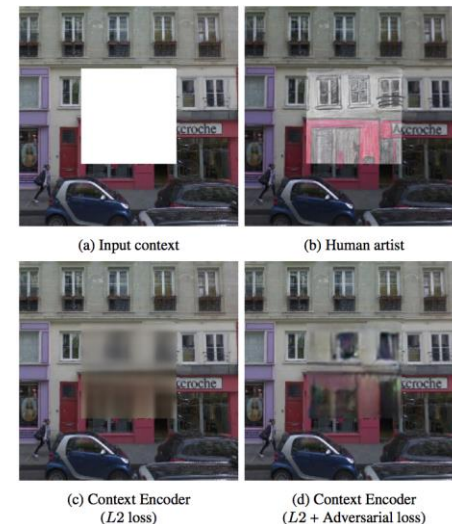
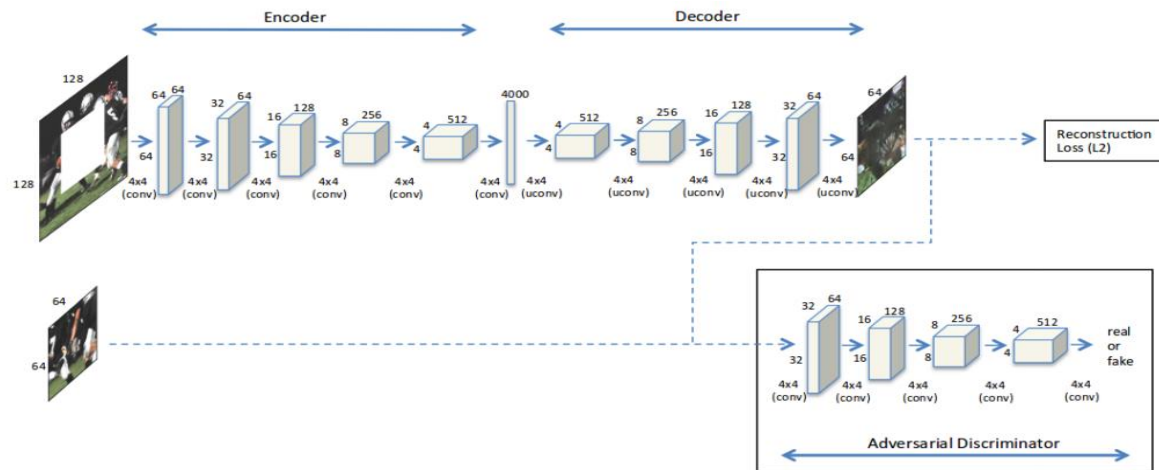


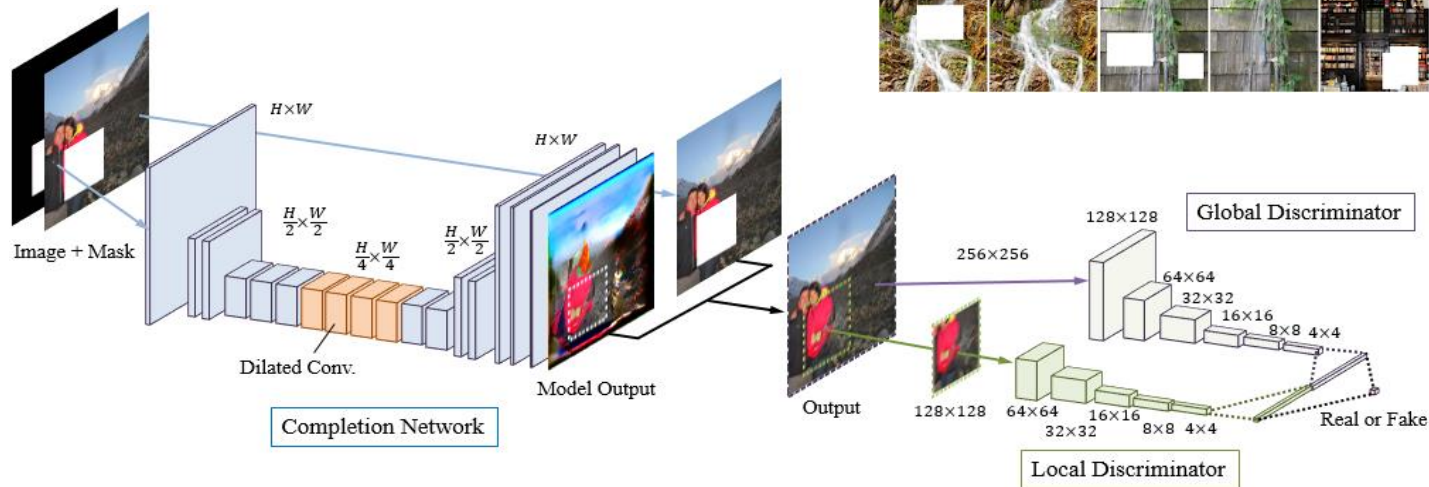
Free-Form Image Inpainting with Gated Convolution (ICCV 2019)

EdgeConnect: Structure Guided Image Inpainting using Edge Prediction (ICCVW 2019)

Context Encoders: Feature Learning by Inpainting (CVPR 2016)



Globally and Locally Consistent Image Completion (SIGGRAPH 2017)

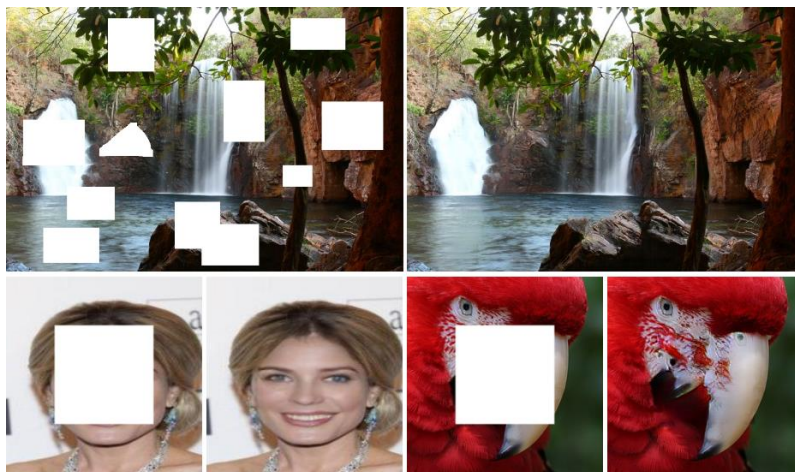


Generative Image Inpainting with Contextual Attention

Jiahui Yu¹ Zhe Lin² Jimei Yang² Xiaohui Shen² Xin Lu² Thomas S. Huang¹

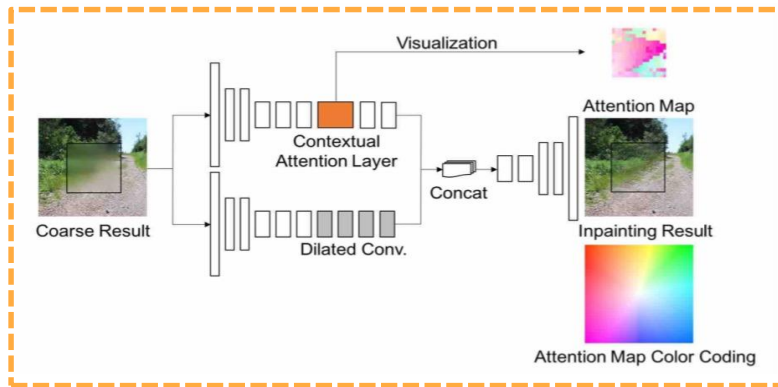
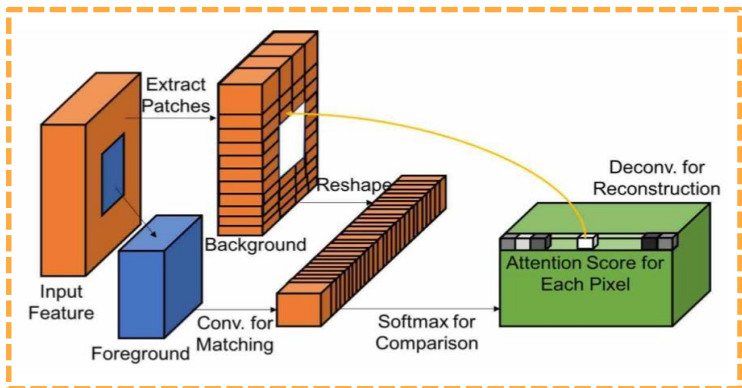
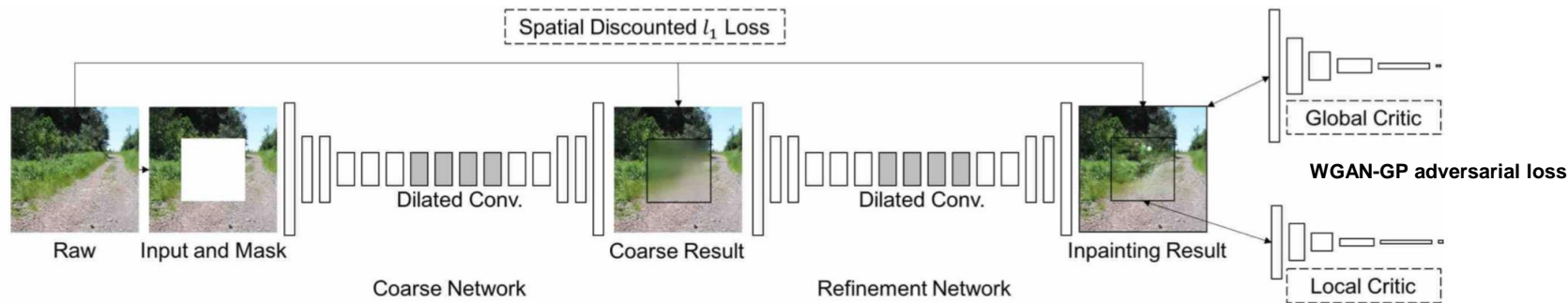
¹University of Illinois at Urbana-Champaign

²Adobe Research



Generative Image Inpainting with Contextual Attention (CVPR 2018)

Deepfill v1 / Contextual Attention



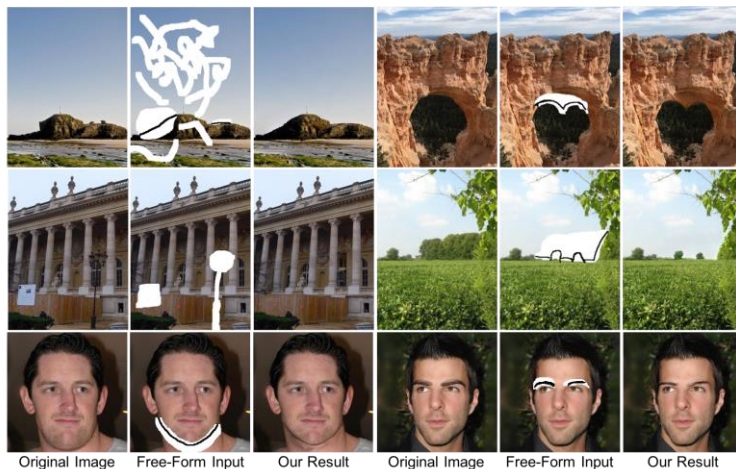
Free-Form Image Inpainting with Gated Convolution

Jiahui Yu¹ Zhe Lin² Jimei Yang² Xiaohui Shen³ Xin Lu² Thomas Huang¹

¹University of Illinois at Urbana-Champaign

²Adobe Research

³ByteDance AI Lab



Free-Form Image Inpainting with Gated Convolution (ICCV 2019)

Deepfill v2 / Gated Convolution

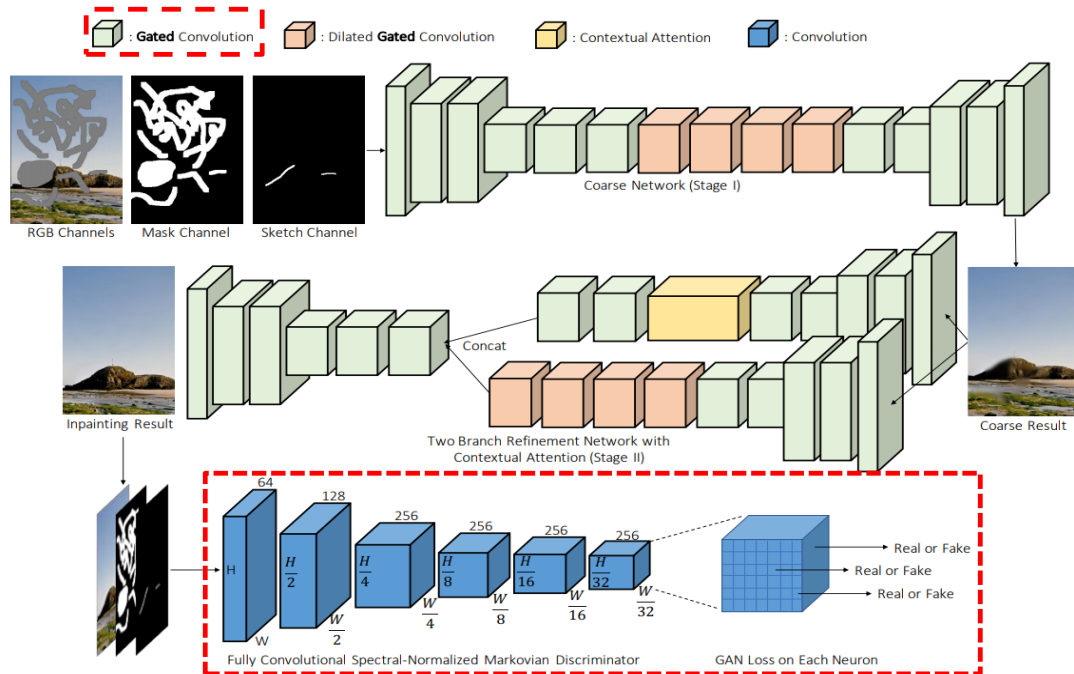


Figure 3: Overview of our framework with gated convolution and SN-PatchGAN for free-form image inpainting.

Free-Form Image Inpainting with Gated Convolution (ICCV 2019)

$$O_{y,x} = \sum_{i=-k'_h}^{k'_h} \sum_{j=-k'_w}^{k'_w} W_{k'_h+i, k'_w+j} \cdot I_{y+i, x+j},$$

$$O_{y,x} = \begin{cases} \sum \sum W \cdot (I \odot \frac{M}{\text{sum}(M)}), & \text{if } \text{sum}(M) > 0 \\ 0, & \text{otherwise} \end{cases}$$

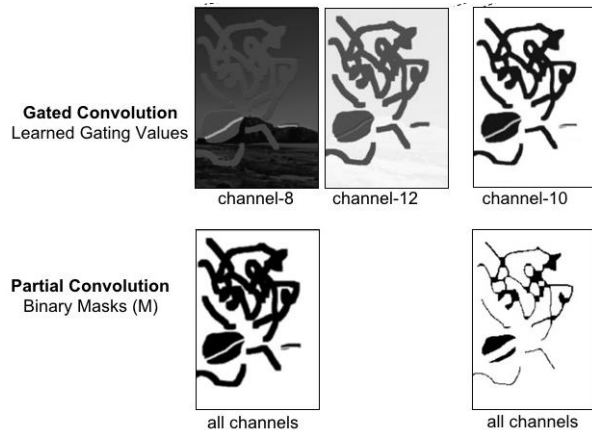
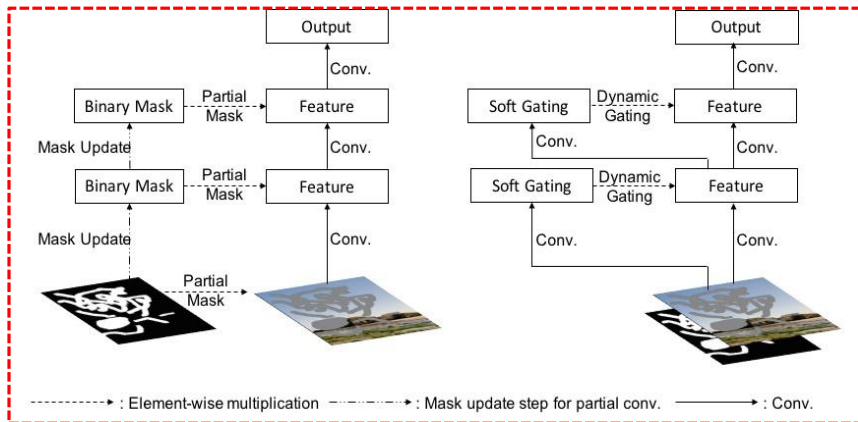
$$m'_{y,x} = \begin{cases} 1, & \text{if } \text{sum}(M) > 0 \\ 0, & \text{otherwise.} \end{cases}$$

$$\begin{aligned} \text{Gating}_{y,x} &= \sum \sum W_g \cdot I \\ \text{Feature}_{y,x} &= \sum \sum W_f \cdot I \\ O_{y,x} &= \phi(\text{Feature}_{y,x}) \odot \sigma(\text{Gating}_{y,x}) \end{aligned}$$

vanilla conv

Partial conv (ECCV 2018)

Gated conv



Free-Form Image Inpainting with Gated Convolution (ICCV 2019)

SN-PatchGAN (Spectral-Normalized Markovian Discriminator)

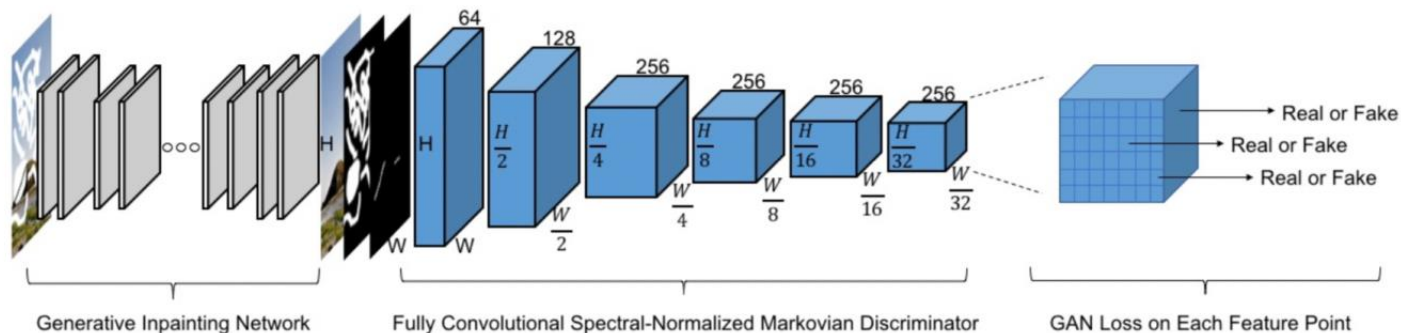


Fig. 4. Overview of SN-PatchGAN and our architecture for **learning free-form image inpainting network**. Details of generative inpainting network is shown in Figure 3. We aim at free-form image inpainting for which the masks may appear anywhere in images with any shapes. Previous global and local GANs [Iizuka et al. 2017] designed for a single rectangular mask are not suitable. **Thus we introduce SN-PatchGAN that directly applies GAN loss for each point in output feature map of convolutional discriminator.** It is simple in formulation, fast and stable for training and produces high-quality inpainting results. Note that we use convolutional **kernel size 5×5 and the receptive fields of each point in output map** can still cover entire input image in our training setting thus a global GAN is not used.

Method	rectangular mask		free-form mask	
	ℓ_1 err.	ℓ_2 err.	ℓ_1 err.	ℓ_2 err.
PatchMatch [3]	16.1%	3.9%	11.3%	2.4%
Global&Local [15]	9.3%	2.2%	21.6%	7.1%
ContextAttention [49]	8.6%	2.1%	17.2%	4.7%
PartialConv* [23]	9.8%	2.3%	10.4%	1.9%
Ours	8.6%	2.0%	9.1%	1.6%

Free-Form Image Inpainting with Gated Convolution (ICCV 2019)

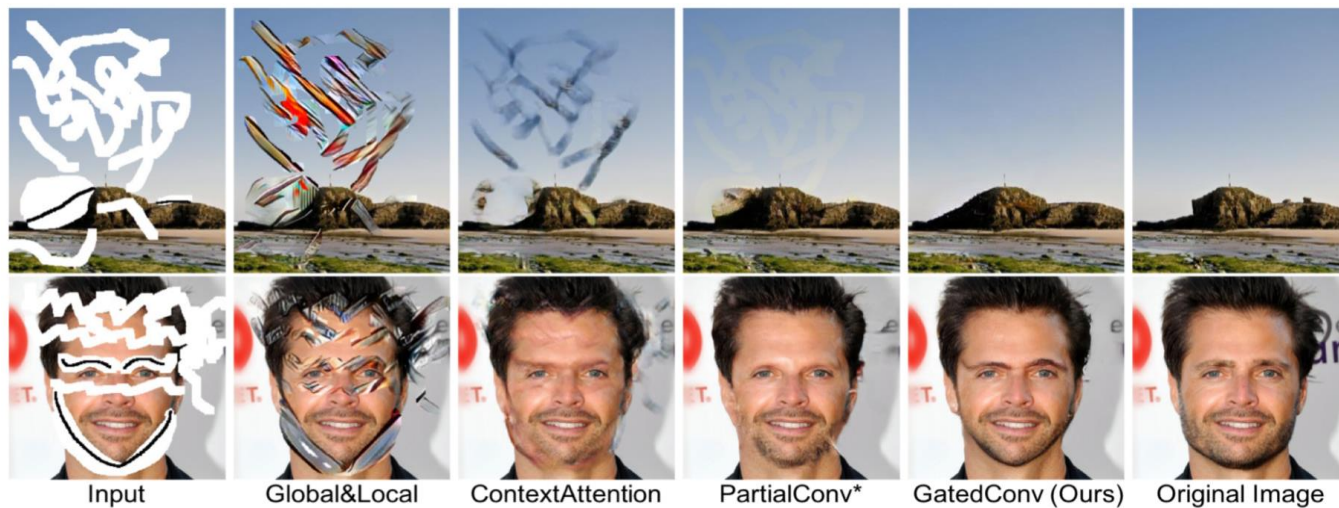


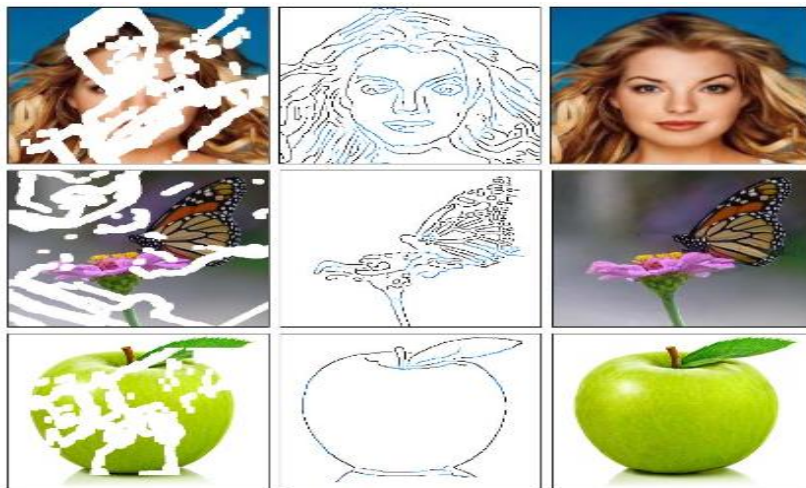
Fig. 7. Qualitative Comparisons on the Places2 and CelebA-HQ validation sets.

EdgeConnect: Structure Guided Image Inpainting using Edge Prediction

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<http://www.ImagingLab.ca> <http://www.VCLab.ca>



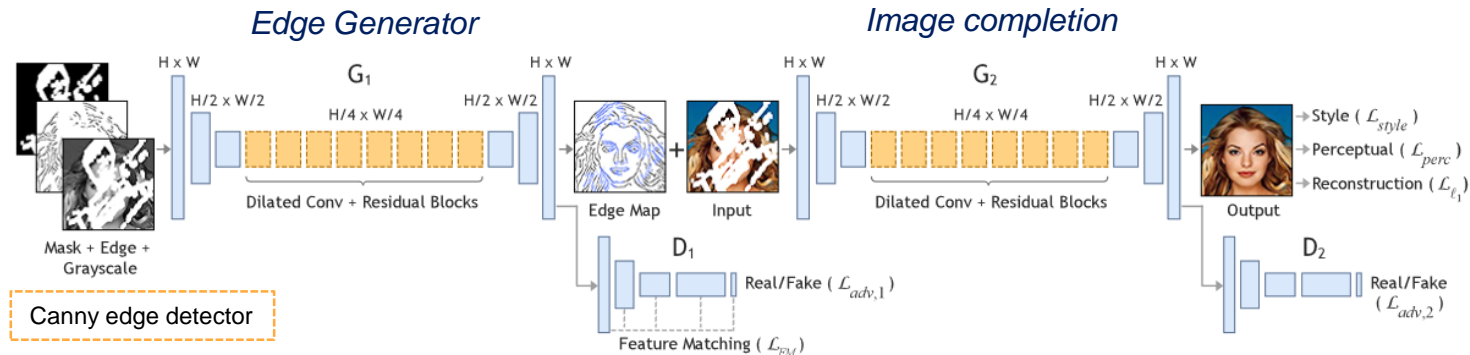


Figure 2: Summary of our proposed method. Incomplete grayscale image and edge map, and mask are the inputs of G_1 to predict the full edge map. Predicted edge map and incomplete color image are passed to G_2 to perform the inpainting task.

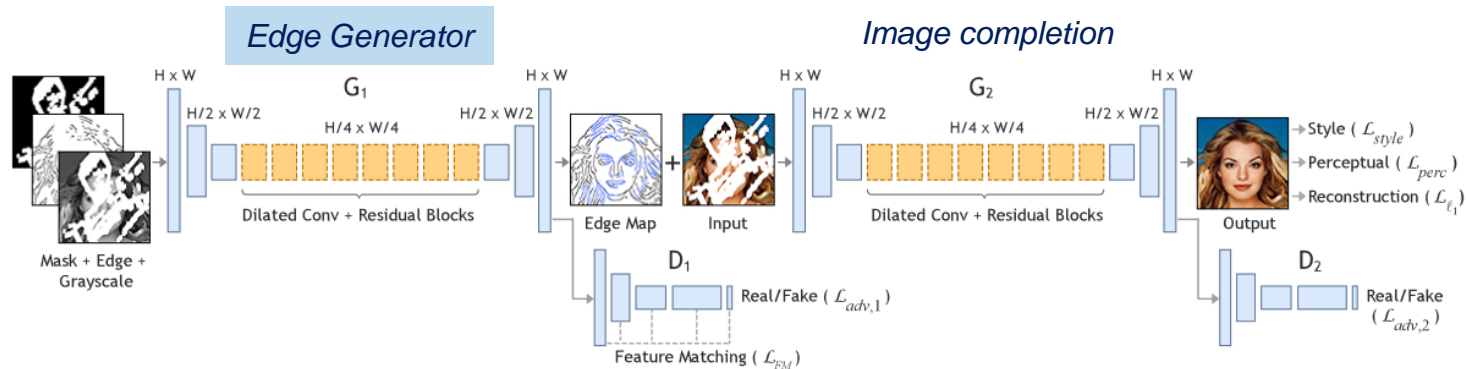


Figure 2: Summary of our proposed method. Incomplete grayscale image and edge map, and mask are the inputs of G_1 to predict the full edge map. Predicted edge map and incomplete color image are passed to G_2 to perform the inpainting task.

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

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

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

$$\mathcal{L}_{G_1} = -\mathbb{E}_{\mathbf{I}_{gray}} [D_1(\mathbf{C}_{pred}, \mathbf{I}_{gray})],$$

$$\begin{aligned} \mathcal{L}_{D_1} = & \mathbb{E}_{(\mathbf{C}_{gt}, \mathbf{I}_{gray})} [\max(0, 1 - D_1(\mathbf{C}_{gt}, \mathbf{I}_{gray}))] \\ & + \mathbb{E}_{\mathbf{I}_{gray}} [\max(0, 1 + D_1(\mathbf{C}_{pred}, \mathbf{I}_{gray}))]. \end{aligned}$$

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

$$\mathcal{J}_{G_1} = \lambda_{G_1} \mathcal{L}_{G_1} + \lambda_{FM} \mathcal{L}_{FM}$$

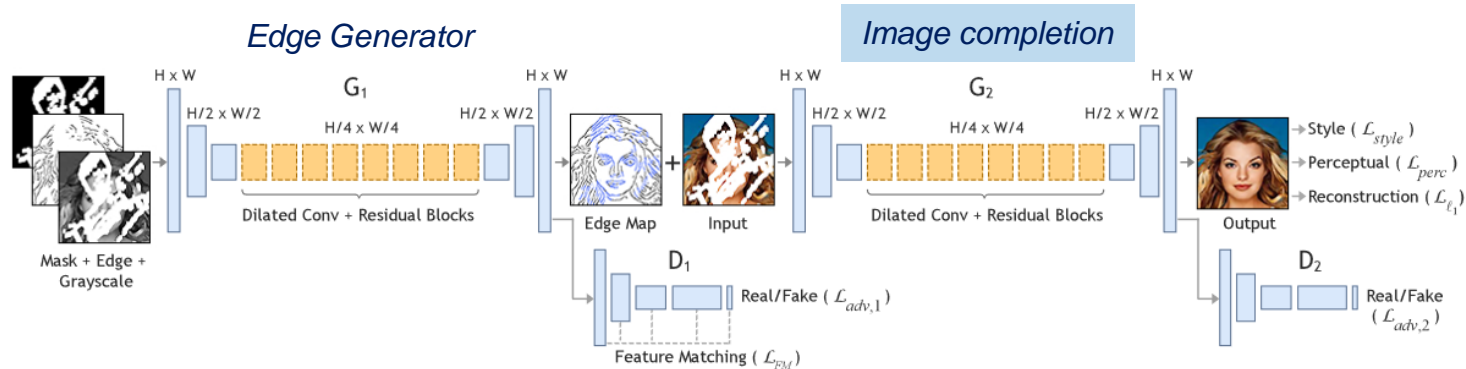


Figure 2: Summary of our proposed method. Incomplete grayscale image and edge map, and mask are the inputs of G_1 to predict the full edge map. Predicted edge map and incomplete color image are passed to G_2 to perform the inpainting task.

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

$$\begin{aligned} \mathcal{L}_{G_2} &= -\mathbb{E}_{\mathbf{C}_{comp}} [D_2(\mathbf{I}_{pred}, \mathbf{C}_{comp})], \\ \mathcal{L}_{D_2} &= \mathbb{E}_{(\mathbf{I}_{gt}, \mathbf{C}_{comp})} [\max(0, 1 - D_2(\mathbf{I}_{gt}, \mathbf{C}_{comp}))] \\ &\quad + \mathbb{E}_{\mathbf{C}_{comp}} [\max(0, 1 + D_2(\mathbf{I}_{pred}, \mathbf{C}_{comp}))]. \end{aligned}$$

$$\begin{aligned} \mathcal{L}_{perc} &= \mathbb{E} \left[\sum_i \frac{1}{N_i} \|\phi_i(\mathbf{I}_{gt}) - \phi_i(\mathbf{I}_{pred})\|_1 \right] \\ \mathcal{L}_{style} &= \mathbb{E} \left[\sum_j \|G_j^\phi(\tilde{\mathbf{I}}_{pred}) - G_j^\phi(\tilde{\mathbf{I}}_{gt})\|_1 \right] \end{aligned}$$

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

	Mask	CA	GLCIC	PConv	Ours
ℓ_1 (%) [†]	10-20%	2.41	2.66	1.55	1.50
	20-30%	4.23	4.70	2.71	2.59
	30-40%	6.15	6.78	3.94	3.77
	40-50%	8.03	8.85	5.35	5.14
	Fixed	4.37	4.12	3.95	3.86
SSIM*	10-20%	0.893	0.862	0.916	0.920
	20-30%	0.815	0.771	0.854	0.861
	30-40%	0.739	0.686	0.789	0.799
	40-50%	0.662	0.603	0.720	0.731
	Fixed	0.818	0.814	0.818	0.823
PSNR*	10-20%	24.36	23.49	27.54	27.95
	20-30%	21.19	20.45	24.47	24.92
	30-40%	19.13	18.50	22.42	22.84
	40-50%	17.75	17.17	20.77	21.16
	Fixed	20.65	21.34	21.54	21.75
FID [†]	10-20%	6.16	11.84	2.26	2.32
	20-30%	14.17	25.11	4.88	4.91
	30-40%	24.16	39.88	8.84	8.91
	40-50%	35.78	54.30	15.18	14.98
	Fixed	8.31	8.42	10.53	8.16

	Mask	CA	GLCIC	PConv	Ours
JND (%)	10-20%	20.98	16.91	36.04	39.69
	20-30%	15.45	14.27	30.09	36.99
	30-40%	12.86	12.29	20.60	27.53
	40-50%	12.74	10.91	18.31	25.44
Y-N (%)	10-20%	38.71	22.46	79.72	88.66
	20-30%	23.44	12.09	64.11	77.59
	30-40%	13.49	4.32	52.50	66.44
	40-50%	9.89	2.77	37.73	58.02

Edges	CelebA		Places2	
	No	Yes	No	Yes
ℓ_1 (%)	4.11	3.03	6.69	5.14
SSIM	0.802	0.846	0.682	0.731
PSNR	23.33	25.28	19.59	21.16
FID	6.16	2.82	32.18	14.98

StructureFlow: Image Inpainting via *Structure-aware Appearance Flow*(ICCV 2019)

Image Inpainting with Learnable Bidirectional *Attention* Maps(ICCV 2019)

Coherent Semantic *Attention* for Image Inpainting(ICCV 2019)

MUSICAL: Multi-Scale Image Contextual *Attention* Learning for Inpainting(IJCAI 2019)

Coarse-to-Fine Image Inpainting via Region-wise Convolutions and *Non-Local Correlation*(In IJCAI 2019)

Question ?