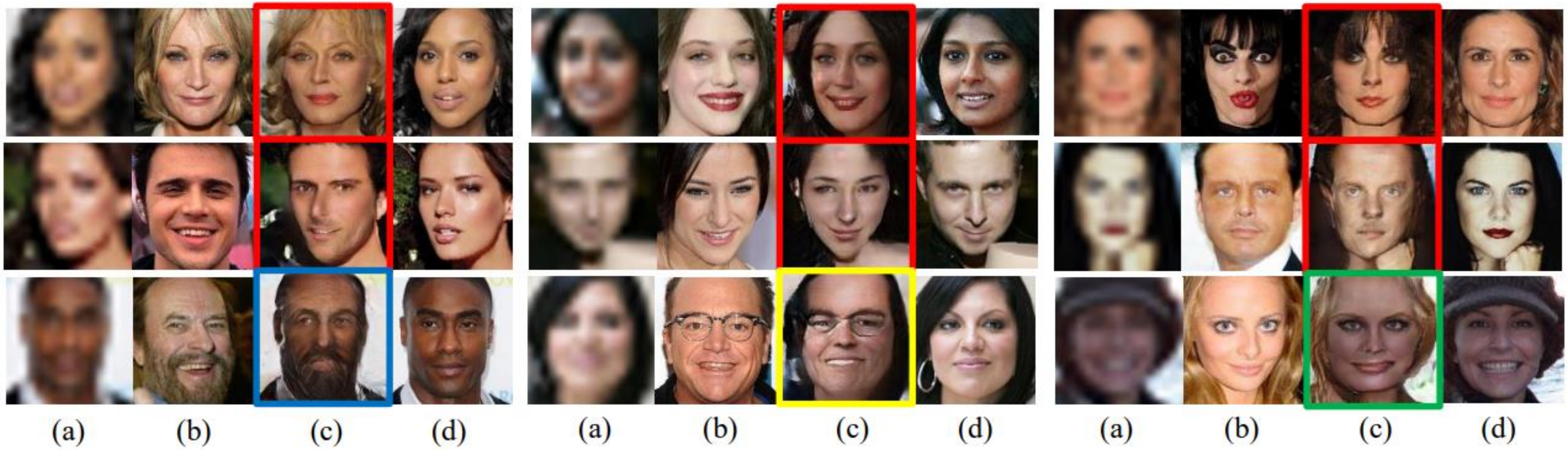


Fig. 9. Identity-guided face generation results on low-res input and high-res identity of the same person, i.e., identity-preserving face superresolution. (a) low-res inputs; (b) input identity of the same person; (c) our high-res face outputs (red boxes) from (a); (d) the high-res ground truth of (a).

Attribute-Guided Face Generation Using Conditional CycleGAN

Lu, Yongyi, Yu-Wing Tai, and Chi-Keung Tang. "Attribute-guided face generation using conditional cyclegan." Proceedings of the European conference on computer vision (ECCV). 2018.

저해상도 이미지 + 다른 사람 신원 = 고해상도 이미지



(a): 저해상도
(b): 신원 정보
(c): 합성
(d): (a)의 GT

CAFE-GAN: Arbitrary Face Attribute Editing with Complementary Attention Feature

Kwak, Jeong-gi, David K. Han, and Hanseok Ko. "CAFE-GAN: Arbitrary Face Attribute Editing with Complementary Attention Feature." Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XIV 16. Springer International Publishing, 2020.

- 제목: CAFE-GAN: Arbitrary Face Attribute Editing with Complementary Attention Feature
  → CAFE-GAN: Complementary Attention Feature를 사용한 임의의 얼굴 속성 수정

- 해결하고자 하는 문제: 얼굴의 속성을 변환 시에 목표한 속성 외에 다른 영역까지 변경

- 해결 방법
  - CAFE(Complementary Attention Feature)-GAN
    - 대상 속성과 관련된 얼굴 영역만 편집하도록 설계된 GAN
    - CAFE: 대상 속성과 입력 얼굴 이미지에 없는 속성으로 정의한 Complementary attribute를 모두 고려하여 변환 영역 식별

- 구조: GAN

CAFE-GAN: Arbitrary Face Attribute Editing with Complementary Attention Feature

Kwak, Jeong-gi, David K. Han, and Hanseok Ko. "CAFE-GAN: Arbitrary Face Attribute Editing with Complementary Attention Feature." Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XIV 16. Springer International Publishing, 2020.

Fig. 1: Face editing results of AttGAN [10], StarGAN [6], STGAN [21] and our model given a target attribute *Blond hair*. While AttGAN, StarGAN and STGAN deliver blond hair, they also create unwanted changes (e.g. halo, different hair style, etc.) in resultant images.

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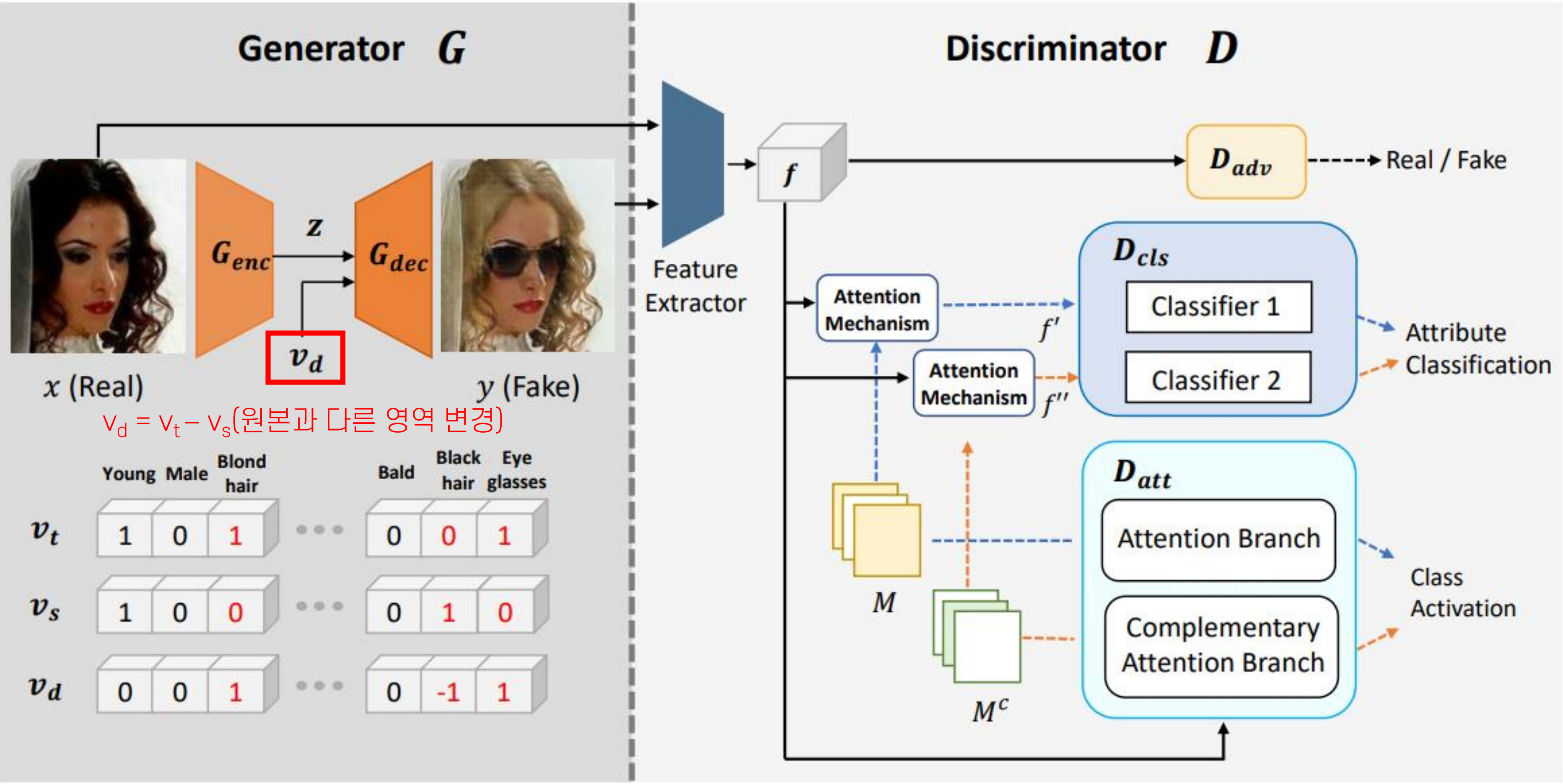

v_t: target attribute vector

v_s: source attribute vector

v_t: source, target이 서로 다른 attribute vector

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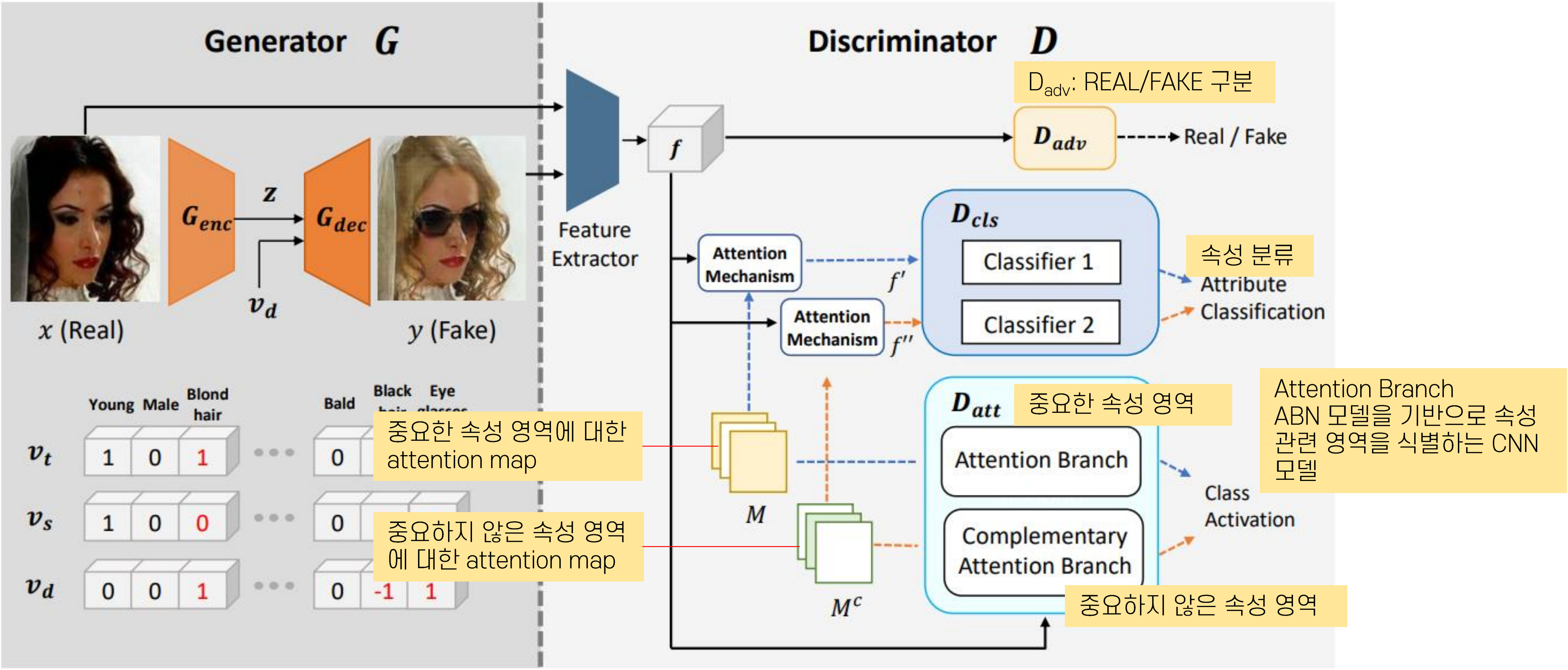

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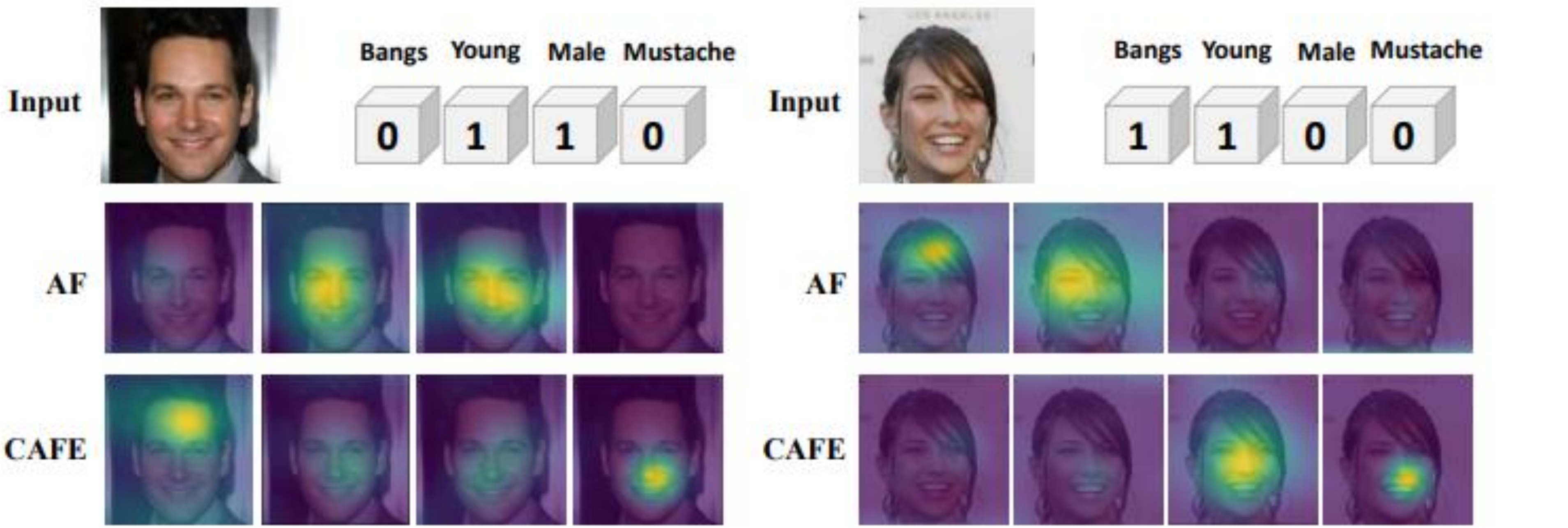

Fig. 7: Visualization results of the attention features (AF) and the complementary attention features (CAFE).

CAFE-GAN: Arbitrary Face Attribute Editing with Complementary Attention Feature

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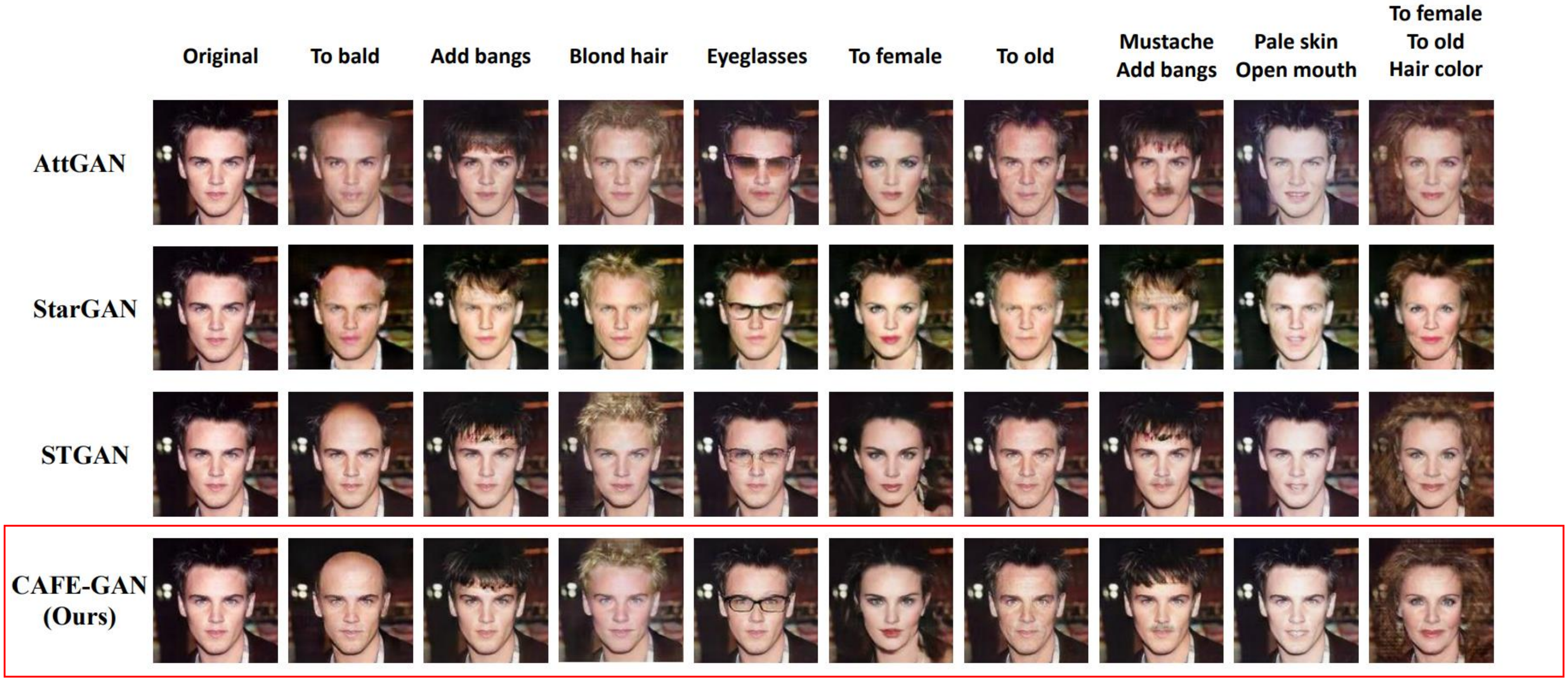

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Table 1: Comparisons on the attribute classification accuracy. Numbers indicate the classification accuracy on each attribute.

	Bald	Bangs	Blond h.	Musta.	Gender	Pale s.	Aged	Open m.	Avg.
AttGAN [10]	23.67	91.08	41.51	21.78	82.85	86.28	65.69	96.91	63.72
STGAN [21]	59.76	95.48	79.98	**42.10**	92.70	97.81	85.86	**98.65**	81.54
CAFE-GAN	**79.03**	**98.59**	**88.14**	40.13	**95.22**	**98.20**	**88.61**	97.15	**85.64**

CONFIG: Controllable Neural Face Image Generation

Kowalski, Marek, et al. "Config: Controllable neural face image generation." Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XI 16. Springer International Publishing, 2020.

- 제목: CONFIG: Controllable Neural Face Image Generation
  → CONFIG: 제어 가능한 Neural Face 이미지 생성

- 해결하고자 하는 문제: 현실적으로 자연스러우면서 미세하게 속성을 조절하는 데에 한계가 존재

- 해결 방법
  - ConfigNet
    - 실제 얼굴 및 합성 얼굴 이미지 생성 모델 학습
      - 합성 이미지: 기존 그래픽 파이프 라인으로 생성 → 매개 변수를 쉽게 사용 가능
    - 머리 포즈, 표정, 헤어 스타일, 조명 등 실제 주석을 달기 어려운 속성 분리
    - 출력 이미지 속성에 대해 제어

- 구조: GAN

CONFIG: Controllable Neural Face Image Generation

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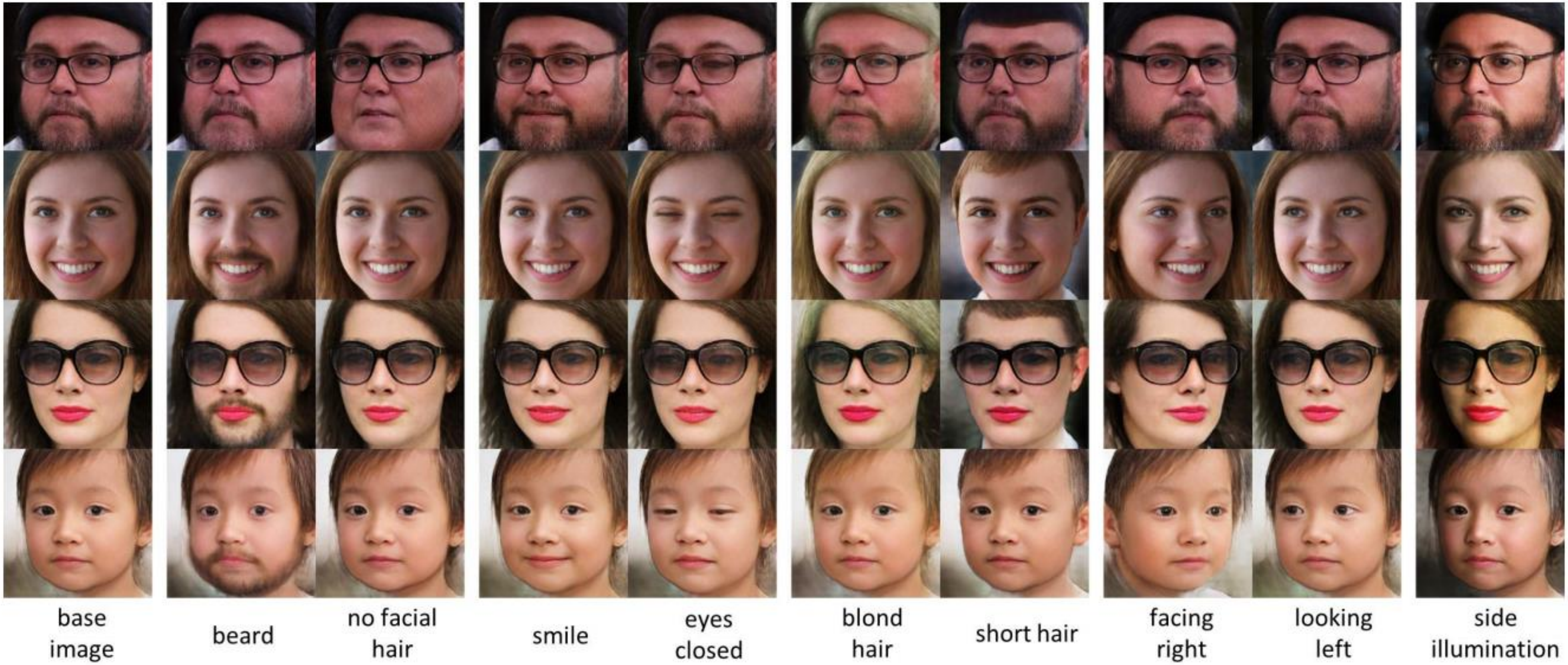

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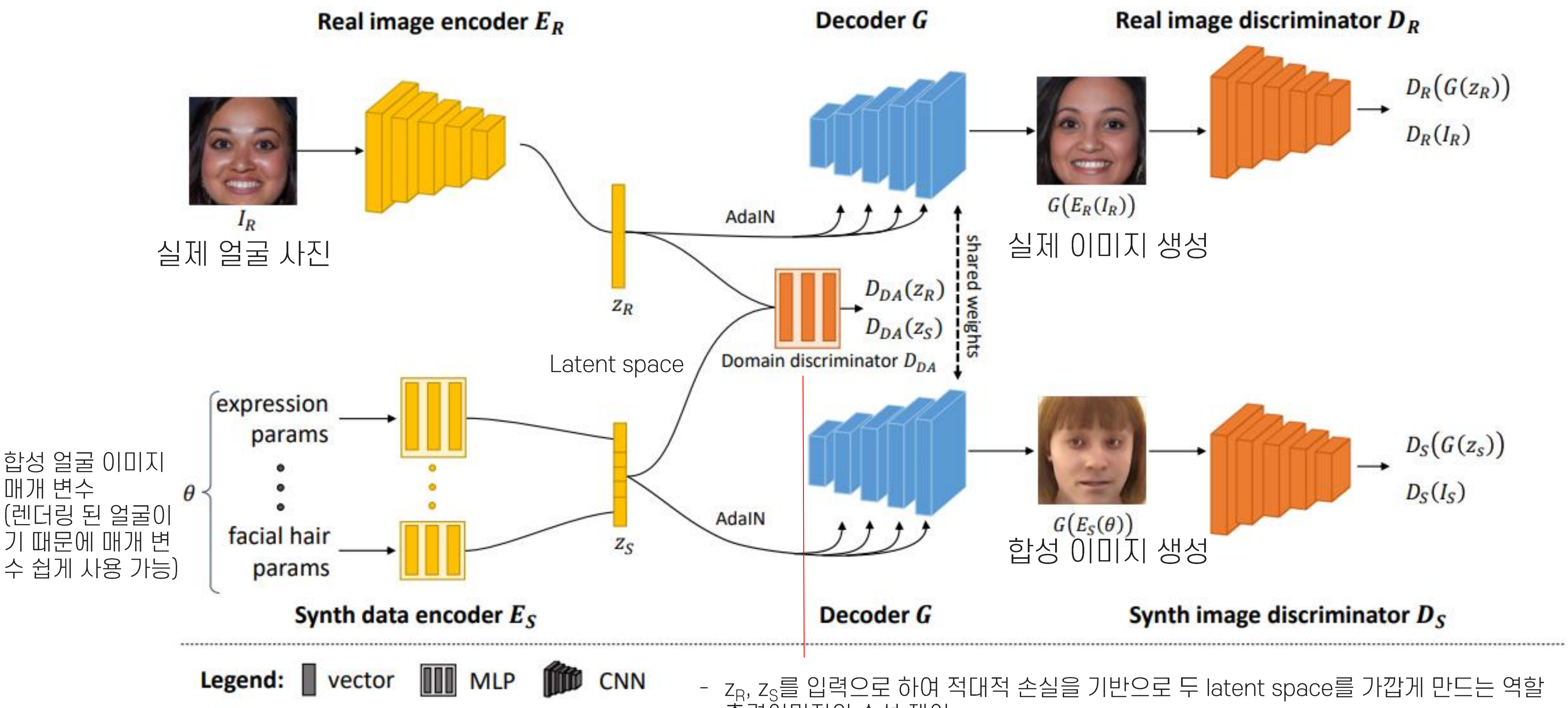

- z_R, z_S를 입력으로 하여 적대적 손실을 기반으로 두 latent space를 가깝게 만드는 역할
- 출력이미지의 속성 제어

CONFIG: Controllable Neural Face Image Generation

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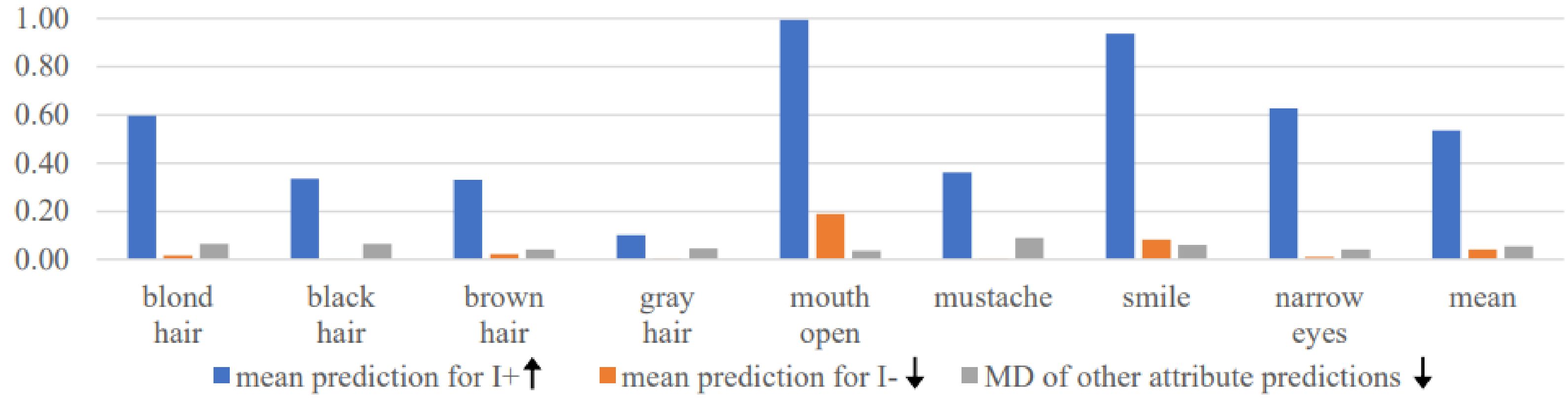
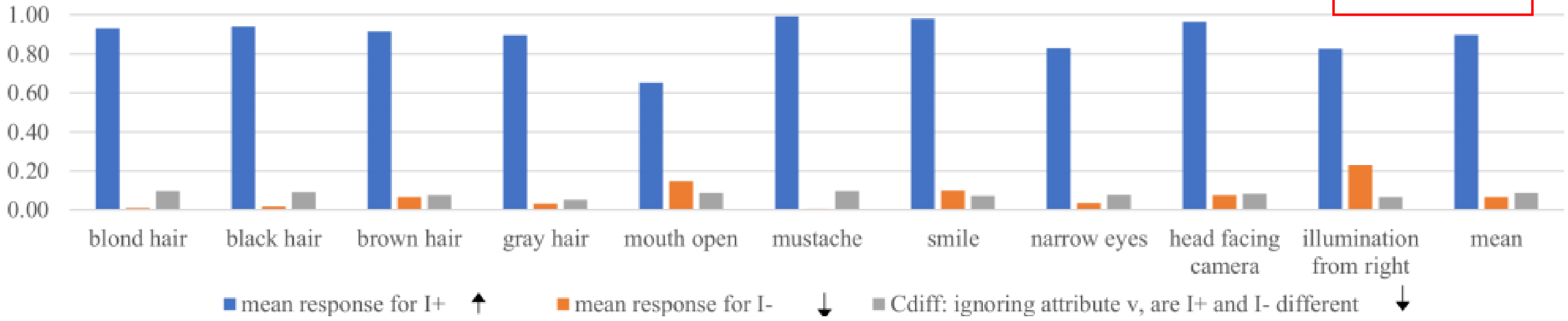


(a) Evaluation of controllability and disentanglement with an attribute predictor.



(b) Evaluation of controllability and disentanglement with a user study.

Fig. 5: Evaluation of control and disentanglement of ConfigNet. Blue and orange bars show the predicted values of given attribute for images with that attribute (I_+, higher better) and images with an opposite attribute (I_-, lower better). The gray bars measure differences of other attributes (MD and C_{diff}, lower better).

CONFIG: Controllable Neural Face Image Generation

Kowalski, Marek, et al. "Config: Controllable neural face image generation." Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XI 16. Springer International Publishing, 2020.

Fig. 7: Comparison between ConfigNet (left) and PuppetGAN (right). Top row shows the input, left column the desired level of mouth opening for each row. To facilitate comparison, ConfigNet results are cropped to match PuppetGAN.

Consistent Instance False Positive Improves Fairness in Face Recognition

Xu, Xingkun, et al. "Consistent Instance False Positive Improves Fairness in Face Recognition." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2021.

- 제목: Consistent Instance False Positive Improves Fairness in Face Recognition
  →일관된 instance FP는 얼굴 인식의 공정성을 향상시킨다.

- 해결하고자 하는 문제: 인구학적 편견은 실제 얼굴 인식 시스템에서 중요한 문제
  → 인구 통계학적 주석에 의존하면 실제 시나리오에서 사용하기 힘듦(일반적이지 못함)
  → Dataset을 공정하게 수집하더라도 인종적 편견을 완전히 제거하기 어려움

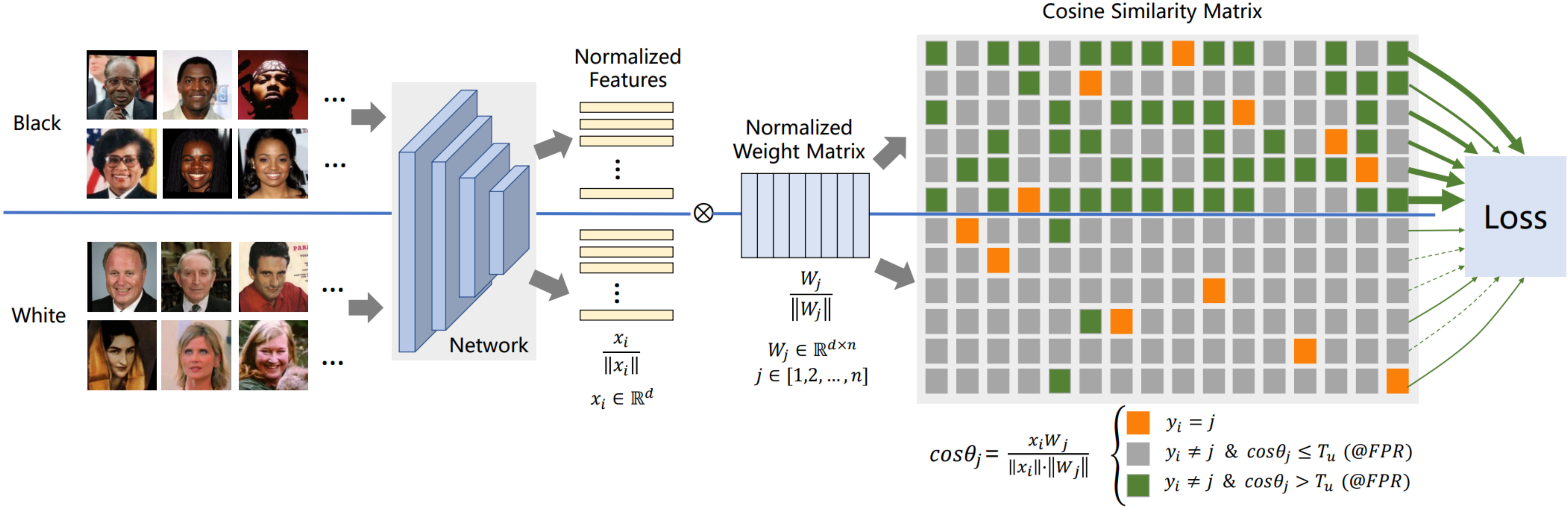
- 해결 방법
    - False positive rate penalty loss 제안
        - FRR(Instance False Positive Rate)의 일관성을 높여 얼굴 인식 편향 완화

- 구조: CNN(ResNet)

Consistent Instance False Positive Improves Fairness in Face Recognition

Xu, Xingkun, et al. "Consistent Instance False Positive Improves Fairness in Face Recognition." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2021.

주황 상자: 샘플과 target 간의 코사인 유사성
회색 상자: 샘플과 non-target 간의 코사인 유사성이 임계값보다 작거나 같을 경우
녹색 상자: 샘플과 non-target 간의 코사인 유사성이 임계값보다 클 경우(거짓 긍정)
FPR = 녹색 상자 / 회색 상자



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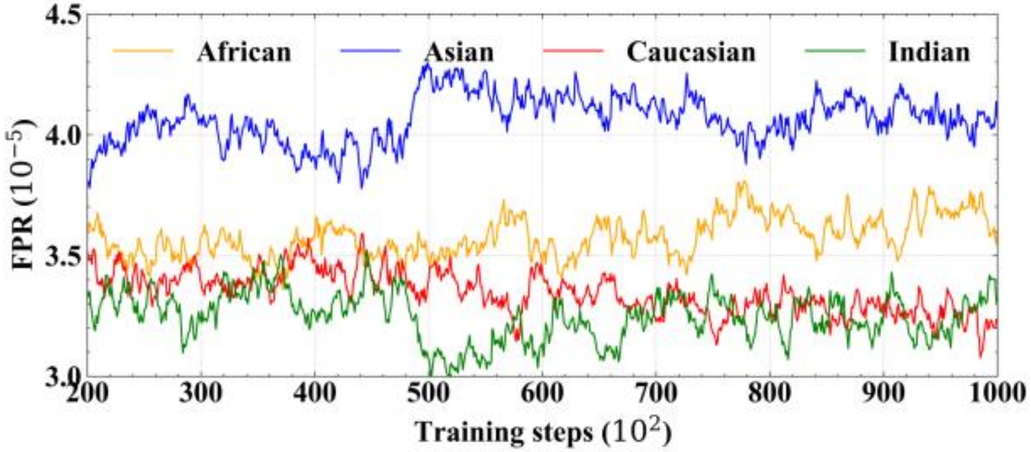
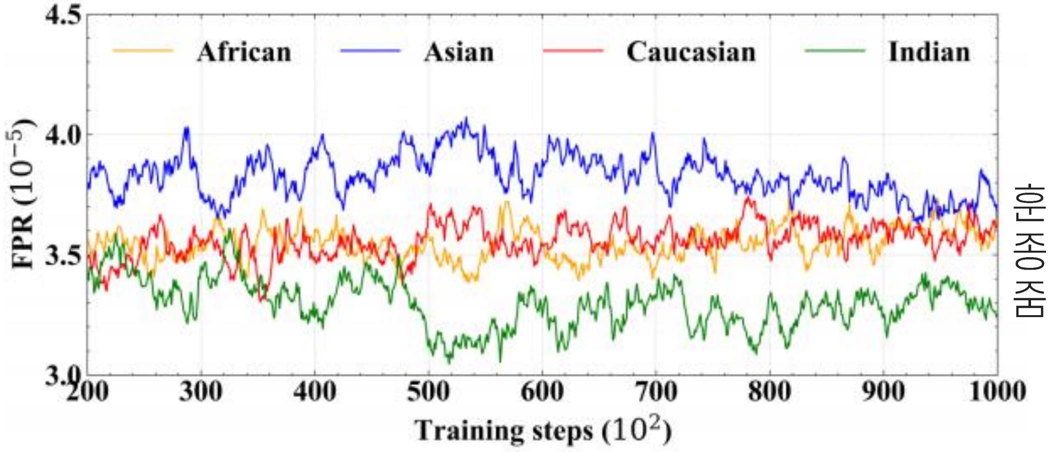


(a) Demographic FPR (ArcFace)



(b) Demographic FPR (ours)

훈련이 끝날 때 인도인을 제외한 나머지 인종 그룹의 FPR이 수렴하여 일관성을 보여줌을 확인할 수 있음

Decorrelated Adversarial Learning for Age-Invariant Face Recognition

Wang, Hao, et al. "Decorrelated adversarial learning for age-invariant face recognition." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2019.

- 제목: Decorrelated Adversarial Learning for Age-Invariant Face Recognition
  → 연령 불변 얼굴 인식을 위한 Decorrelated 적대적 학습

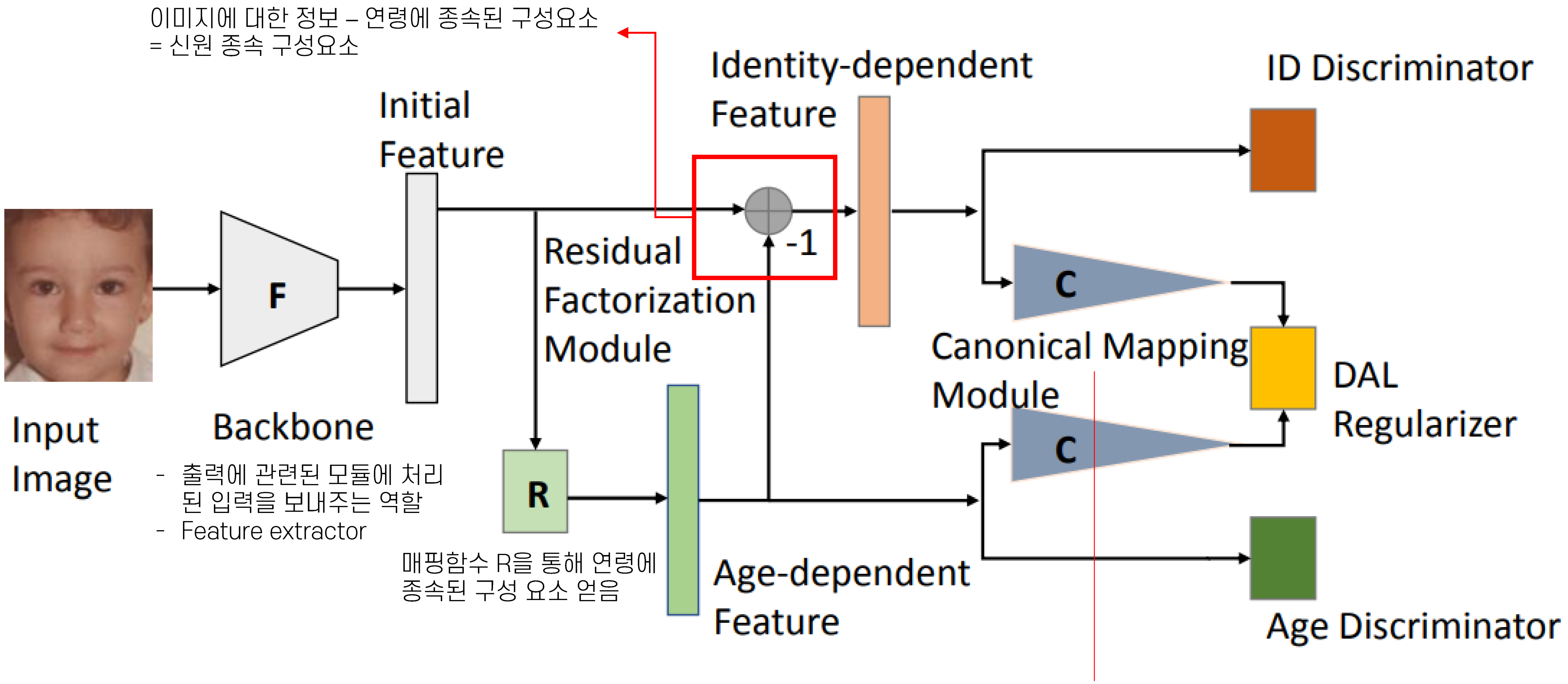
- 해결하고자 하는 문제: 노화로 인한 외모 불일치로 동일한 얼굴을 인식하기 어려움

- 해결 방법
  - DAL(Decorrelated Adversarial Learning) 알고리즘 제안
    - 신원 종속 feature와 연령 종속 feature로 분해
    - 신원 정보와 연령 정보의 상관 관계를 적대적으로 최소화

- 구조: CNN

Decorrelated Adversarial Learning for Age-Invariant Face Recognition

Wang, Hao, et al. "Decorrelated adversarial learning for age-invariant face recognition." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2019.



$$\forall t \in \{id, age\} : \mathbf{v_t} = \mathcal{C}(\mathbf{x_t}) = \mathbf{w_t^T x_t},$$

Decorrelated Adversarial Learning for Age-Invariant Face Recognition

Wang, Hao, et al. "Decorrelated adversarial learning for age-invariant face recognition." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2019.

Method	#Test Subjects	Rank-1
HFA [13]	10,000	91.14%
CARC [5]	10,000	92.80%
MEFA [15]	10,000	93.80%
MEFA+SIFT+MLBP [15]	10,000	94.59%
LPS+HFA [24]	10,000	94.87%
LF-CNNs [48]	10,000	97.51%
OE-CNNs	10,000	98.55%
Ours	10,000	**98.93%**
GSM [27]	3,000	94.40%
AE-CNNs [59]	3,000	98.13%
OE-CNNs [46]	3,000	98.67%
Ours	3,000	**98.97%**

Table 2. Evaluation results on the MORPH Album 2 dataset.

Method	Acc.	AUC.
High-Dimensional LBP [7]	81.6%	88.8%
HFA [13]	84.4%	91.7%
CARC [5]	87.6%	94.2%
LF-CNNs [48]	98.5%	99.3%
Human, Average [6]	85.7%	94.6%
Human, Voting [6]	94.2%	99.0%
Softmax	98.4%	99.4%
A-Softmax	98.7%	99.5%
OE-CNNs [46]	99.2%	99.5%
Ours	**99.4%**	**99.6%**

Table 3. Evaluation results on the CACD-VS dataset.

Discovering Fair Representations in the Data Domain

Quadrianto, Novi, Viktoriia Sharmanska, and Oliver Thomas. "Discovering fair representations in the data domain." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2019.

- 제목: Discovering Fair Representations in the Data Domain
  → 데이터 도메인에서 공정한 표현 발견하기

- 해결하고자 하는 문제: 기계 학습 모델의 공정함을 확인하기 쉽지 않다
  (예: 지원자 중 누구를 합격시킬 것인지 등 차별하지 않음을 보장하기 쉽지 않음)
  +) 본 논문에서의 공정성은 기회 균등을 의미

- 해결 방법
  - 남성, 여성 얼굴 → 남성과 여성의 중간 얼굴 사진으로 변환하는 등 기회 균등성 적용

- 구조: -

Domain Balancing: Face Recognition on Long-Tailed Domains

Cao, Dong, et al. "Domain balancing: Face recognition on long-tailed domains." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2020.

- 제목: Domain Balancing: Face Recognition on Long-Tailed Domains
  → Domain Balancing: Long-tailed Domains에서 얼굴 인식

- 해결하고자 하는 문제: 학습 세트와 동일한 도메인에서만 잘 작동하고 보지 못한 도메인에서는 제대로 수행되지 않음

- 해결 방법
  - DB(Domain Balancing) mechanism
    - DFI(Domain Frequency Indicator): 각 클래스의 도메인 주파수 자동 평가
    - RBM(Residual Balancing Mapping): 네트워크 조정
    - DBM(Domain Balancing Margin): 도메인 분포에 따라 loss 조정
- 구조: -

Domain Balancing: Face Recognition on Long-Tailed Domains

Cao, Dong, et al. "Domain balancing: Face recognition on long-tailed domains." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2020.

DFI	RBM	DBM
- 클래스가 분산된 정도를 파악하여 균일하게 분산되도록 함 - DFI는 클래스 압축(IC)에 반비례 - 예를 들어 백인>흑인>아시아인 인종 순으로 도메인 분포가 구성되어 있을 때 백인의 DFI가 가장 낮음	- x + f(x) + R(x) - x: 최상위 feature - f(x): DFI 기반 soft gate(x와 DFI 연관) - DFI가 클 수록 long tailed에 속함 - 따라서 f(x)와 R(x)의 조합은 도메인 분포 정보 채택 후 다음 layer로 전달되는 크기 제어	- 도메인 클래스를 적응적으로 강화하기 위해 제안 - 도메인 분포에 따라 loss 조정

Domain Balancing: Face Recognition on Long-Tailed Domains

Cao, Dong, et al. "Domain balancing: Face recognition on long-tailed domains." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2020.

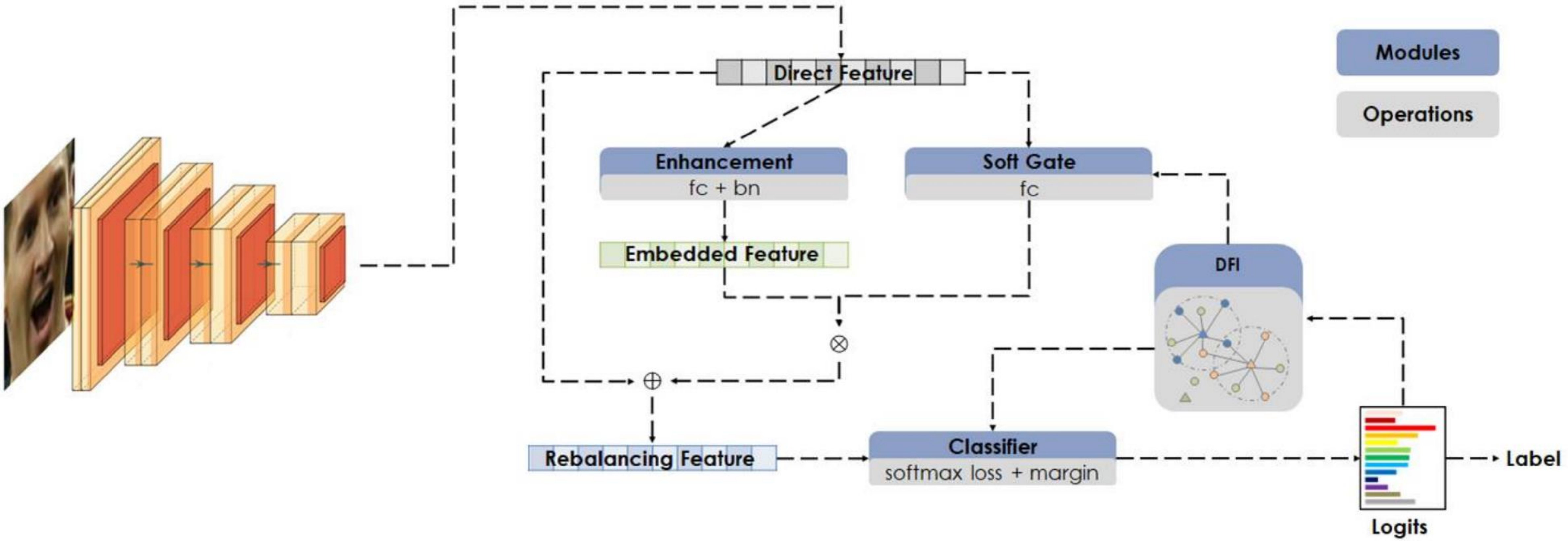


Figure 3. There are three main modules: DFI, RBM and DBM. The DFI indicates the local distances within a local region. The RBM harmonizes the representation ability in the network architecture, while the DBM balances the contribution in the loss.

Domain Balancing: Face Recognition on Long-Tailed Domains

Cao, Dong, et al. "Domain balancing: Face recognition on long-tailed domains." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2020.

Table 7. Face identification and verification on MegaFace Challenge1. ”Rank 1” refers to the rank-1 face identification accuracy, and ”Ver” refers to the face verification TAR at 10^{-6} FAR.

Method	Rank1 (%)	Ver (%)
DeepSense V2	81.29	95.99
YouTu Lab	83.29	91.34
Vocord-deepVo V3	91.76	94.96
SphereFace [18]	92.05	92.42
CosFace [32]	94.84	95.12
ArcFace [4]	95.53	95.88
Ours	**96.35**	**96.56**

Fair Attribute Classification Through Latent Space De-Biasing

Ramaswamy, Vikram V., Sunnie SY Kim, and Olga Russakovsky. "Fair attribute classification through latent space de-biasing." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2021.

- 제목: Fair Attribute Classification Through Latent Space De-Biasing
  → Latent space De-Biasing을 통한 공정한 속성 분류

- 해결하고자 하는 문제: 속성 간의 상관 관계로 인한 편향 문제 발생
  (예1: 모자에 대한 시각적 분류기를 훈련할 때 안경과 연관 되면서 – 외부에서는 모자와 안경을 착용, 내부에서는 둘다 미착용
  모자가 없다 = 모자 & 안경 없음
  모자가 있다 = 모자 & 안경 있음)
- (예2: 특정 인종 그룹을 과소 표현한 dataset에서 훈련된 얼굴 인식 시스템은 해당 그룹에 대한 정확도가 낮음)

- 해결 방법
  - 공정한 분류기를 사용하기 위해 데이터 확대 방법 도입
    - GAN 활용하여 실제 데이터 세트를 확장하는 데 사용

- 구조: GAN

Fair Attribute Classification Through Latent Space De-Biasing

Ramaswamy, Vikram V., Sunnie SY Kim, and Olga Russakovsky. "Fair attribute classification through latent space de-biasing." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2021.

Figure 2: Consider a GAN trained on a biased real-world dataset of faces where the presence of hats is correlated with the presence of glasses. Naively moving in a direction that adds glasses also adds a hat (*Top*). We learn a direction in the latent space that allows us to add glasses, while not adding a hat (*Bottom*). Note that attributes apart from the target attribute can change.

Fair Attribute Classification Through Latent Space De-Biasing

Ramaswamy, Vikram V., Sunnie SY Kim, and Olga Russakovsky. "Fair attribute classification through latent space de-biasing." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2021.

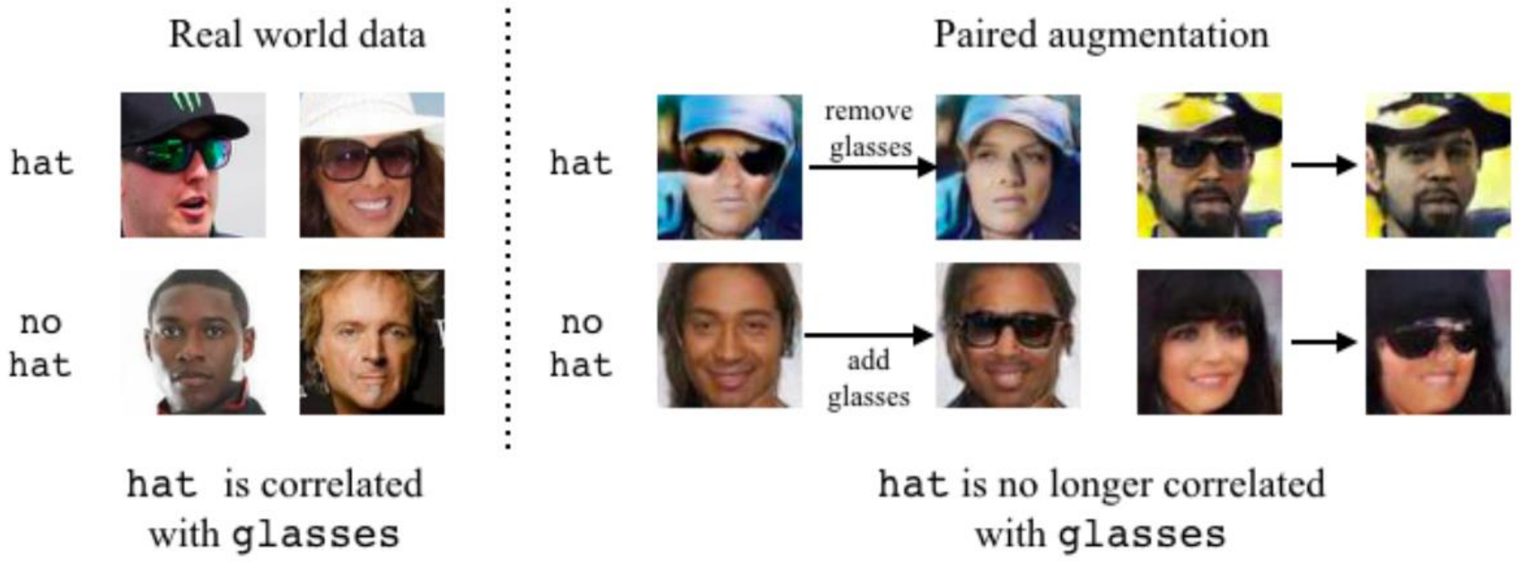
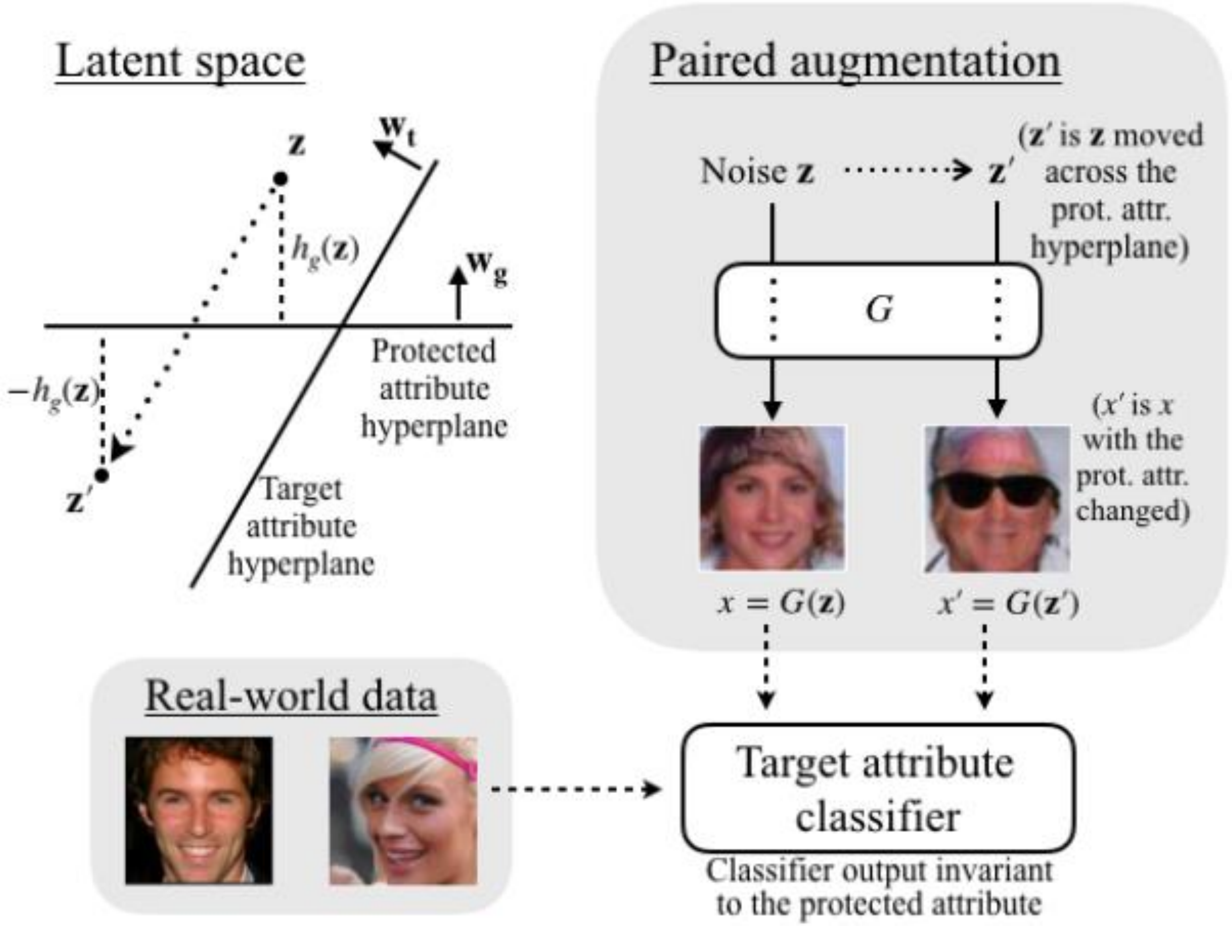


Figure 1: Training a visual classifier for an attribute (e.g., hat) can be complicated by correlations in the training data. For example, the presence of hats can be correlated with the presence of glasses. We propose a dataset augmentation strategy using Generative Adversarial Networks (GANs) that successfully removes this correlation by adding or removing glasses from existing images, creating a balanced dataset.

Fair Attribute Classification Through Latent Space De-Biasing

Ramaswamy, Vikram V., Sunnie SY Kim, and Olga Russakovsky. "Fair attribute classification through latent space de-biasing." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2021.



Fair Attribute Classification Through Latent Space De-Biasing

Ramaswamy, Vikram V., Sunnie SY Kim, and Olga Russakovsky. "Fair attribute classification through latent space de-biasing." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2021.

Attr. type	AP ↑		DEO ↓	
	Baseline	Ours	Baseline	Ours
Incons.	**66.3 ± 1.8**	65.2 ± 1.9	21.5 ± 4.4	**16.5 ± 4.2**
G-dep	**78.6 ± 1.4**	77.8 ± 1.4	25.7 ± 3.5	**23.4 ± 3.6**
G-indep.	**83.9 ± 1.5**	83.0 ± 1.6	16.7 ± 5.0	**13.9 ± 5.2**
Attr. type	BA ↓		KL ↓	
	Baseline	Ours	Baseline	Ours
Incons.	2.1 ± 0.6	**0.5 ± 0.6**	1.7 ± 0.3	**1.3 ± 0.4**
G-dep	2.3 ± 0.5	**1.6 ± 0.5**	1.3 ± 0.2	**1.2 ± 0.2**
G-indep.	0.3 ± 0.6	**0.0 ± 0.5**	1.1 ± 0.5	**0.9 ± 0.6**

Table 1: Comparison of our model (i.e. attribute classifier trained with our data augmentation method) to the baseline model. Arrows indicate which direction is better. Numbers are averages over all attributes within the specific category. As expected, we have slightly lower AP than the baseline, but perform better on the three fairness metrics, DEO, BA, and KL.