Face Aging with Identity-Preserved Conditional Generative Adversarial Networks

报告人：王宗伟
导师：高盛华

Face Aging

- Face aging is a task of synthesizing faces of a certain person under a given age.

Images are from FG-net.

Challenges: *the lack of labeled faces of the same person across a long age range.*

Recent Progress of Generative Adversarial Networks(GANs)

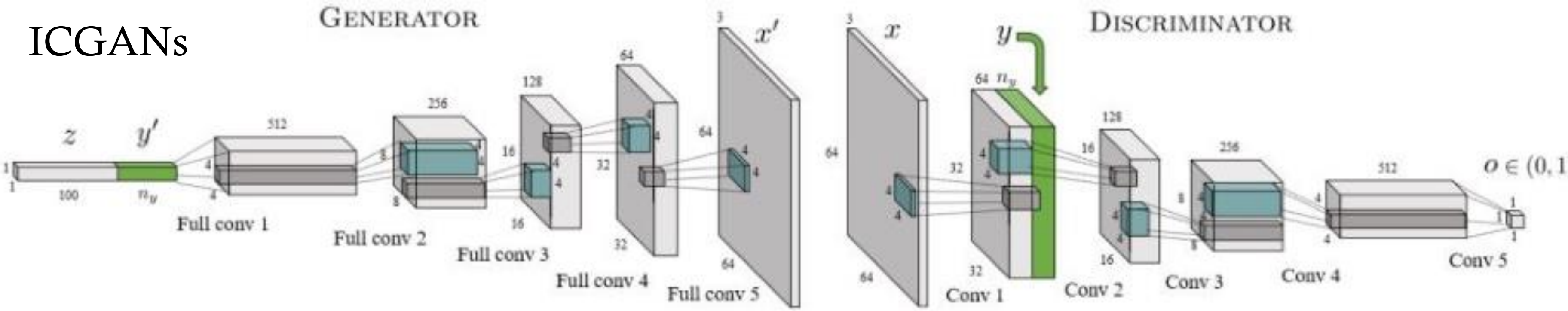
- GANs

$$\min_G \max_D \mathbb{E}_{x\sim p_{data}(x)}[\log D(x)]+\mathbb{E}_{z\sim p_z(z)}[\log(1-D(G(z)))]$$

- Deep Convolutional GANs, DCGANs
- Energy Based GANs
- Wasserstein GANs, WGANs
- Least Squares GANs, LSGANs
- Improved WGANs

Typical Conditional GANs

ICGANs

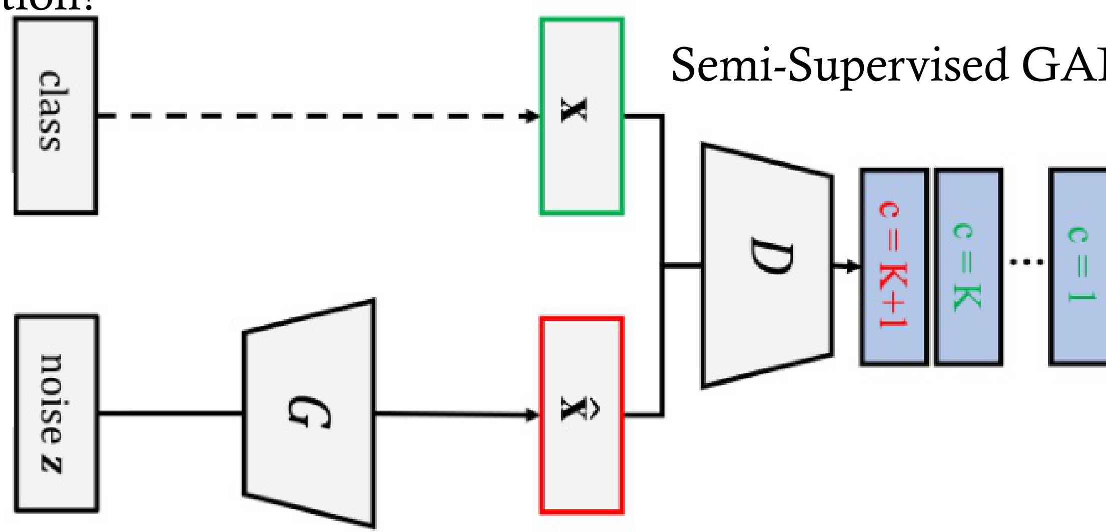


(a) (b)

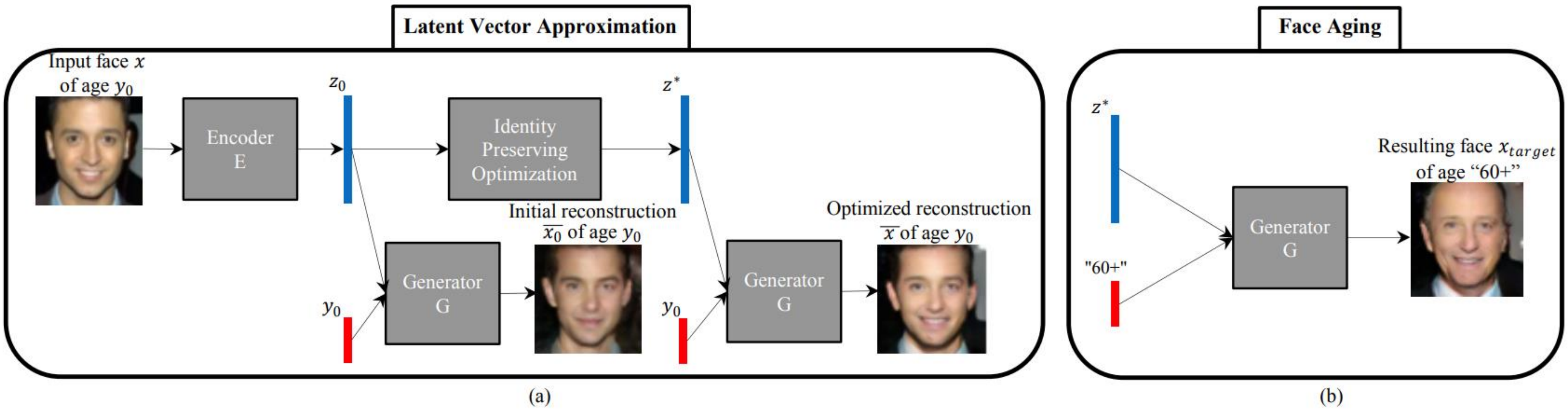
Where to insert condition information?
How to train condition GANs?

Matching-aware Discriminator:
(real image x, right condition y)
(real image x, wrong condition $\hat{y}$)
(fake image $\hat{x}$, right condition y)

Semi-Supervised GANs



Related work

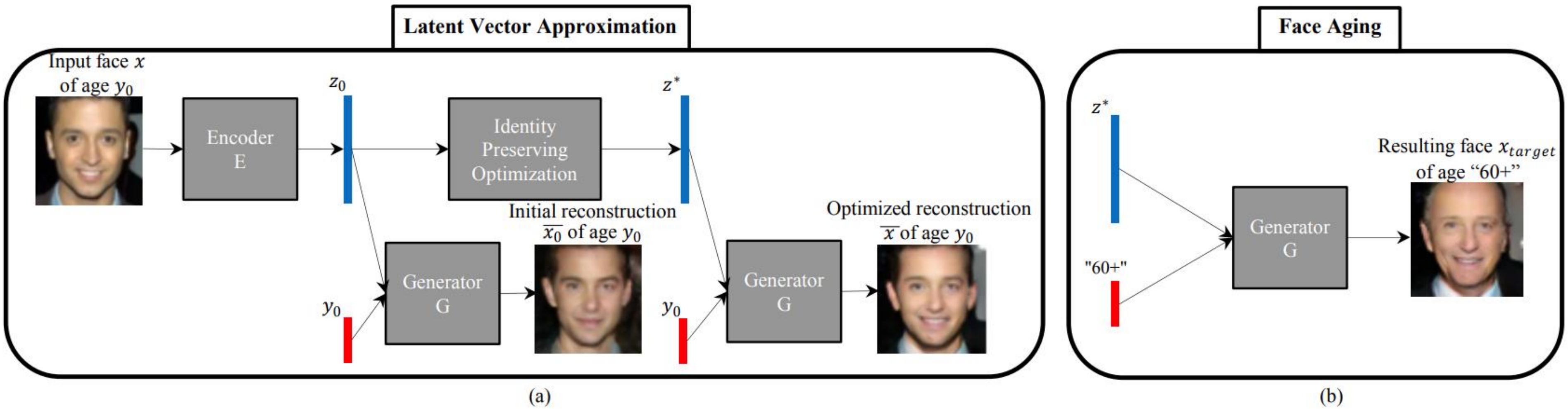


$$z^* = \underset{z}{\operatorname{argmin}} ||FR(x) - FR(\bar{x})||_{L_2}$$
$$= \underset{z}{\operatorname{argmin}} ||FR(x) - FR(G(z, y))||_{L_2}$$

Face Aging with Conditional Generative Adversarial Networks --Antipov et al

Obtain about 80% of identity-preservation.

Related work

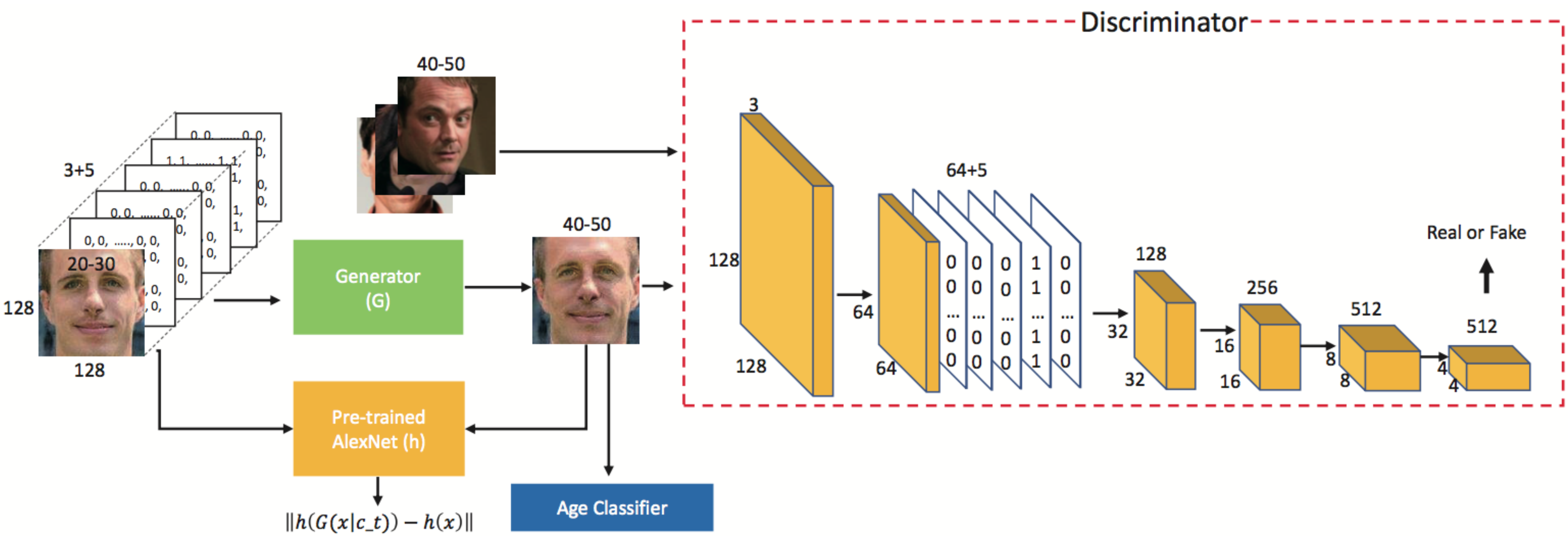


$$G^* = \underset{G}{argmin} \|FR(x) - FR(\hat{x})\|_{L_2}$$
$$= \underset{G}{argmin} \|FR(x) - FR(G(z^*, y))\|_{L_2}$$

Boosting Cross-age Face Verification via Generative Age Normalization

-Antipov et al

Our Work



Discriminator
40-50
3+5
128
20-30
128
Generator
(G)
40-50
Pre-trained
AlexNet (h)
$||h(G(x|c\_t)) - h(x)||$
Age Classifier
3
128
128
64
64
64+5
128
32
32
256
16
16
512
8
8
512
4
4
Real or Fake

Loss Function

$$G_{loss} = \lambda_1 L_G + \lambda_2 L_{identity} + \lambda_3 L_{age}$$
$$D_{loss} = L_D$$

$$L_D = \frac{1}{2}\mathbb{E}_{y \sim p_y(y)}[(D(y|C_t) - 1)^2] + \frac{1}{4}\mathbb{E}_{x \sim p_x(x)}[(D(G(x|C_t)))^2 + (D(y|C_f))^2]$$
$$L_G = \frac{1}{2}\mathbb{E}_{x \sim p_x(x)}[(D(G(x|C_t)) - 1)^2]$$

$$L_{identity} = \sum_{x \in p_x(x)} \|h(x) - h(G(x|C_t)\|^2$$

x is from source age group.
y is from target age group.

$$L_{age} = \sum_{x \in p_x(x)} \ell(G(x|C_t), C_t)$$

Datasets

- Cross-Age Celebrity Dataset(CACD)
- More than 160, 000 faces of 2000 celebrities with age ranging from 16 to 62.
- Image resolution is 128 x 128
- We split images into 5 age groups, 10-20, 21-30, 31-40,

41-50, 50+

Experiments: quantitative comparison

Table 1. The performance of different methods.

	CAAE	acGANs	IPCGANs
Face verification (%)	91.53	85.83	**96.90**
Image quality (%)	68.85	39.67	**71.74**
Age classification (%)	24.84	**32.70**	31.74
VGG-face score	19.53 ± 1.76	23.42 ± 1.82	$\mathbf{36.33 \pm 1.85}$
Time cost (s)	0.71	38.68	**0.28**

100 test images in the 11-20 age group. For each test image, we generate 4 aged faces with different target age conditions.

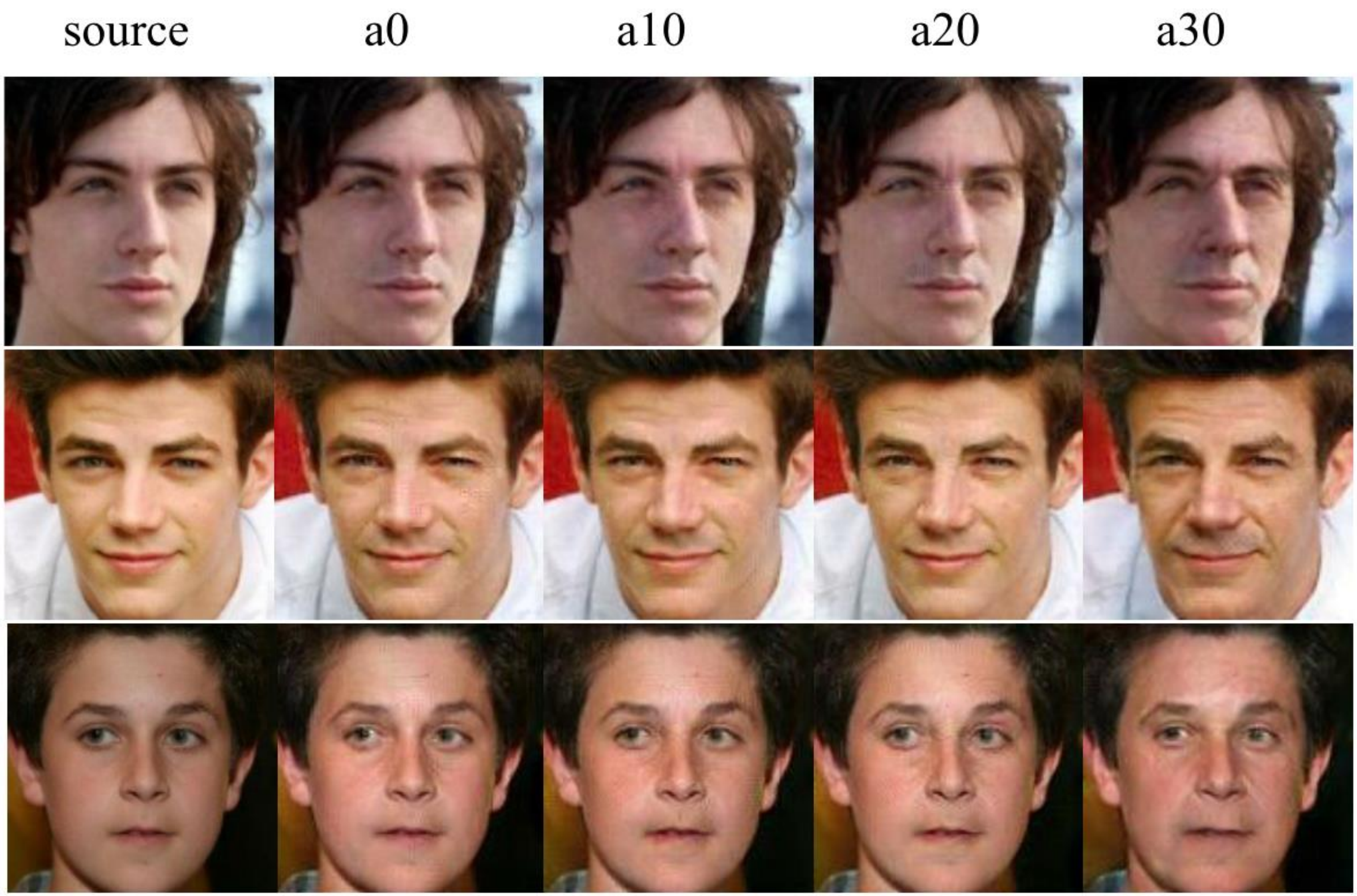
80 volunteers

Experiments: quantitative comparison

Table 2. The effect of with/without identity-preserved module and age classifier module(%)

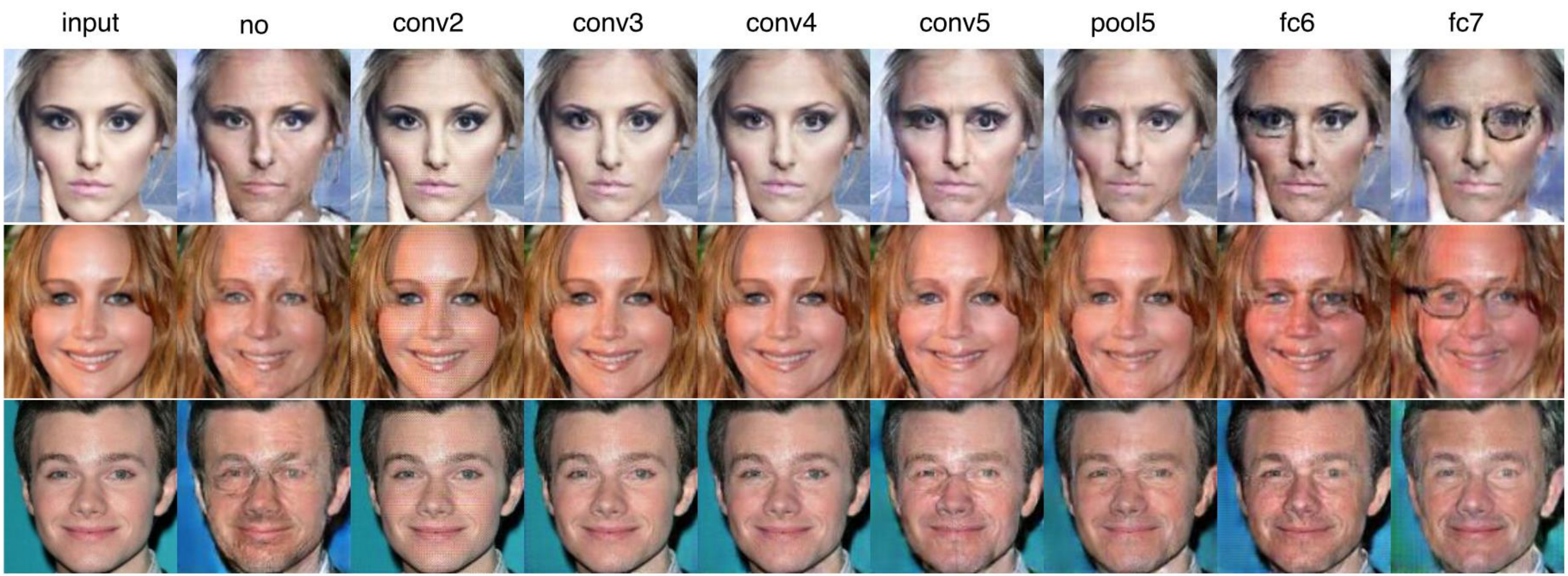
age classification		face verification	
with age classifier	w/o age classifier	with identity-preserved term	w/o identity-preserved term
31.37	28.73	**99.07**	98.15

Experiments: qualitative comparison

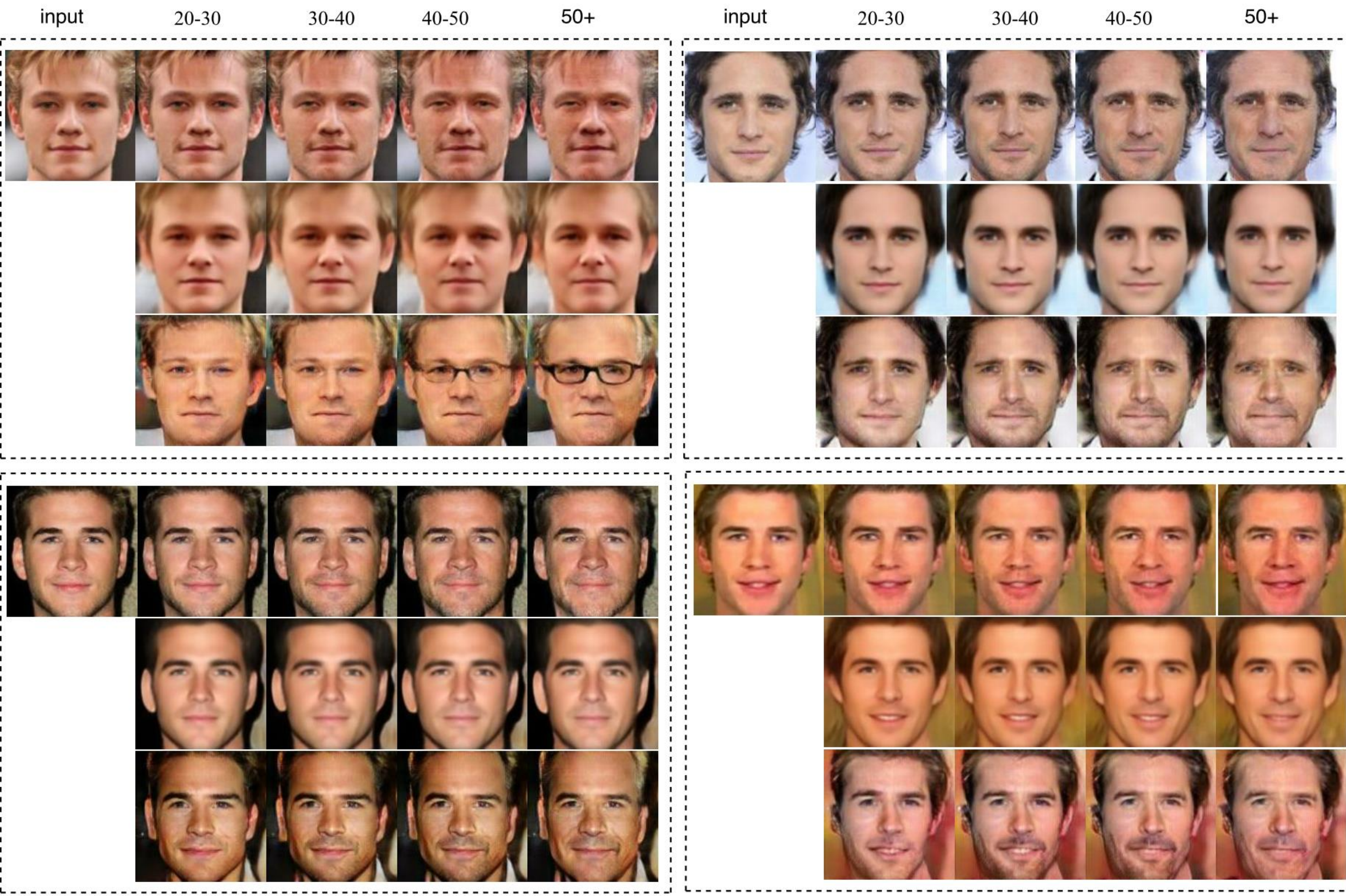


The aging effect of different age classification loss weights.

Experiments: qualitative comparison



The aging effect with different feature layers.


input
20-30
30-40
40-50
50+
input
20-30
30-40
40-50
50+

Thank you!