EdgeConnect: Generative Image Inpainting with Adversarial Edge Learning

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CONTENTS

CHAPTER 01

서론

01

Image Inpainting이란?

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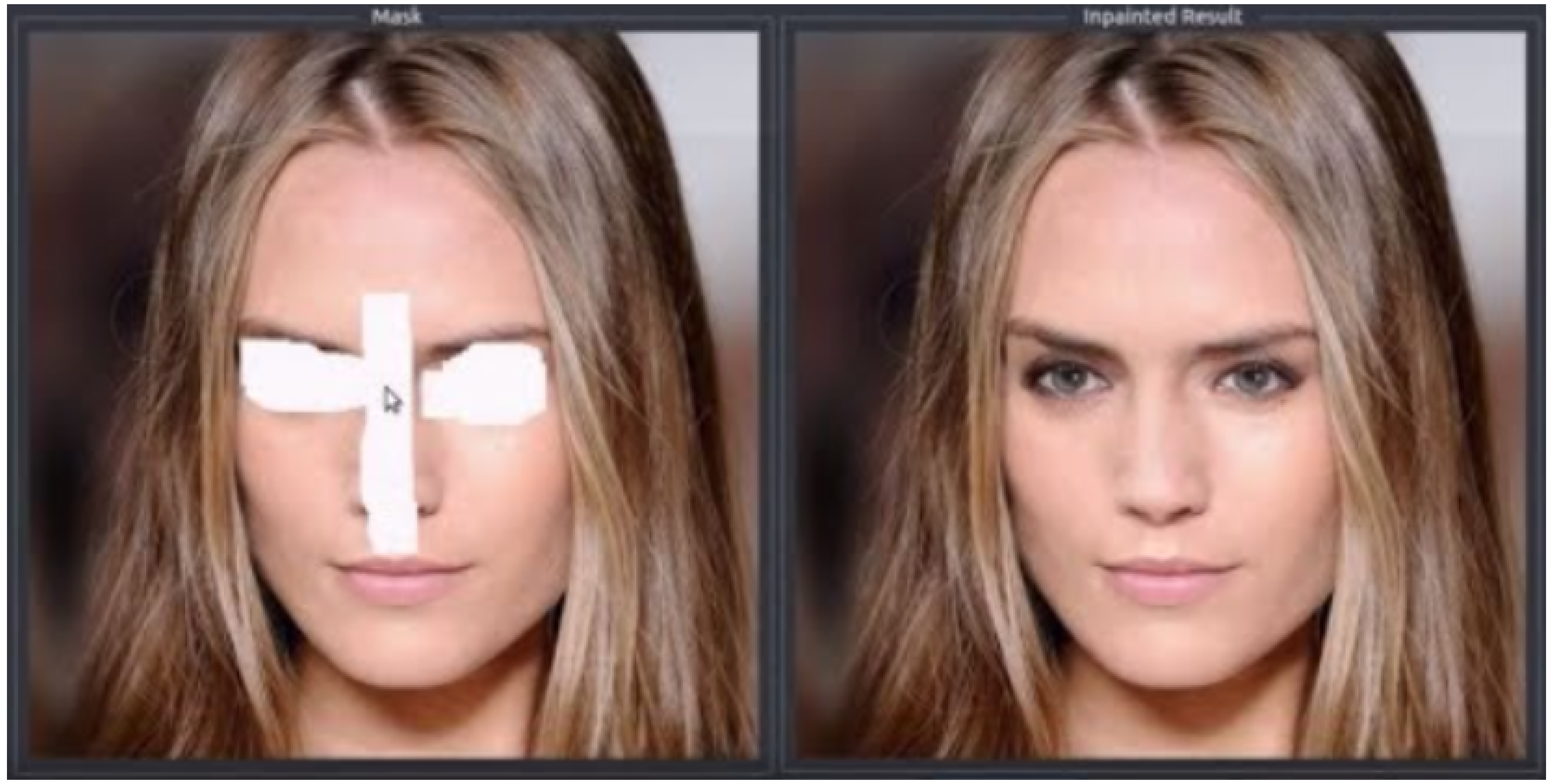
이미지의 손상된 또는 누락된 부분을
재구성하는 기술



기존 기술

(1) Diffusion-based method

인접한 픽셀 값을 토대로 조금씩 채워나가는(Propagate) 형태

(2) Patch-based method

유사성이 가장 높은 영역을 찾아서 복사하는 형태

(3) Learning-based method

Adversarial model 을 기반하여 Image와 Mask를 통해 Generator 를 학습하는 형태

Line First, Color Next

—

Two-stage process

(1) 이미지에서 삭제된 영역의 선을 생성하는 Edge Generator 의 도입

(2) 생성된 Edge에 색과 질감를 칠하는 Image Completion Network의 연계

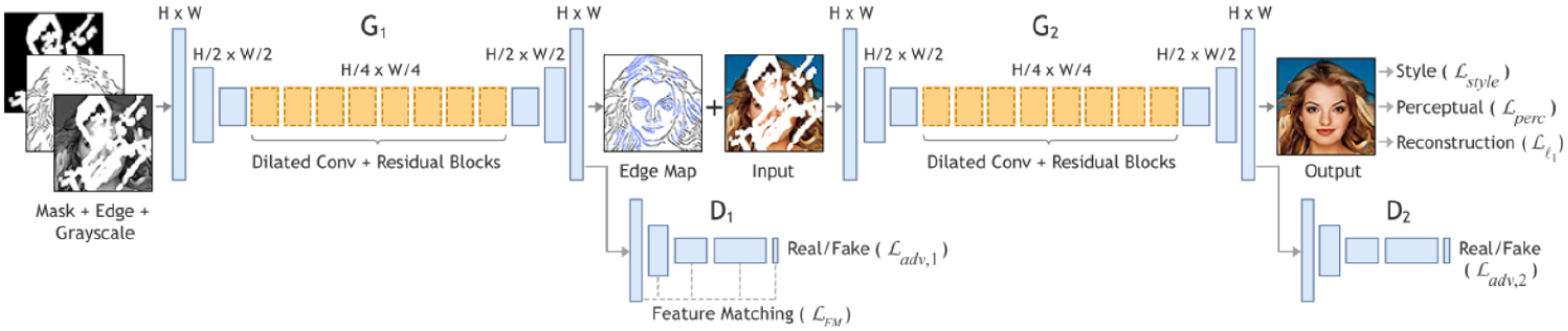
(3) 앞서 소개된 두 가지 네트워크의 End-to-End Training

CHAPTER 02

본론

학습 방법

<Two-stage process model>

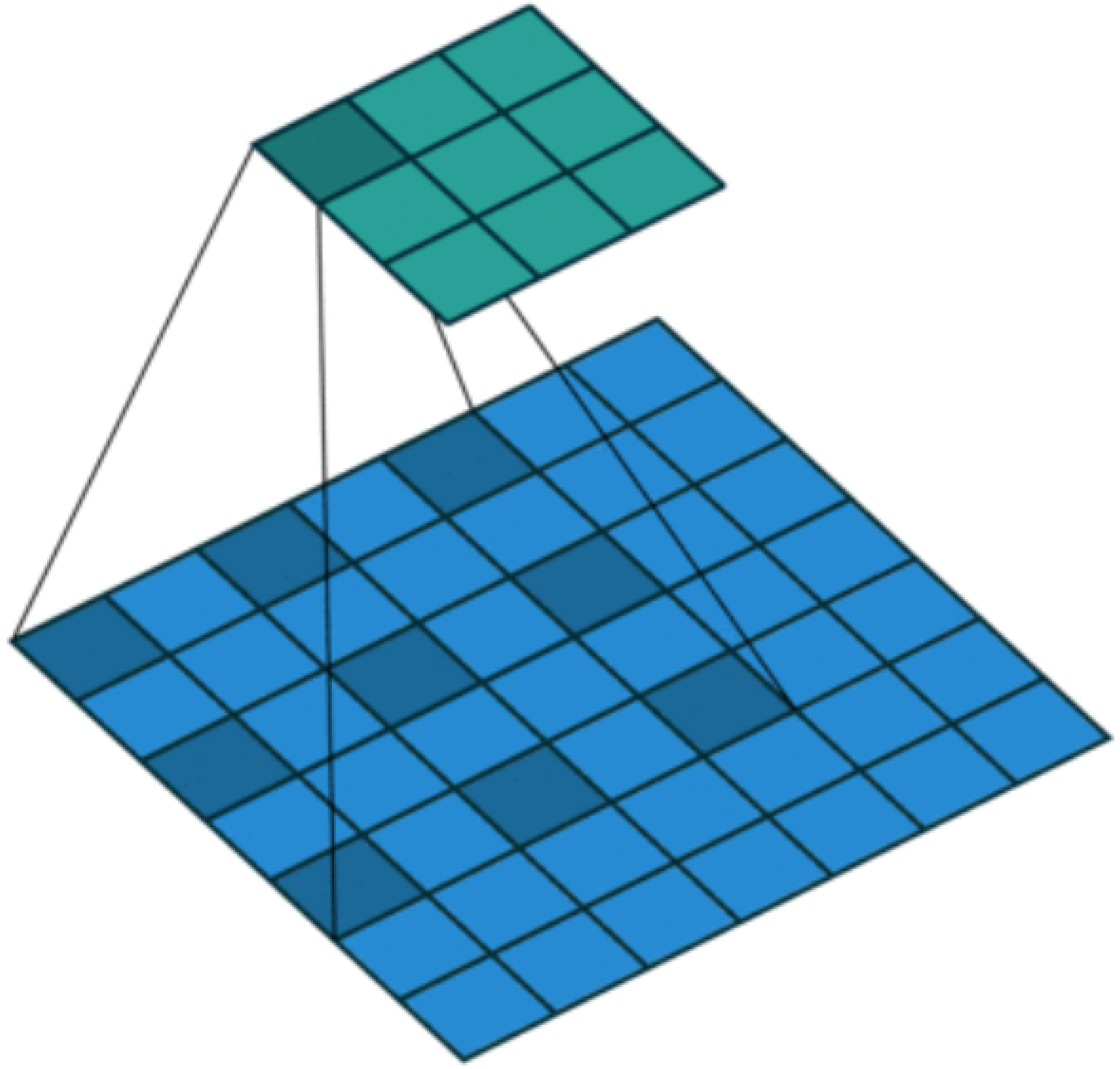


Edge Generator

Image Completion Network

Dilated Conv

—

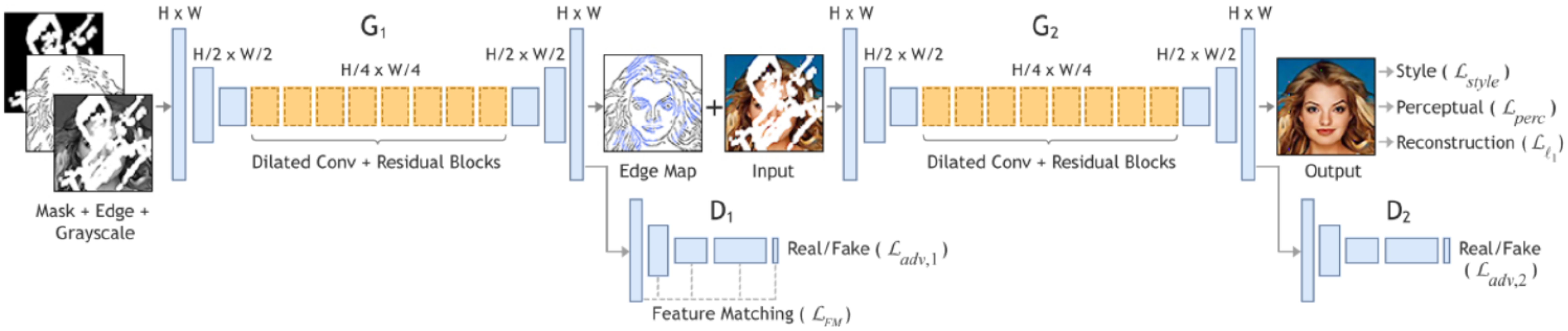


3x3 커널은 9개의 파라미터를 사용하면서

5x5 커널과 동일한 시야를 가짐

학습 방법

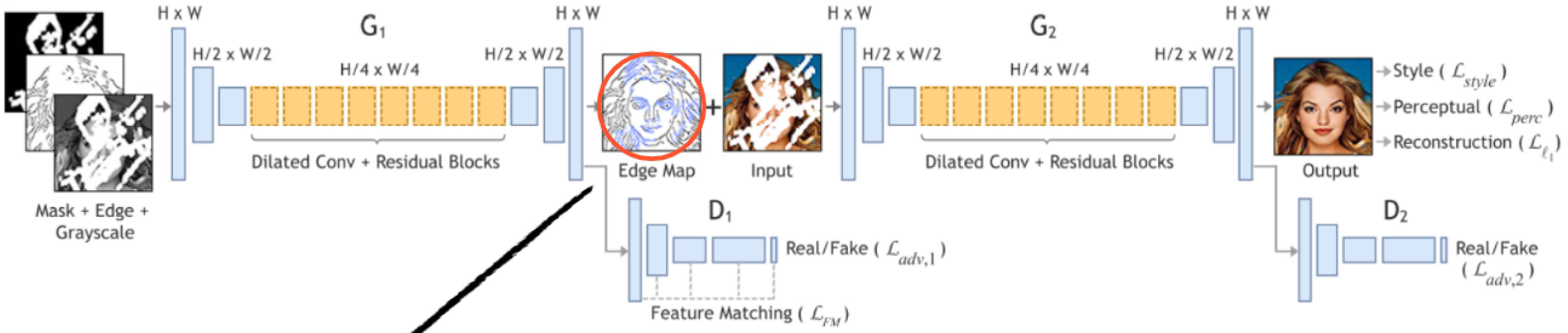
<Two-stage process model>



Edge Generator

Image Completion Network

Edge Generator



01

$$\mathbf{C}_{pred} = G_1\left(\tilde{\mathbf{I}}_{gray}, \tilde{\mathbf{C}}_{gt}, \mathbf{M}\right).$$

Edge map 생성

02

$$\tilde{\mathbf{I}}_{gray} = \mathbf{I}_{gray} \odot (\mathbf{1} - \mathbf{M})$$

$$\tilde{\mathbf{C}}_{gt} = \mathbf{C}_{gt} \odot (\mathbf{1} - \mathbf{M})$$

Edge Generator

—

$$\min_{G_1} \max_{D_1} \mathcal{L}_{G_1} = \min_{G_1} \left(\lambda_{adv,1} \max_{D_1} (\mathcal{L}_{adv,1}) + \lambda_{FM} \mathcal{L}_{FM} \right)$$

L_adv = 1, L_FM = 10

01

$$\mathcal{L}_{adv,1} = \mathbb{E}_{(\mathbf{C}_{gt}, \mathbf{I}_{gray})} \left[\log D_1(\mathbf{C}_{gt}, \mathbf{I}_{gray}) \right] + \mathbb{E}_{\mathbf{I}_{gray}} \log \left[1 - D_1(\mathbf{C}_{pred}, \mathbf{I}_{gray}) \right].$$

Edge Generator

—

$$\min_{G_1} \max_{D_1} \mathcal{L}_{G_1} = \min_{G_1} \left(\lambda_{adv,1} \max_{D_1} (\mathcal{L}_{adv,1}) + \lambda_{FM} \mathcal{L}_{FM} \right)$$

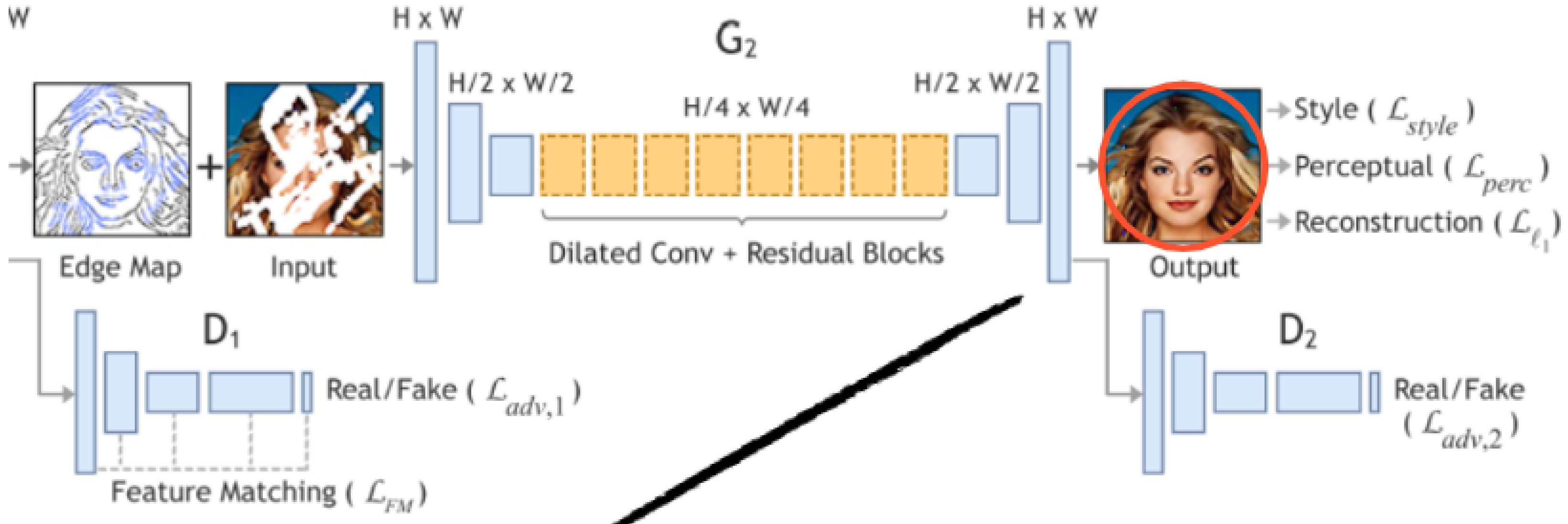
L_adv = 1, L_FM = 10

02

$$\mathcal{L}_{FM} = \mathbb{E} \left[\sum_{i=1}^{L} \frac{1}{N_i} \left\| D_1^{(i)} (\mathbf{C}_{gt}) - D_1^{(i)} (\mathbf{C}_{pred}) \right\|_1 \right]$$

Image Completion Network

—



$$\mathbf{I}_{pred} = G_2\left(\tilde{\mathbf{I}}_{gt}, \mathbf{C}_{comp}\right).$$

$$\tilde{\mathbf{I}}_{gt} = \mathbf{I}_{gt} \odot (\mathbf{1} - \mathbf{M})$$

$$\mathbf{C}_{comp} = \mathbf{C}_{gt} \odot (\mathbf{1} - \mathbf{M}) + \mathbf{C}_{pred} \odot \mathbf{M}.$$

$$L = \sum_{i=1}^{n} |y_i - f(x_i)|$$

$$\mathcal{L}_{G_2} = \lambda_{\ell_1}\mathcal{L}_{\ell_1} + \lambda_{adv,2}\mathcal{L}_{adv,2} + \lambda_p\mathcal{L}_{perc} + \lambda_s\mathcal{L}_{style}.$$

l1 = 1, adv = perc = 0.1, style = 250

Image Completion Network

01

—

$$\mathcal{L}_{perc} = \mathbb{E}\left[\sum_i \frac{1}{N_i} \|\phi_i(\mathbf{I}_{gt}) - \phi_i(\mathbf{I}_{pred})\|_1\right]$$

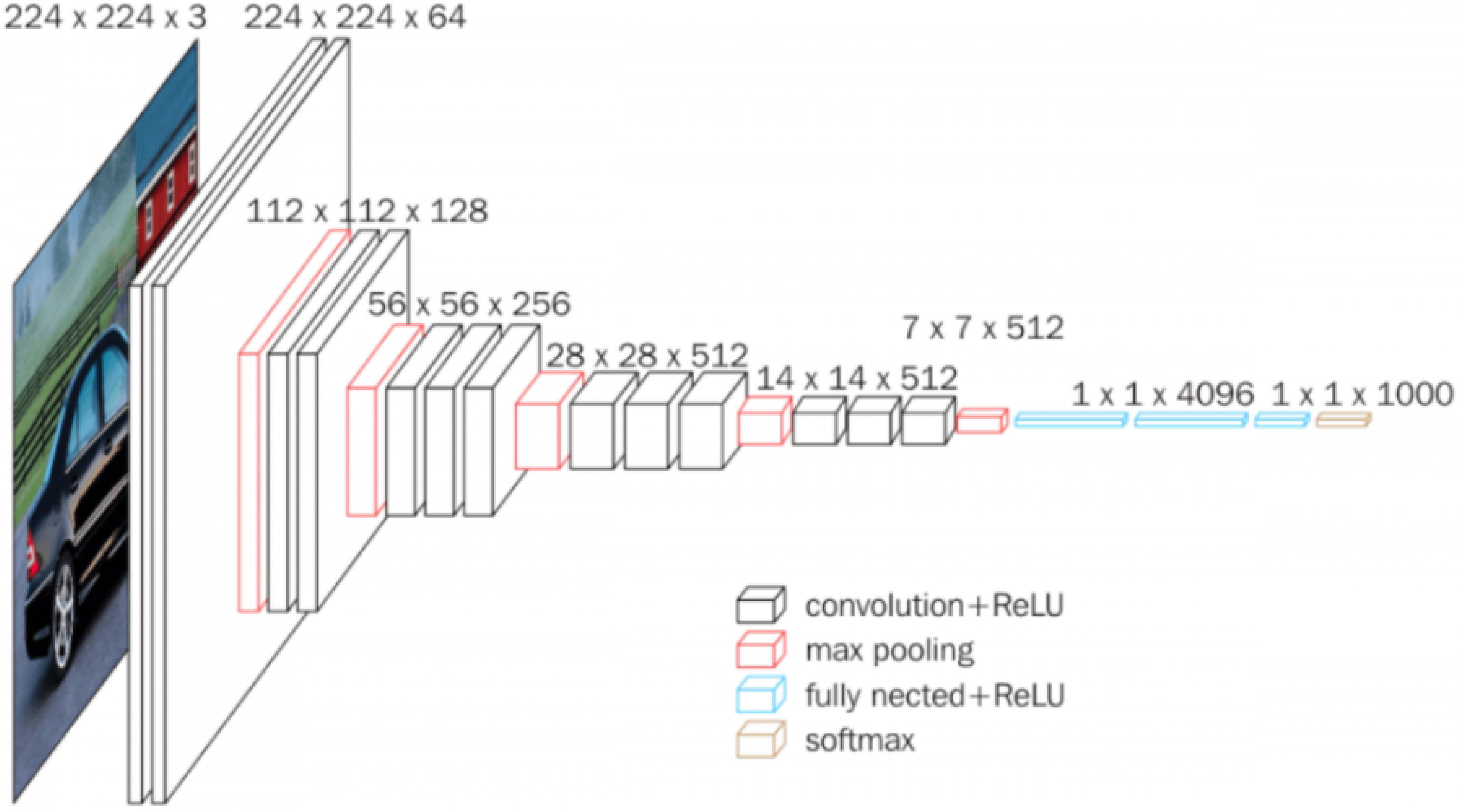


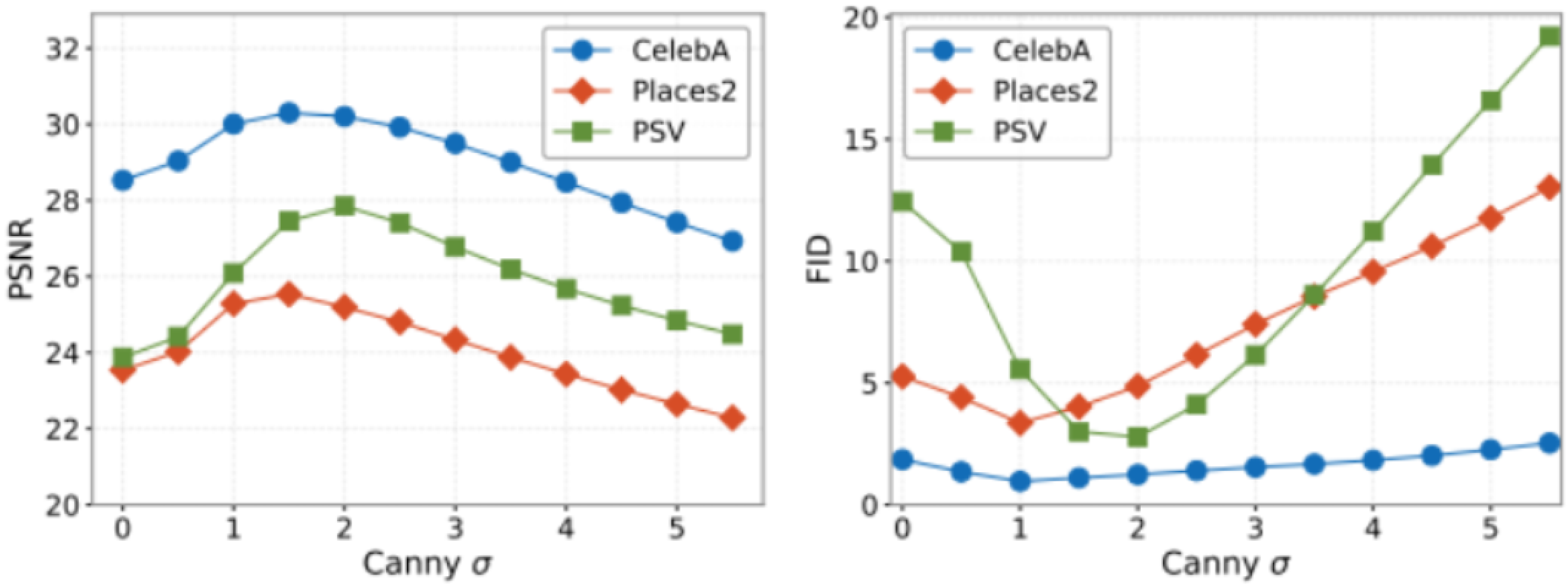
Image Completion Network

—

02

$$\mathcal{L}_{style} = \mathbb{E}_j \left[\| G_j^{\phi}(\tilde{\mathbf{I}}_{pred}) - G_j^{\phi}(\tilde{\mathbf{I}}_{gt}) \|_1 \right]$$

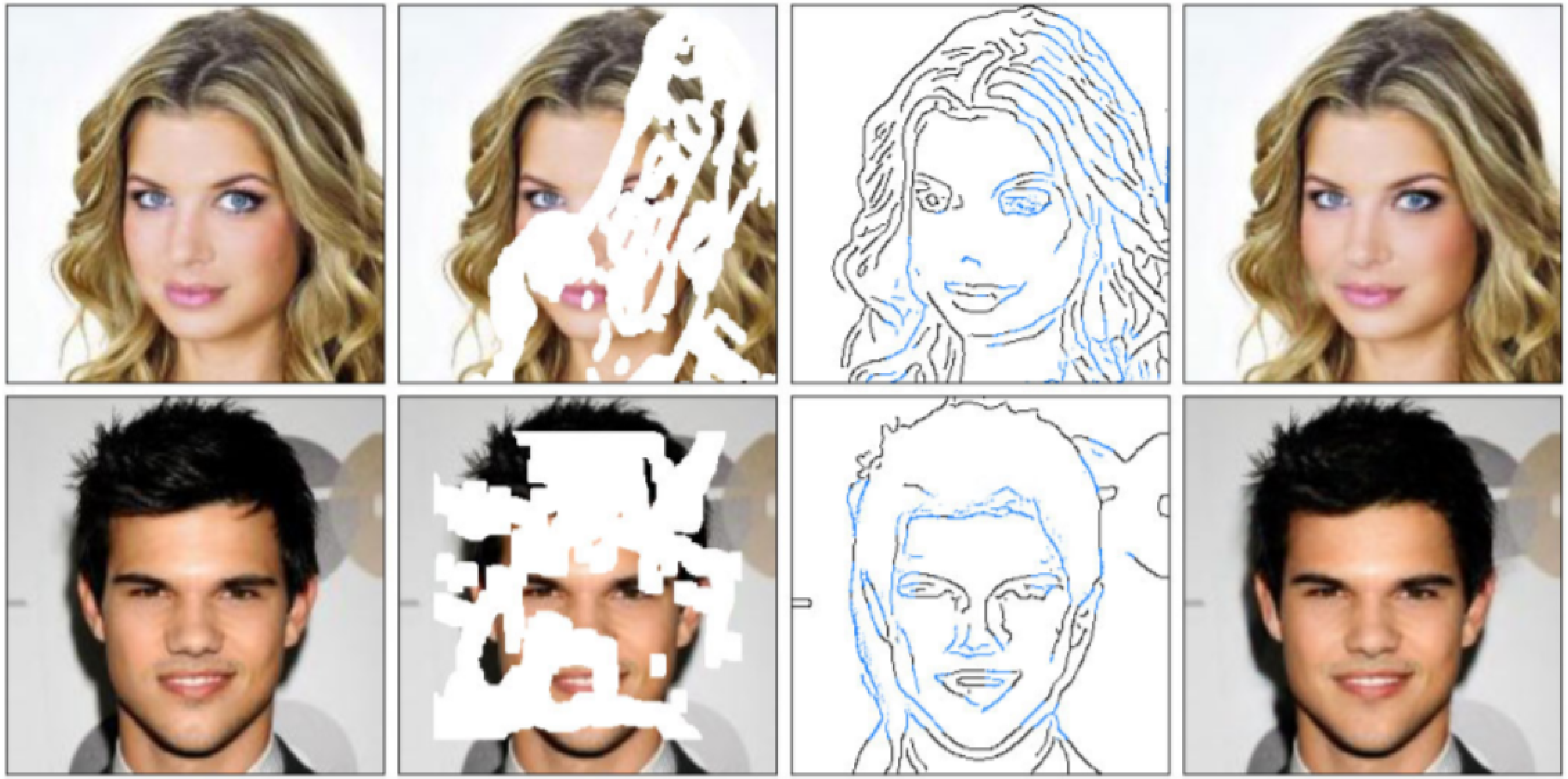
Edge Information &
Image mask



CHAPTER 03

결론

결과



THANK

YOU EVERYONE

감 사 합 니 다