Computer Vision; Image Transformation; Super-Resolution, Denoising, and Colorization

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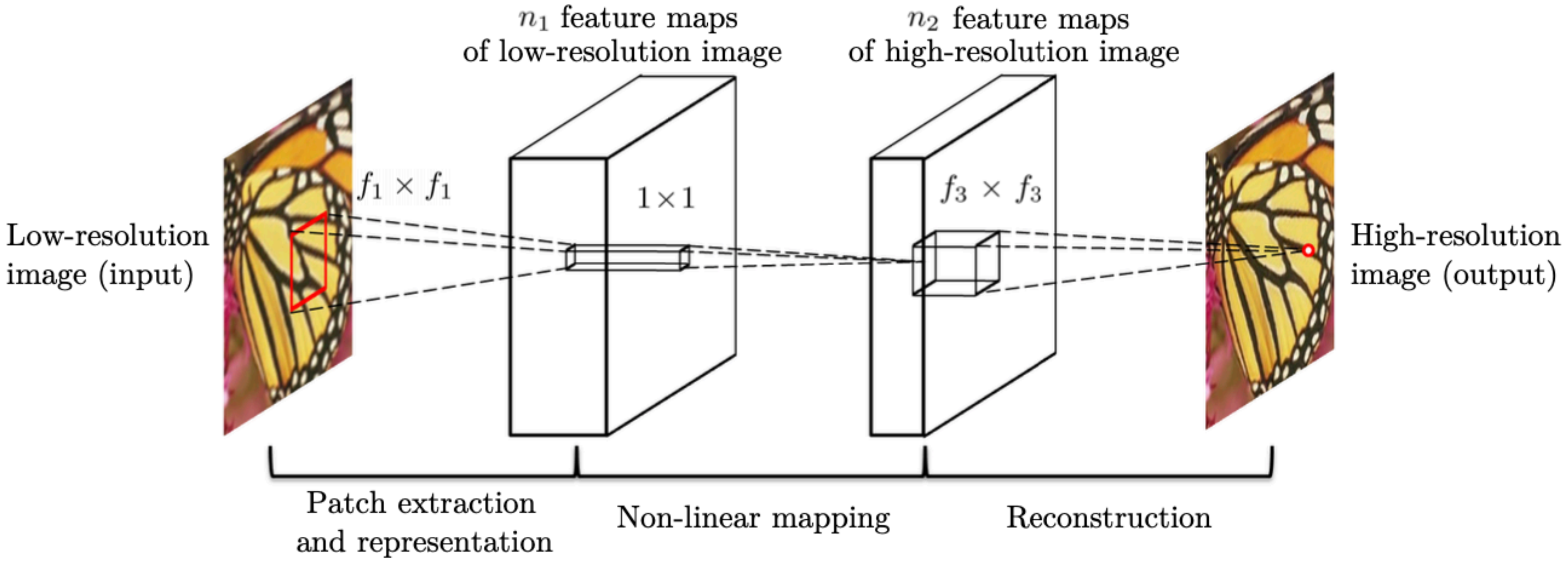
Learning a Deep Convolutional Network for Image Super-Resolution

YouTube Video



Super-Resolution Convolutional Neural Network (SRCNN)

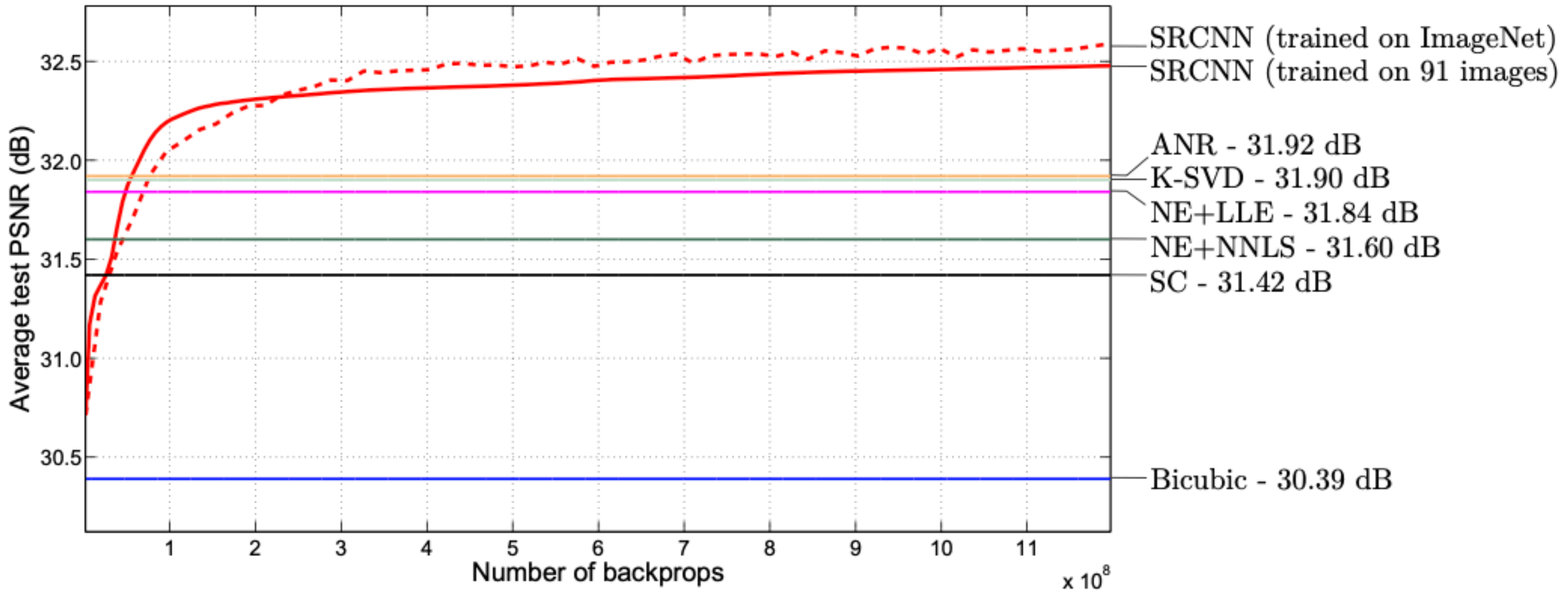
Sparse Coding (SC) based method

Peak Signal-to-Noise Ratio (PSNR)

$$PSNR = 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) = 20 \cdot \log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right) = 20 \cdot \log_{10}(MAX_I) - 10 \cdot \log_{10}(MSE)$$

$$MAX_I = 255$$

Set5 [2] images	$n_1 = 128,\ n_2 = 64$		$n_1 = 64,\ n_2 = 32$		$n_1 = 32,\ n_2 = 16$	
	PSNR	Time	PSNR	Time	PSNR	Time
	32.60	0.60	32.52	0.18	32.26	0.05



low resolution image ▷ bicubic interpolation

$Y \rightarrow$ interpolated image

$F(Y) \rightarrow$ an image as similar as possible to X

$X \rightarrow$ high resolution image

$$F_1(Y) = \max(0, W_1 * Y + B_1)$$

$$W_1 \in \mathbb{R}^{c \times f_1 \times f_1 \times n_1} \qquad B_1 \in \mathbb{R}^{n_1}$$

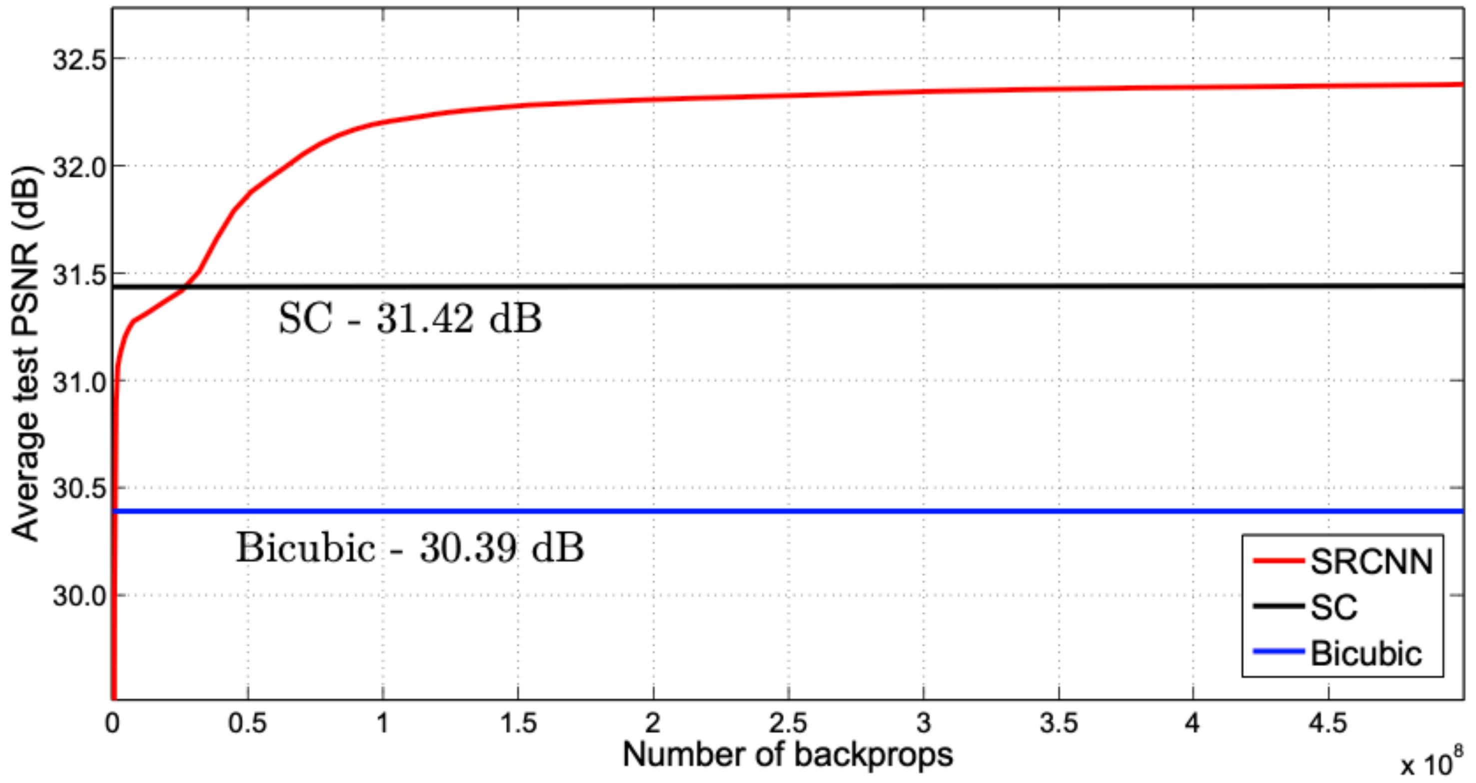
$$F_2(Y) = \max(0, W_2 * F_1(Y) + B_2)$$

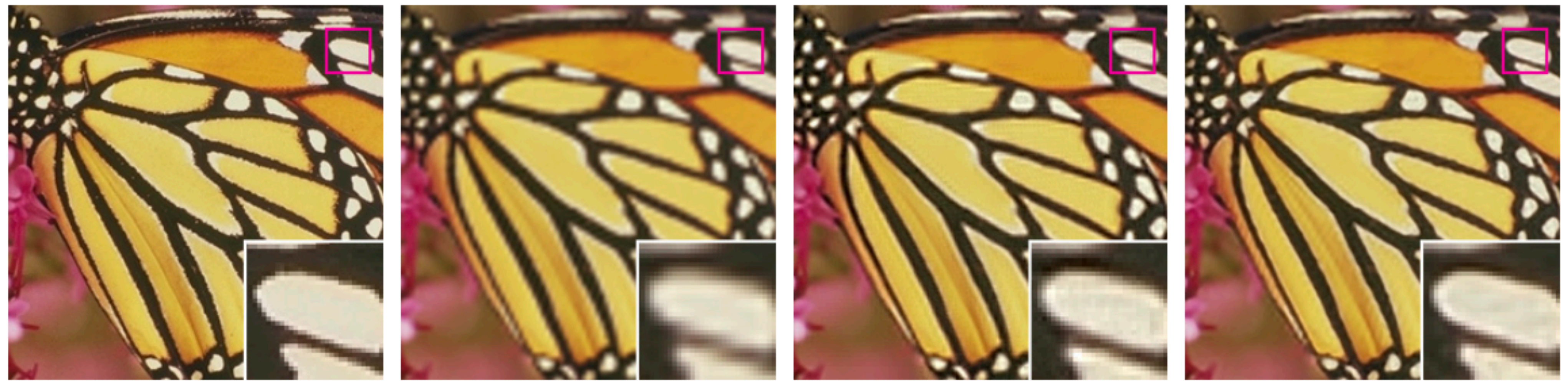
$$W_2 \in \mathbb{R}^{n_1 \times 1 \times 1 \times n_2} \qquad B_2 \in \mathbb{R}^{n_2}$$

$$F_3(Y) = W_3 * F_2(Y) + B_3$$

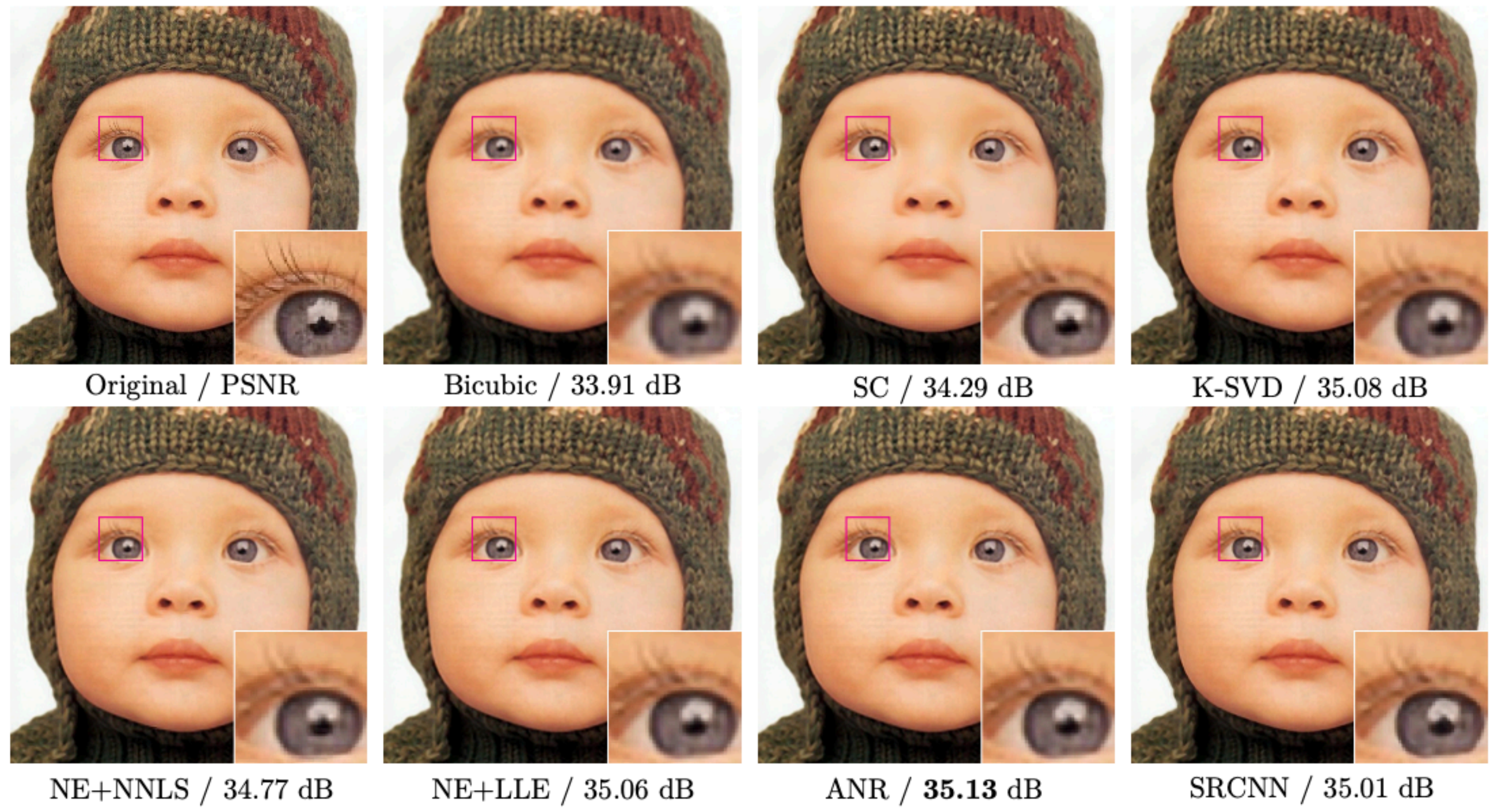
$$W_3 \in \mathbb{R}^{n_2 \times f_3 \times f_3 \times c} \qquad B_3 \in \mathbb{R}^{c}$$

$$L(\Theta) = \frac{1}{n} \sum_{i=1}^{n} \|F(Y_i; \Theta) - X_i\|^2$$





Original / PSNR — Bicubic / 24.04 dB — SC / 25.58 dB — SRCNN / 27.58 dB

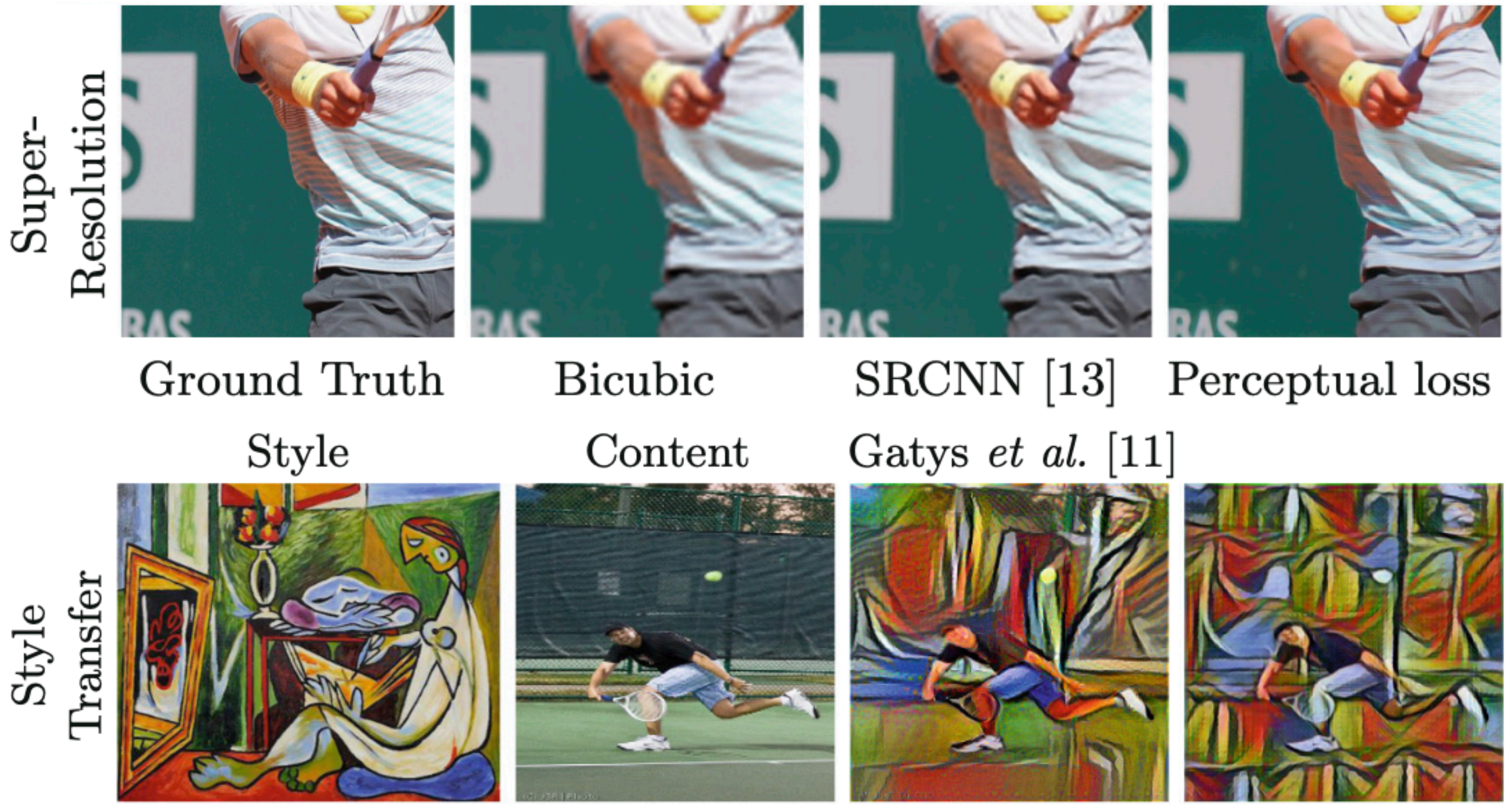


Dong, Chao, et al. "Learning a deep convolutional network for image super-resolution." *European conference on computer vision*. Springer, Cham, 2014.

Dong, Chao, et al. "Image super-resolution using deep convolutional networks." *IEEE transactions on pattern analysis and machine intelligence* 38.2 (2015): 295-307.

Perceptual Losses for Real-Time Style Transfer and Super-Resolution

YouTube Video



Style transfer: $y_c = x$ & train one network per style target y_s

Super-resolution: $y_c =$ high-resolution image & style reconstruction loss is not used

Feature Reconstruction Loss

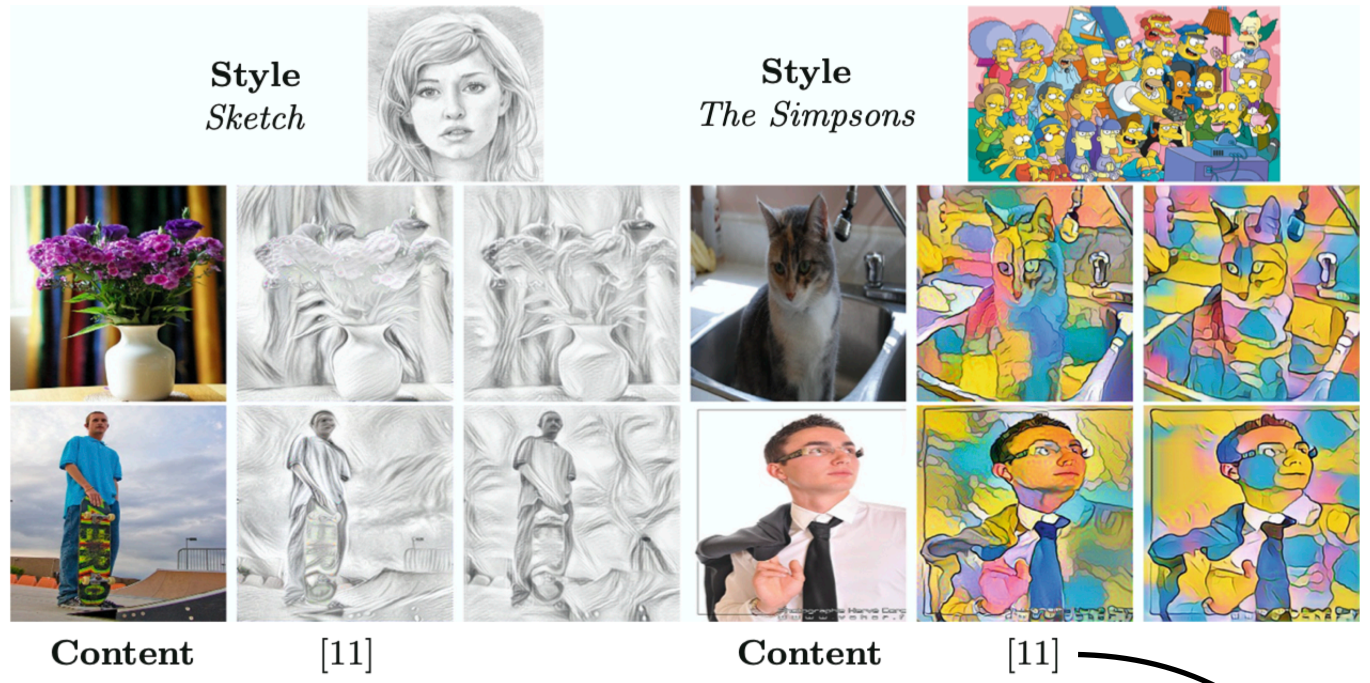
$\phi_j(x) \in \mathbb{R}^{C_j \times H_j \times W_j} \rightarrow$ activations of the j-th layer of network ϕ

$$\ell_{feat}^{\phi,j}(\hat{y}, y) = \frac{1}{C_j H_j W_j} \|\phi_j(\hat{y}) - \phi_j(y)\|_2^2$$

Style Reconstruction Loss

$$G_j^{\phi}(x)_{c,c'} = \frac{1}{C_j H_j W_j} \sum_{h=1}^{H_j} \sum_{w=1}^{W_j} \phi_j(x)_{h,w,c} \phi_j(x)_{h,w,c'}$$

$G_j^{\phi}(x) \in \mathbb{R}^{C_j \times C_j} \rightarrow$ Gram Matrix

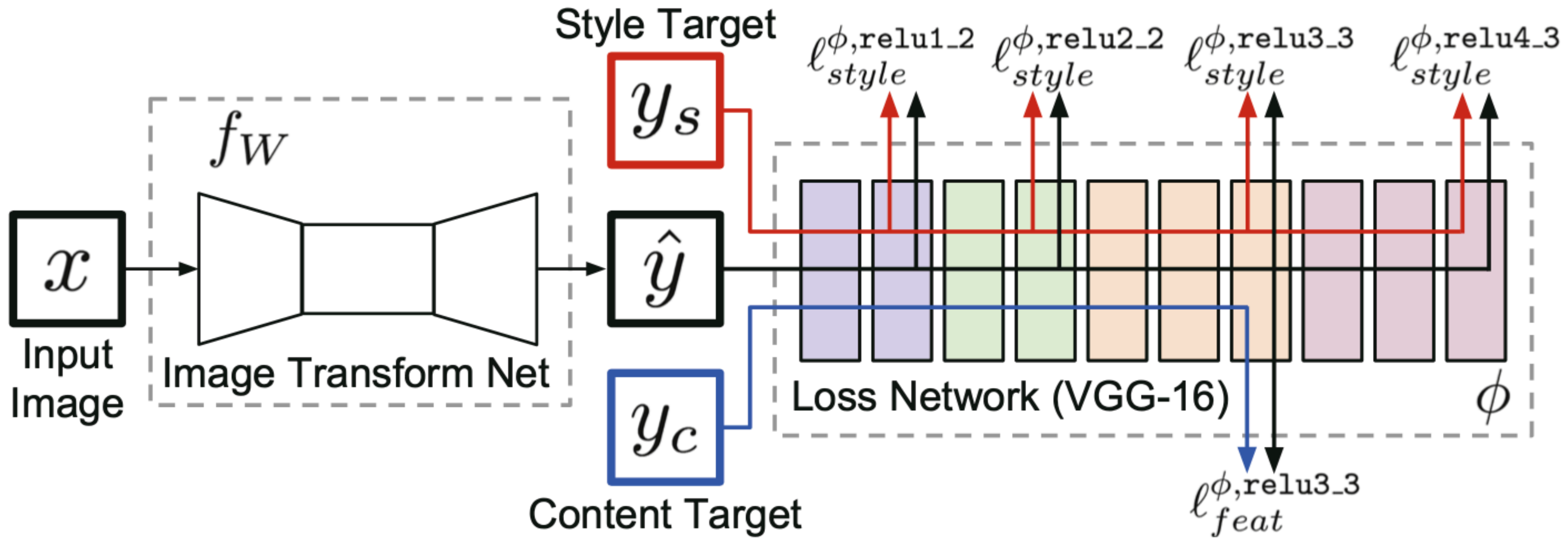


Gram matrix captures information about which features tend to activate together.

$$\ell_{style}^{\phi,j}(\hat{y}, y) = \|G_j^{\phi}(\hat{y}) - G_j^{\phi}(y)\|_F^2$$

$$\hat{y} = \arg\min_y \lambda_c \ell_{feat}^{\phi,j}(y, y_c) + \lambda_s \ell_{style}^{\phi,J}(y, y_s) + \lambda_{TV} \ell_{TV}(y)$$

"For example, consider two identical images offset from each other by one pixel; despite their perceptual similarity they would be very different as measured by per-pixel losses."



$$W^* = \arg\min_W \mathbb{E}_{x,y}\left[\sum_i \lambda_i \ell_i(\underbrace{f_W(x)}_{\hat{y}}, y)\right]$$

Speedup over [11] at 100, 300, 500 optimization iterations

Image Size	Speedup		
	100	300	500
256 × 256	212x	636x	**1060x**
512 × 512	205x	615x	**1026x**
1024 × 1024	208x	625x	**1042x**

Johnson, Justin, Alexandre Alahi, and Li Fei-Fei. "Perceptual losses for real-time style transfer and super-resolution." *European conference on computer vision*. Springer, Cham, 2016.

Image Style Transfer Using Convolutional Neural Networks

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Content Representation

$p \rightarrow$ photograph

$x \rightarrow$ generated image (randomly initialized)

$P^l \rightarrow$ feature representation of p at layer l

$F^l \rightarrow$ feature representation of x at layer l

$$\mathcal{L}_{\text{content}}(\vec{p}, \vec{x}, l) = \frac{1}{2} \sum_{i,j} \left(F^l_{ij} - P^l_{ij}\right)^2$$

$F^l_{i,j} \rightarrow$ activation of i-th filter at position j in layer l

$F^l \in \mathbb{R}^{N_l \times M_l}$

$N_l \rightarrow$ number of feature maps

$M_l \rightarrow$ height times width of the feature map

Style Representation

$G^l \in \mathbb{R}^{N_l \times N_l} \rightarrow$ Gram matrix

$G^l_{ij} = \sum_k F^l_{ik} F^l_{jk} \rightarrow$ inner product between the vectorized feature maps i and j in layer l

captures texture but not global arrangement

$a \rightarrow$ artwork image $\quad A^l \rightarrow$ style representation of a

$G^l \rightarrow$ style representation of x

$$\mathcal{L}_{\text{style}}(\vec{a}, \vec{x}) = \sum_{l=0}^{L} w_l E_l \qquad E_l = \frac{1}{4N_l^2 M_l^2} \sum_{i,j} \left(G^l_{ij} - A^l_{ij}\right)^2$$

Style Transfer

$$\mathcal{L}_{\text{total}}(\vec{p}, \vec{a}, \vec{x}) = \alpha \mathcal{L}_{\text{content}}(\vec{p}, \vec{x}) + \beta \mathcal{L}_{\text{style}}(\vec{a}, \vec{x})$$

$$\frac{\partial \mathcal{L}_{\text{total}}}{\partial \vec{x}}$$

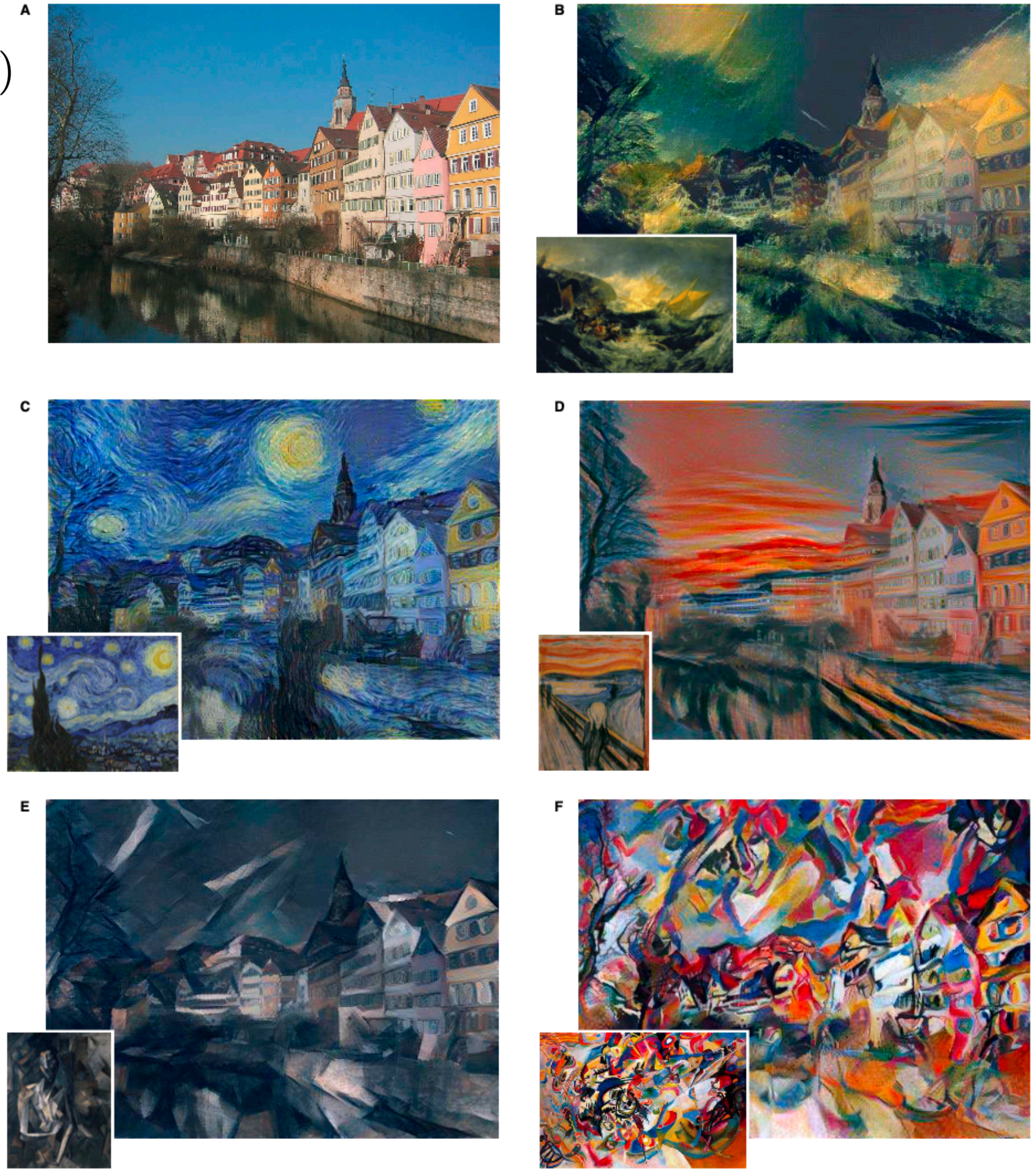
Style Image

Content Image

10^{-4}

10^{-1}

The ratio α/β



Gatys, Leon A., Alexander S. Ecker, and Matthias Bethge. "Image style transfer using convolutional neural networks." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016.

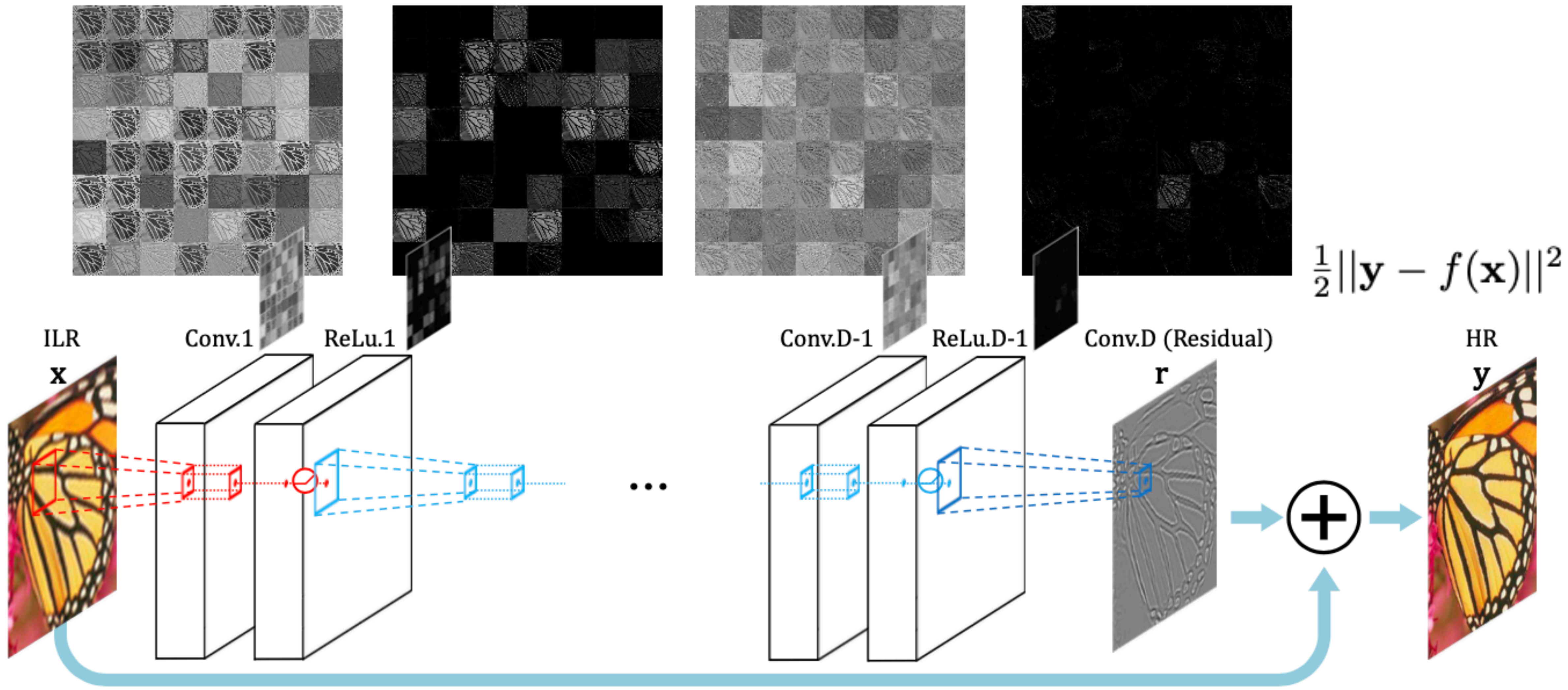
Gatys, Leon A., Alexander S. Ecker, and Matthias Bethge. "A neural algorithm of artistic style." *arXiv preprint arXiv:1508.06576* (2015).

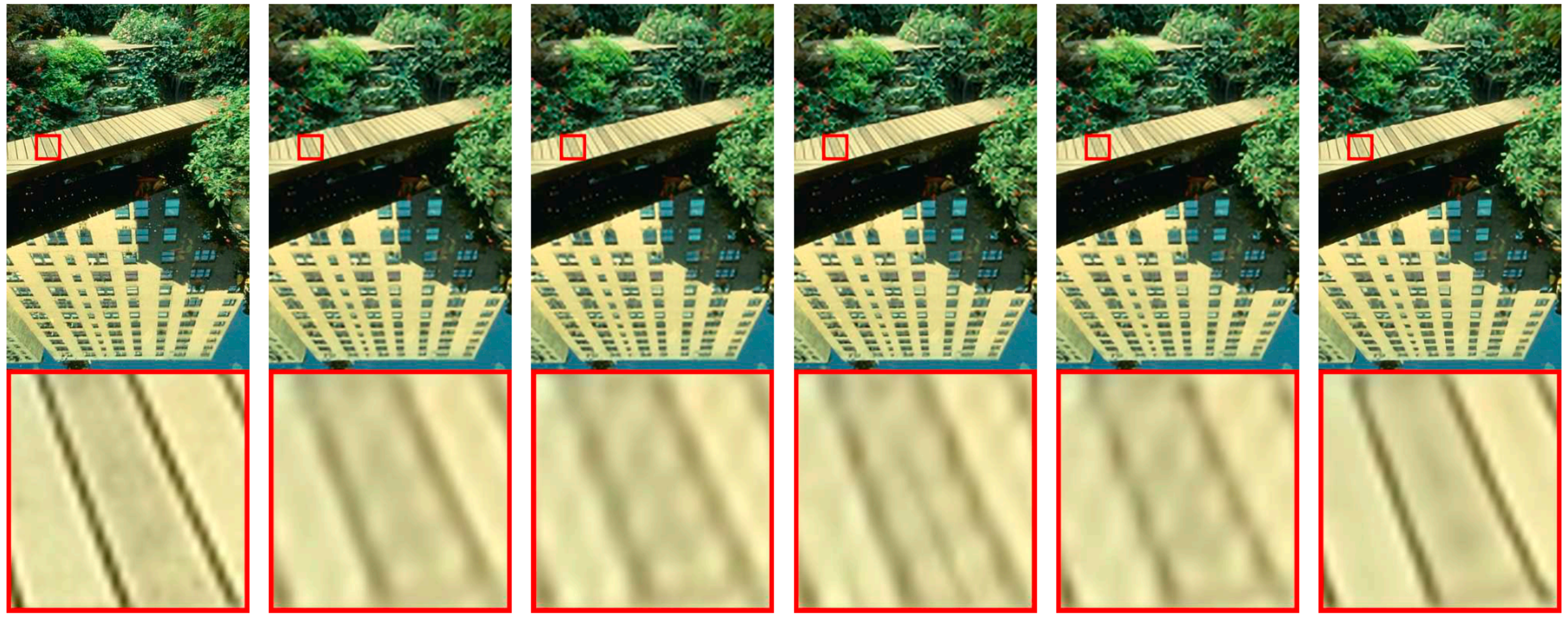
Accurate Image Super-Resolution Using Very Deep Convolutional Networks

Boulder

YouTube Video

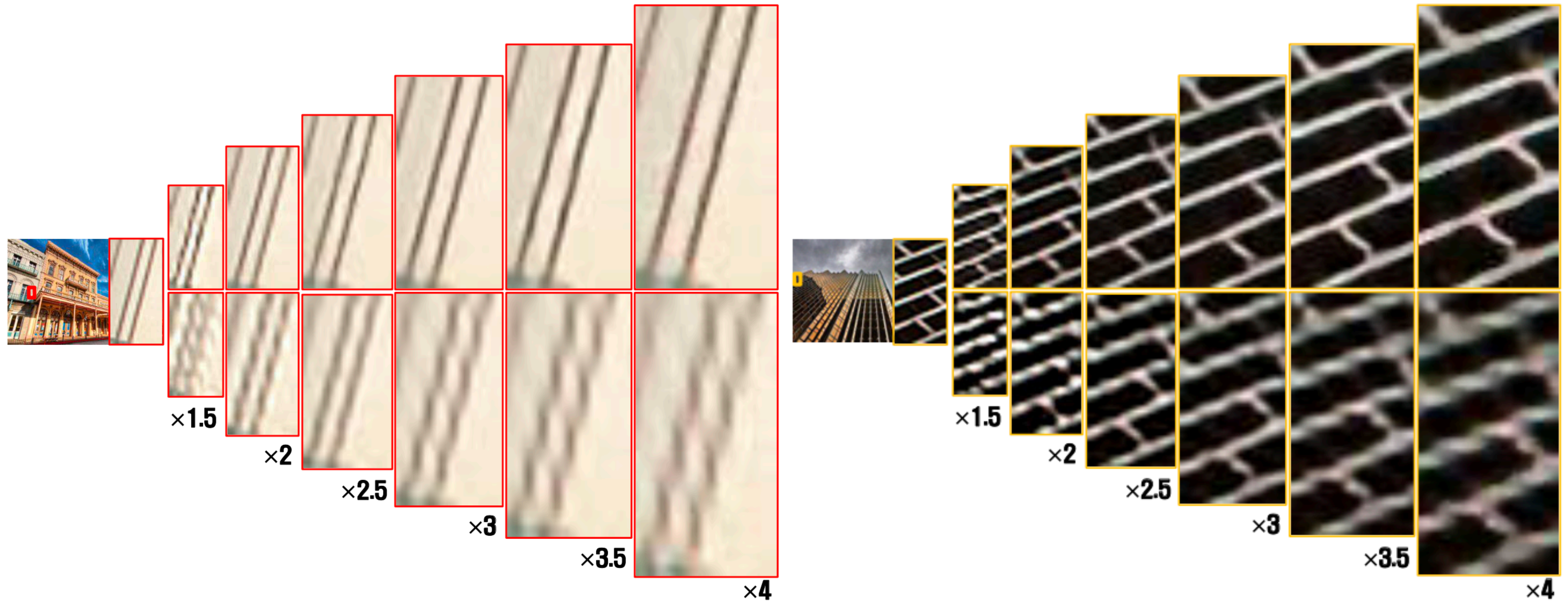
Single Image Super-Resolution (SISR)

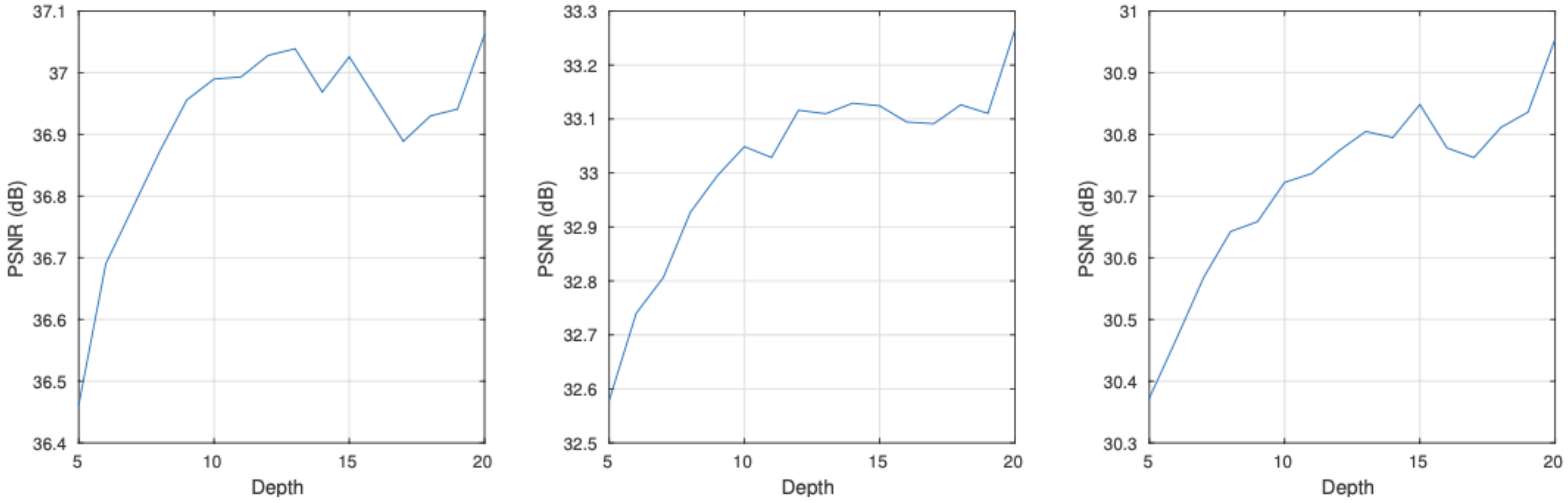




Ground Truth | A+ [22] | RFL [18] | SelfEx [11] | SRCNN [5] | VDSR

- Residual-Learning
- High Learning Rates
- Adjustable Gradient Clipping
- Multi-scale





(a) Test Scale Factor 2 (b) Test Scale Factor 3 (c) Test Scale Factor 4

Kim, Jiwon, Jung Kwon Lee, and Kyoung Mu Lee. "Accurate image super-resolution using very deep convolutional networks." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016.

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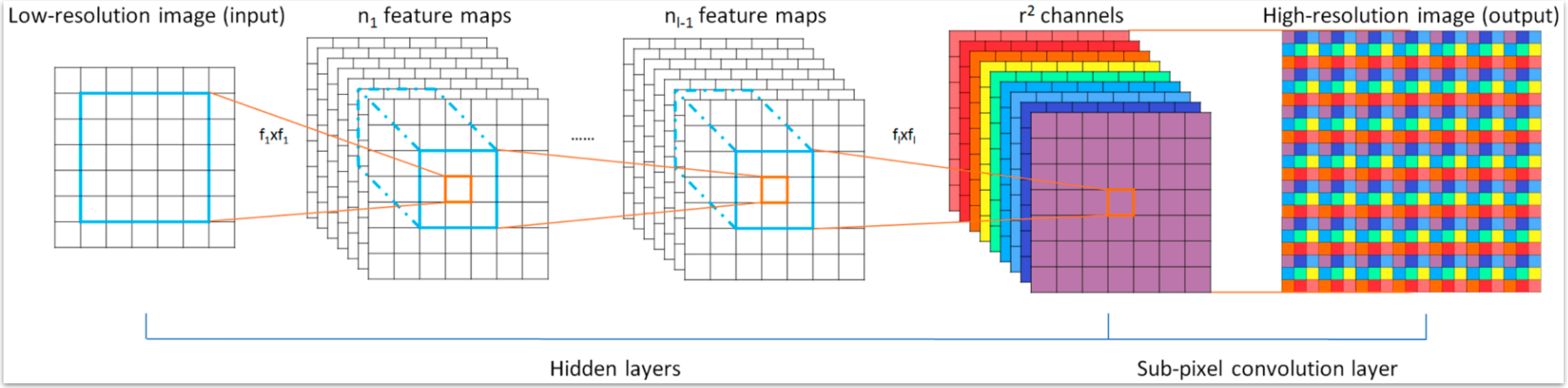
Real-Time Single Image and Video Super-Resolution Using an Efficient Sub-Pixel Convolutional Neural Network

$I^{\mathrm{HR}} \rightarrow$ high-resolution image
$I^{\mathrm{LR}} \rightarrow$ low-resolution image
$I^{\mathrm{LR}} \leftarrow I^{\mathrm{HR}}$ $\triangleright$ Gaussian filter
$\triangleright$ Downsampling
$I^{\mathrm{SR}} \rightarrow$ super-resolved image
$r \rightarrow$ upscaling ratio
$I^{\mathrm{LR}} \in \mathbb{R}^{H \times W \times C}$
$I^{\mathrm{HR}} \in \mathbb{R}^{rH \times rW \times C}$
avoid upscaling I^{LR}
(i.e., bicubic interpolation)
before feeding into the network



$$f^1(I^{\mathrm{LR}}; W_1, b_1) = \tanh(W_1 * I^{\mathrm{LR}} + b_1)$$
$$f^l(I^{\mathrm{LR}}; W_{1:l}, b_{1:l}) = \tanh(W_l * f^{l-1}(I^{\mathrm{LR}}) + b_l), l = 2, \ldots, L-1$$
$$W_l \in \mathbb{R}^{n_{l-1} \times n_l \times k_l \times k_l}, b_l \in \mathbb{R}^{n_l}$$

$n_l \rightarrow$ number of features at layer l
$n_0 = C, k_l \rightarrow$ filter size at layer l

Efficient sub-pixel convolution layer

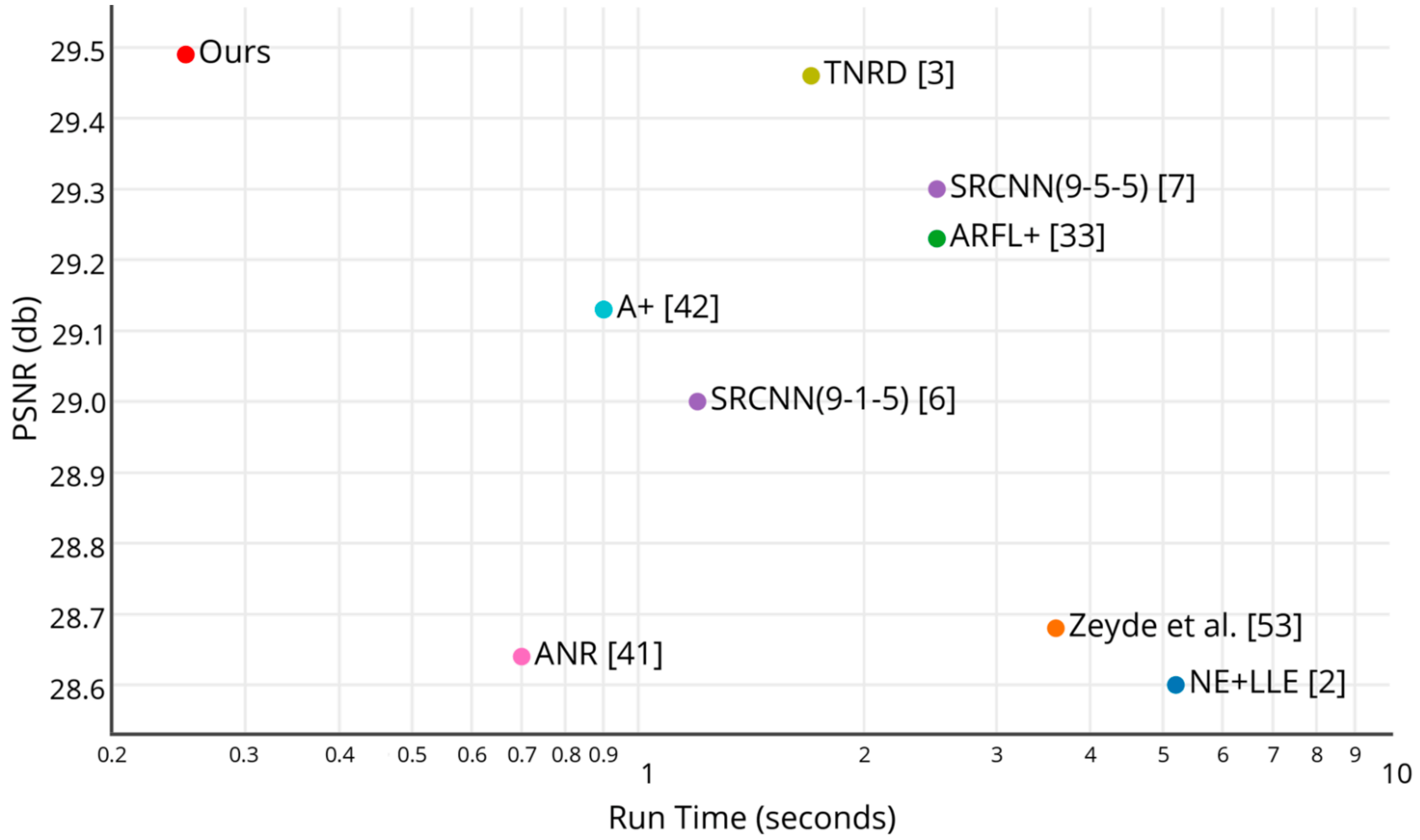
$$\mathbf{I}^{SR} = f^L(\mathbf{I}^{LR}) = \mathcal{PS}\left(W_L * f^{L-1}(\mathbf{I}^{LR}) + b_L\right)$$

$\mathcal{PS} \rightarrow$ periodic shuffling operator $\quad W_L \in \mathbb{R}^{n_{L-1} \times r^2 C \times k_L \times k_L}$

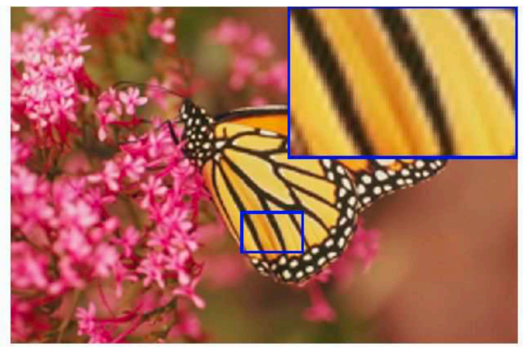
$$H \times W \times C \cdot r^2 \mapsto rH \times rW \times C$$
$$\mathcal{PS}(T)_{x,y,c} = T_{\lfloor x/r \rfloor, \lfloor y/r \rfloor, c \cdot r \cdot \mathrm{mod}(y,r) + c \cdot \mathrm{mod}(x,r)}$$

equivalent to a fractionally-strided convolution
convolution with stride $1/r$ in the LR space
with a filter W_s of size $k_s = rk_L$, but more efficient!

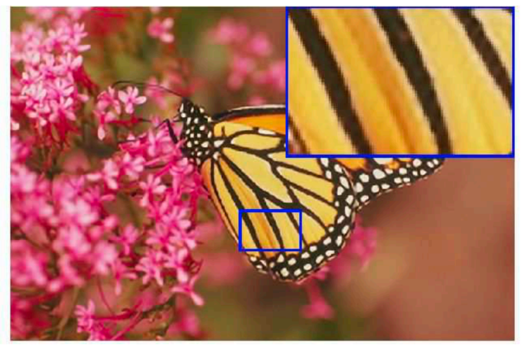
$$\ell(W_{1:L}, b_{1:L}) = \frac{1}{r^2 HW} \sum_{x=1}^{rH} \sum_{x=1}^{rW} \left(\mathbf{I}^{HR}_{x,y} - f^L_{x,y}(\mathbf{I}^{LR})\right)^2$$



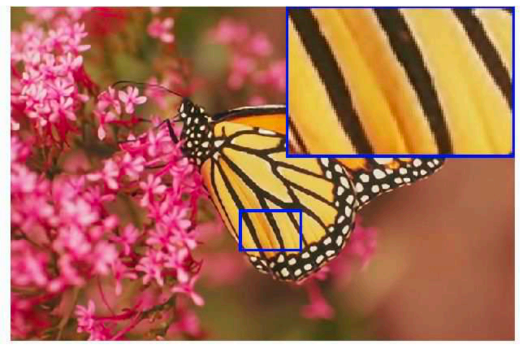
(k) Monarch Original



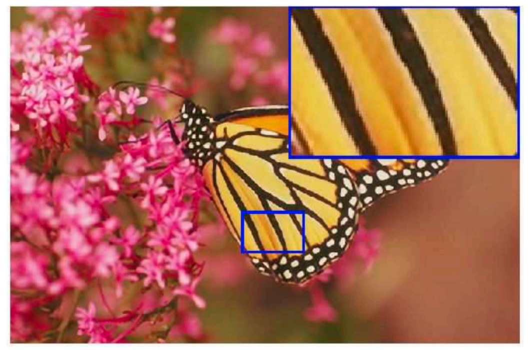
(l) Bicubic / 29.43db



(m) SRCNN [7] / 32.81db



(n) TNRD [3] / 33.62db



(o) ESPCN / **33.66db**

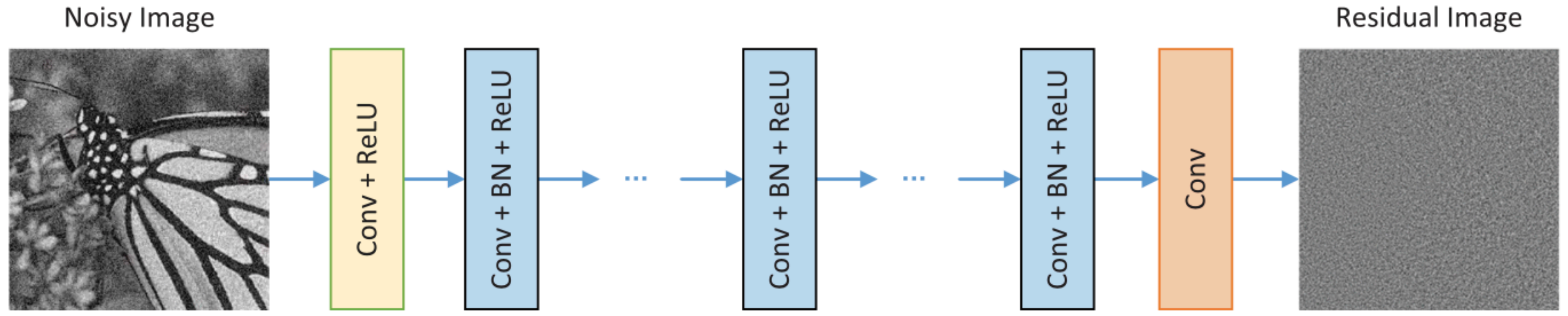
Shi, Wenzhe, et al. "Real-time single image and video super-resolution using an efficient sub-pixel convolutional neural network." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016.

Beyond a Gaussian Denoiser: Residual Learning of Deep CNN for Image Denoising

Boulder

YouTube Video

Denoising Convolutional Neural Networks (DnCNNs)



$x \rightarrow$ clean image

$y \rightarrow$ noisy observation

$y = x + v \rightarrow$ image degradation model

AWGN (Additive White Gaussian Noise) with standard deviation σ

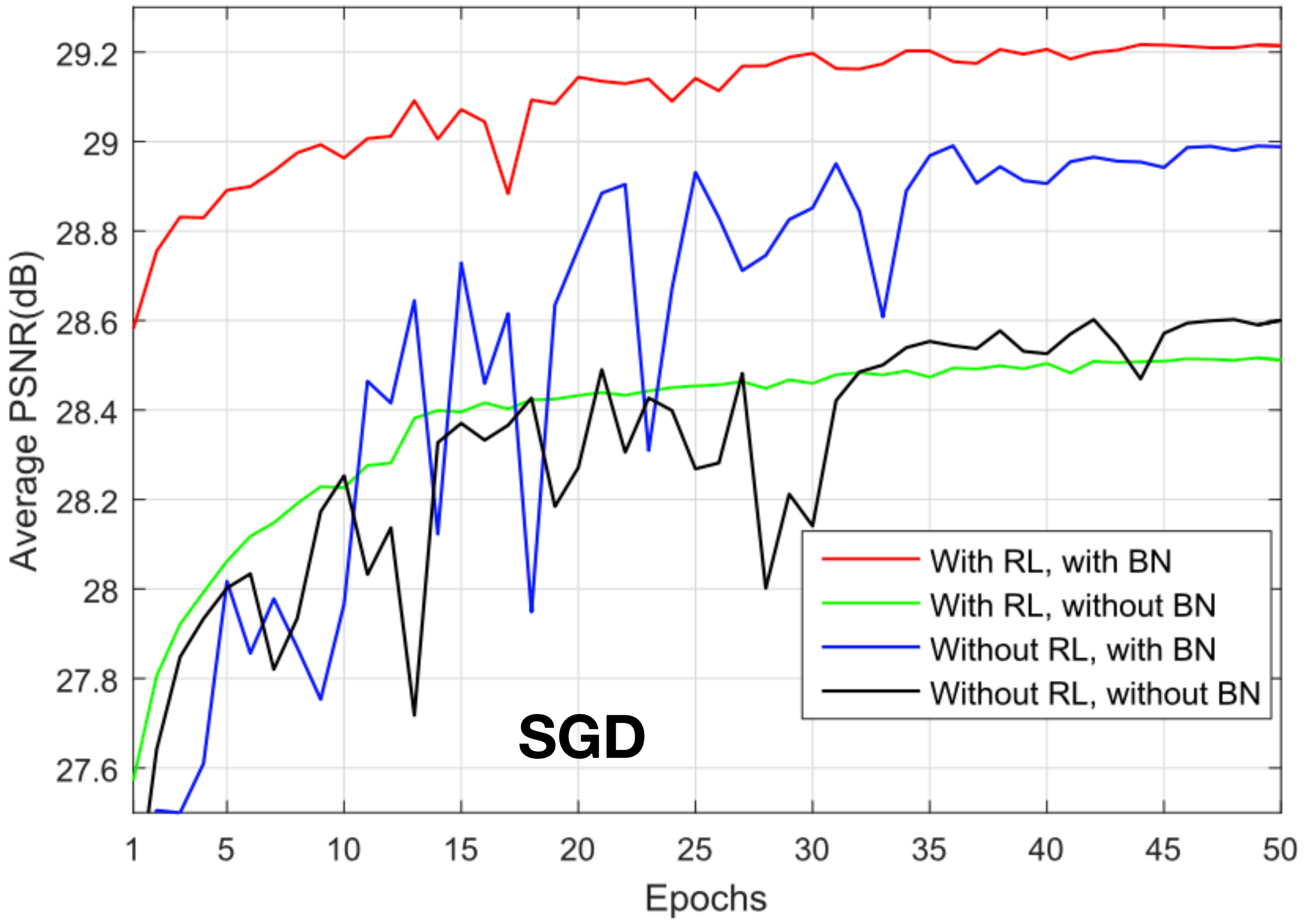
Receptive Field of DnCNN (3×3 conv) with depth d is $(2d+1) \times (2d+1)$

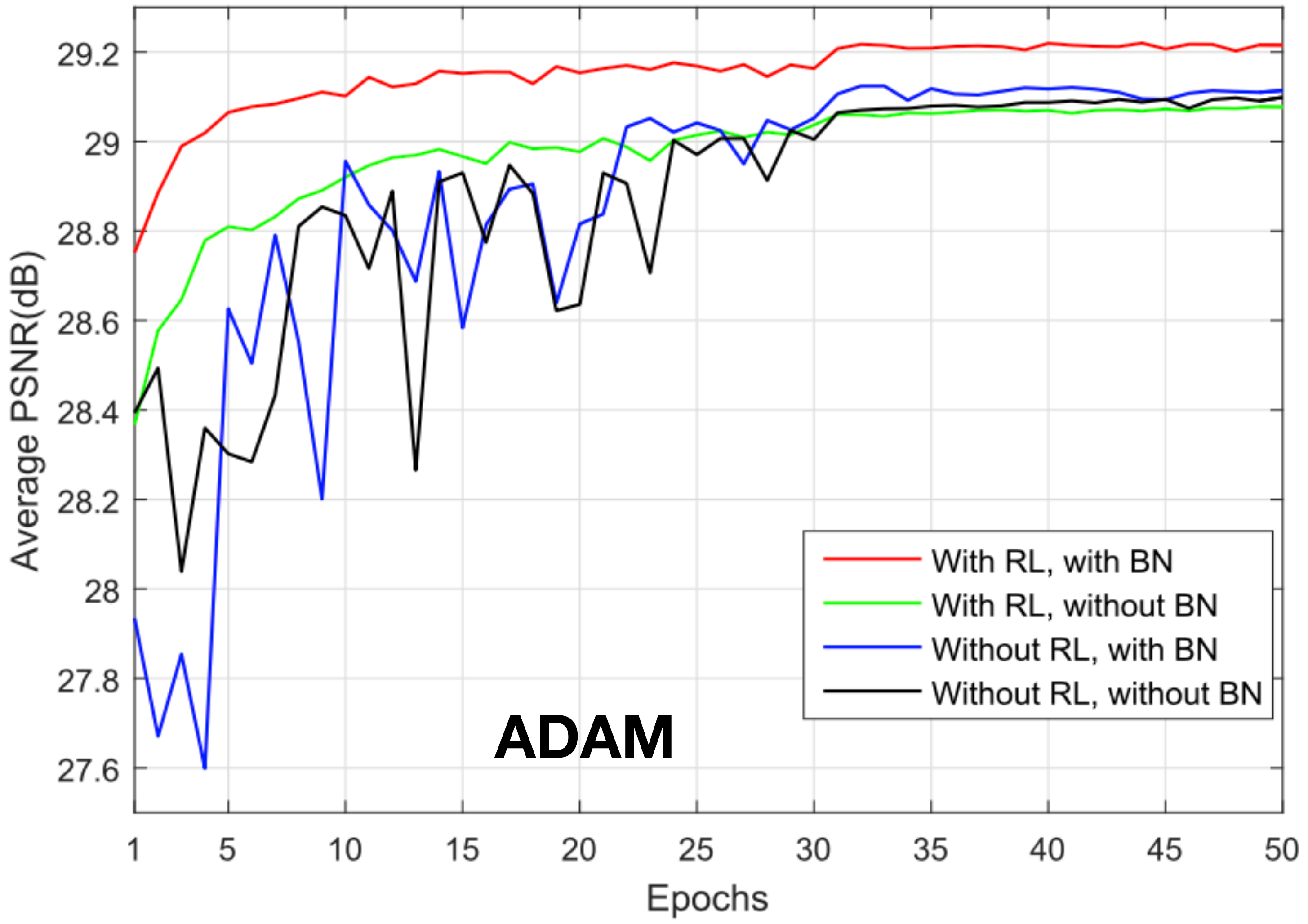
$\mathcal{F}(y) = x$

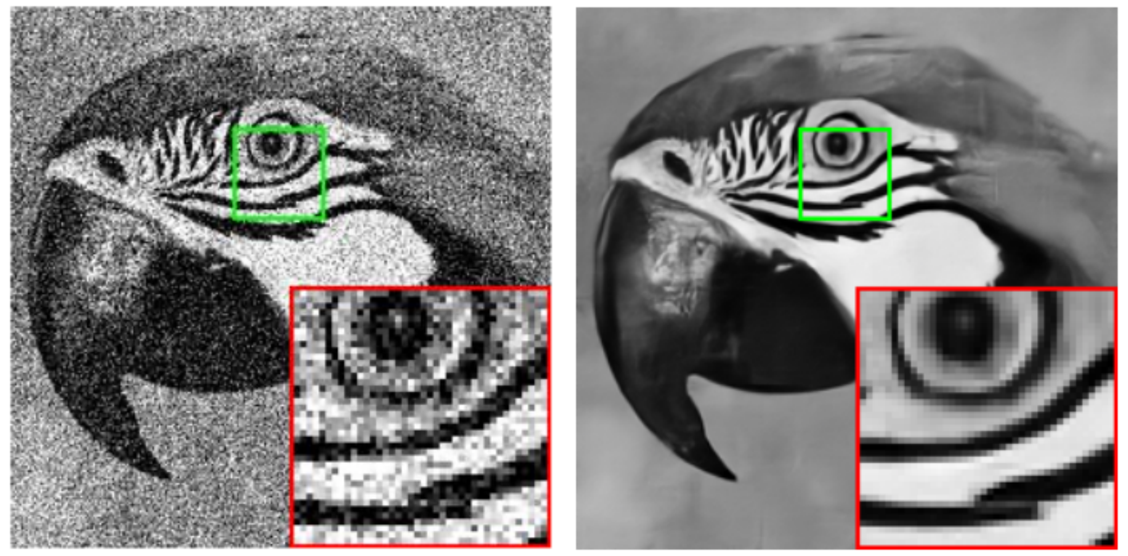
$\mathcal{R}(y) \approx v \rightarrow$ residual mapping

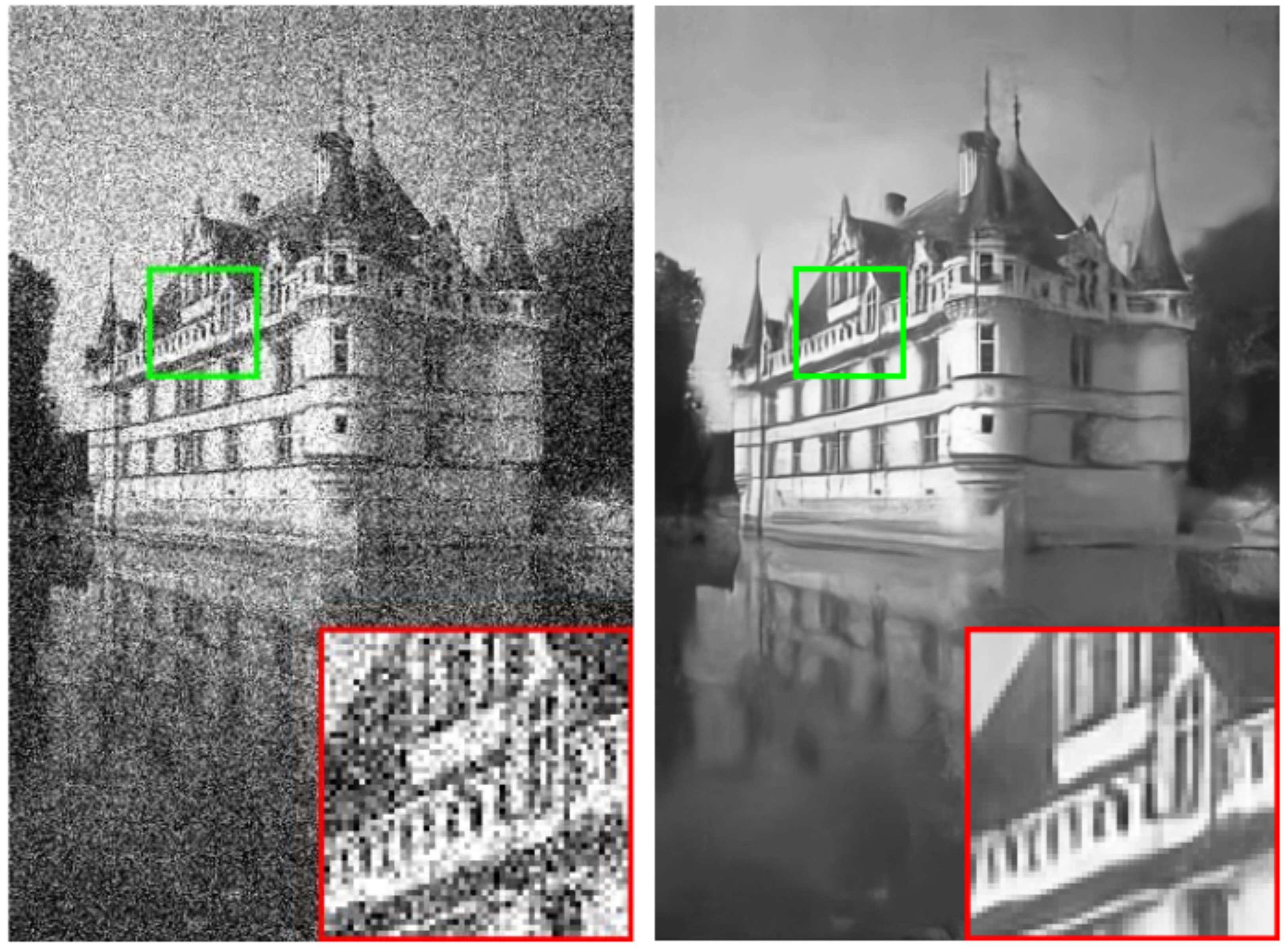
$\implies x = y - \mathcal{R}(y)$

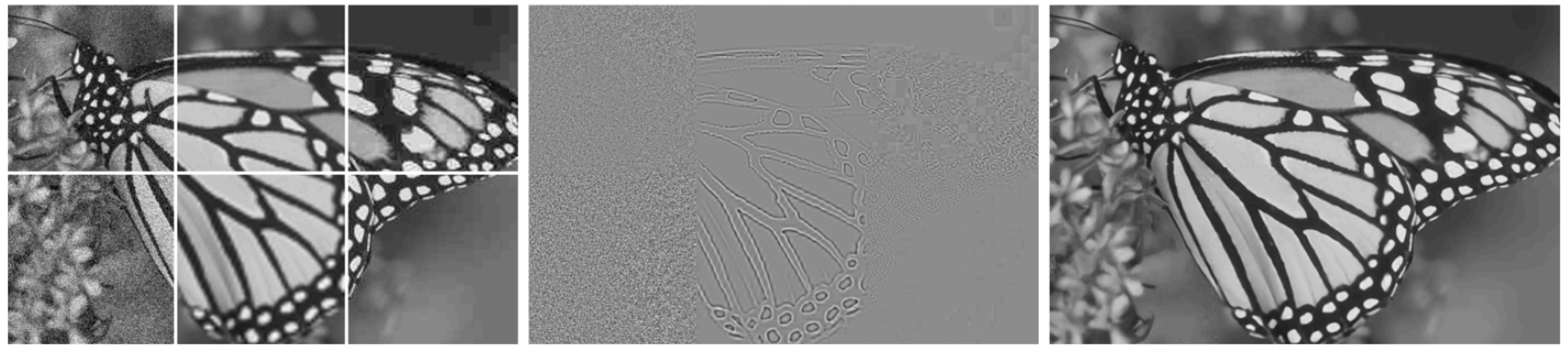
$$\ell(\theta) = \frac{1}{2N} \sum_{i=1}^{N} \| R(y_i;\theta) - (y_i - x_i) \|_F^2$$







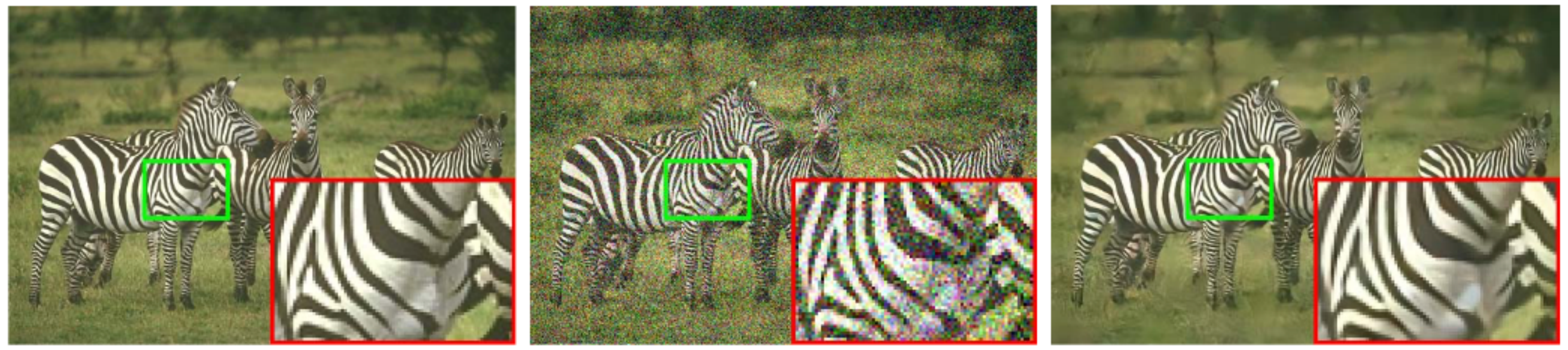




JPEG image de-blocking

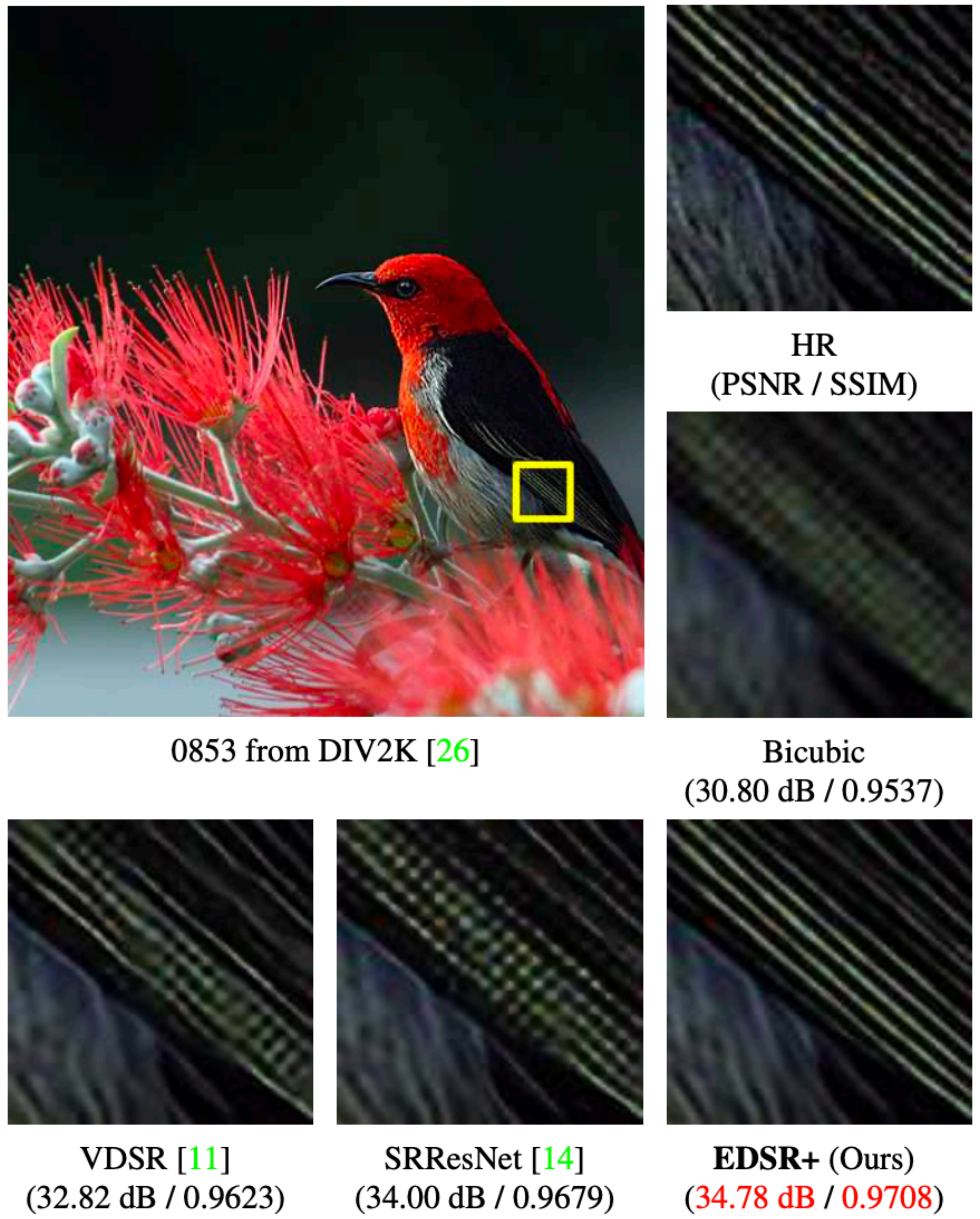
Single Image Super-resolution

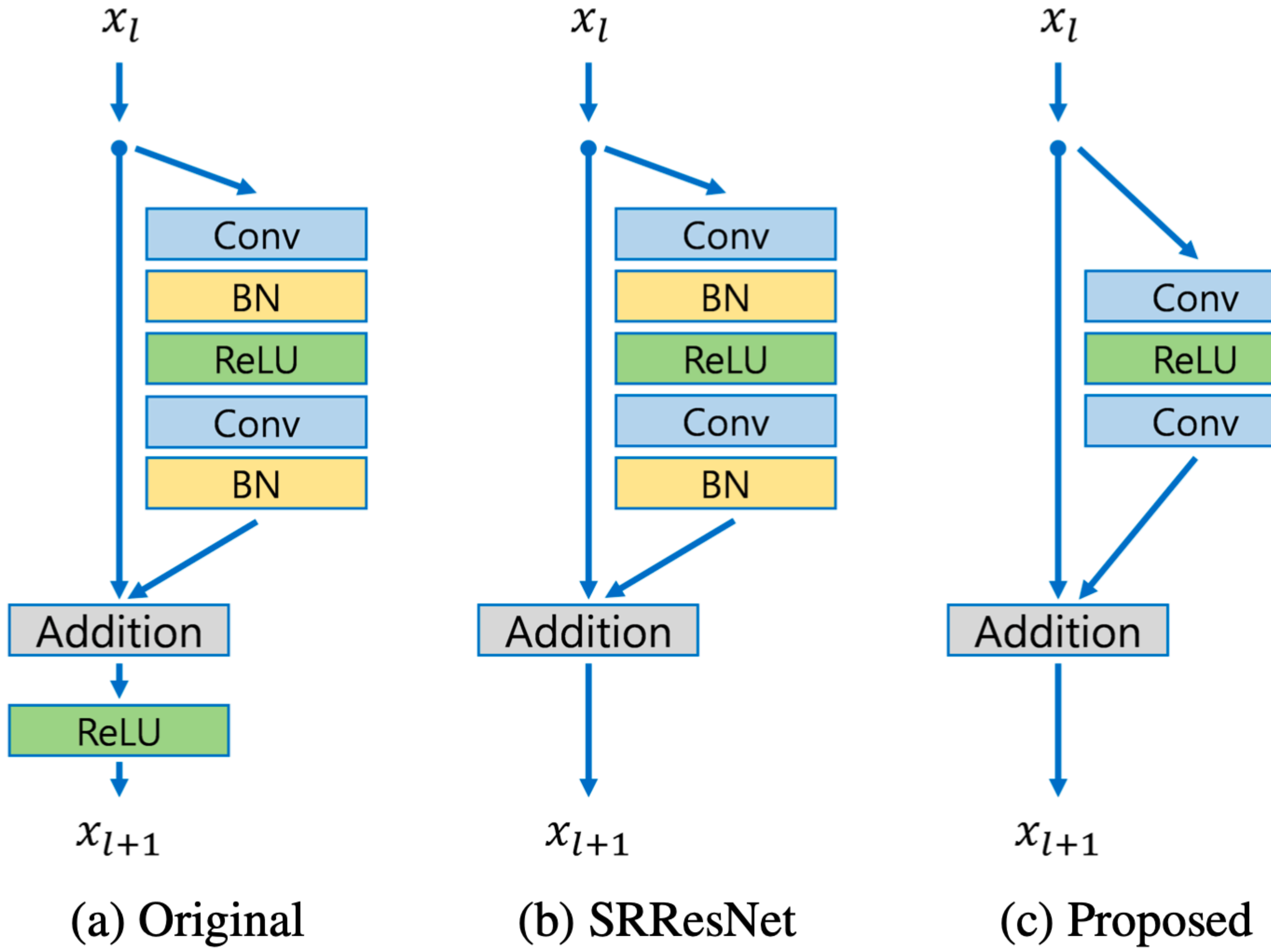
Gaussian Denoising

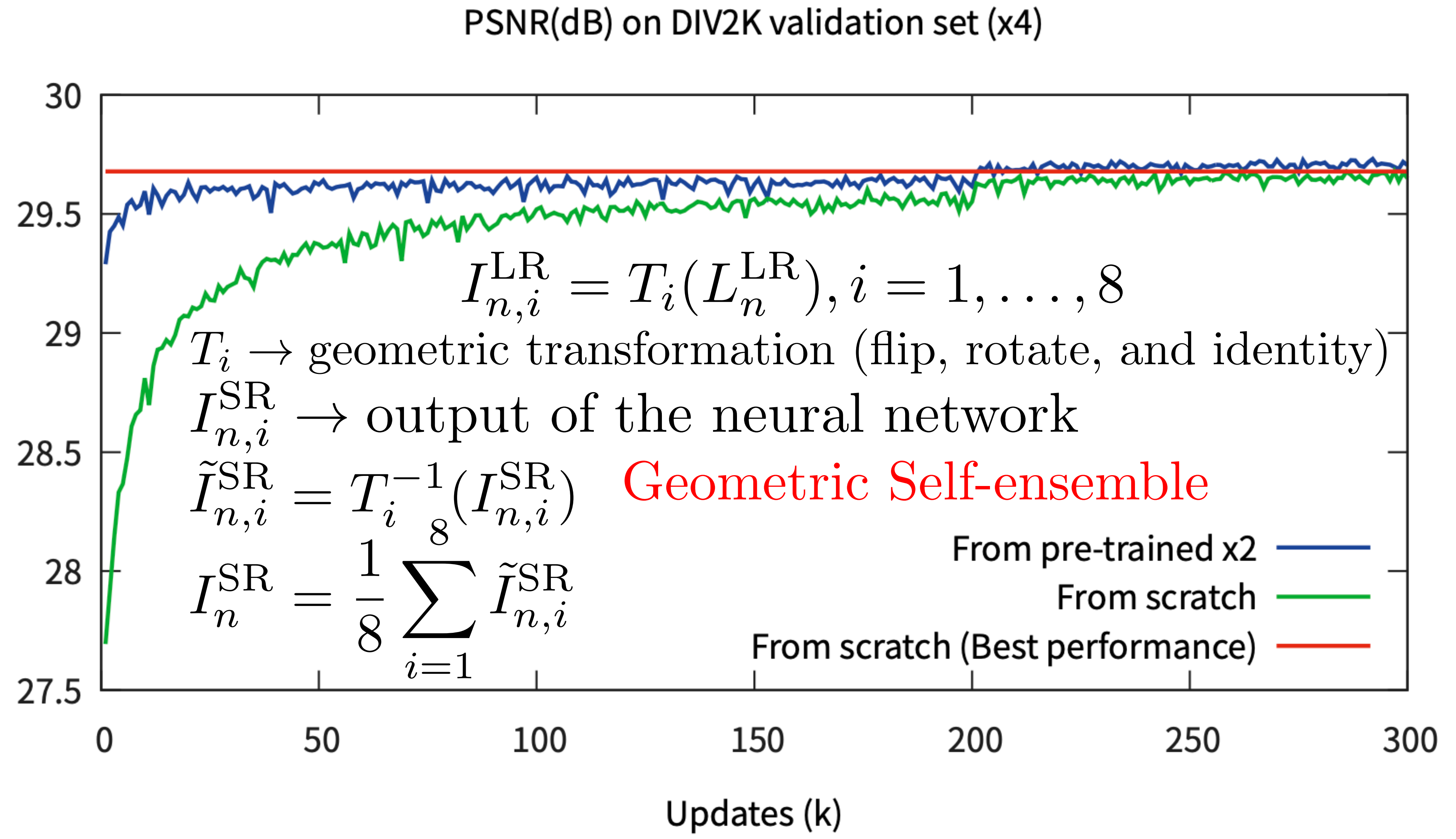


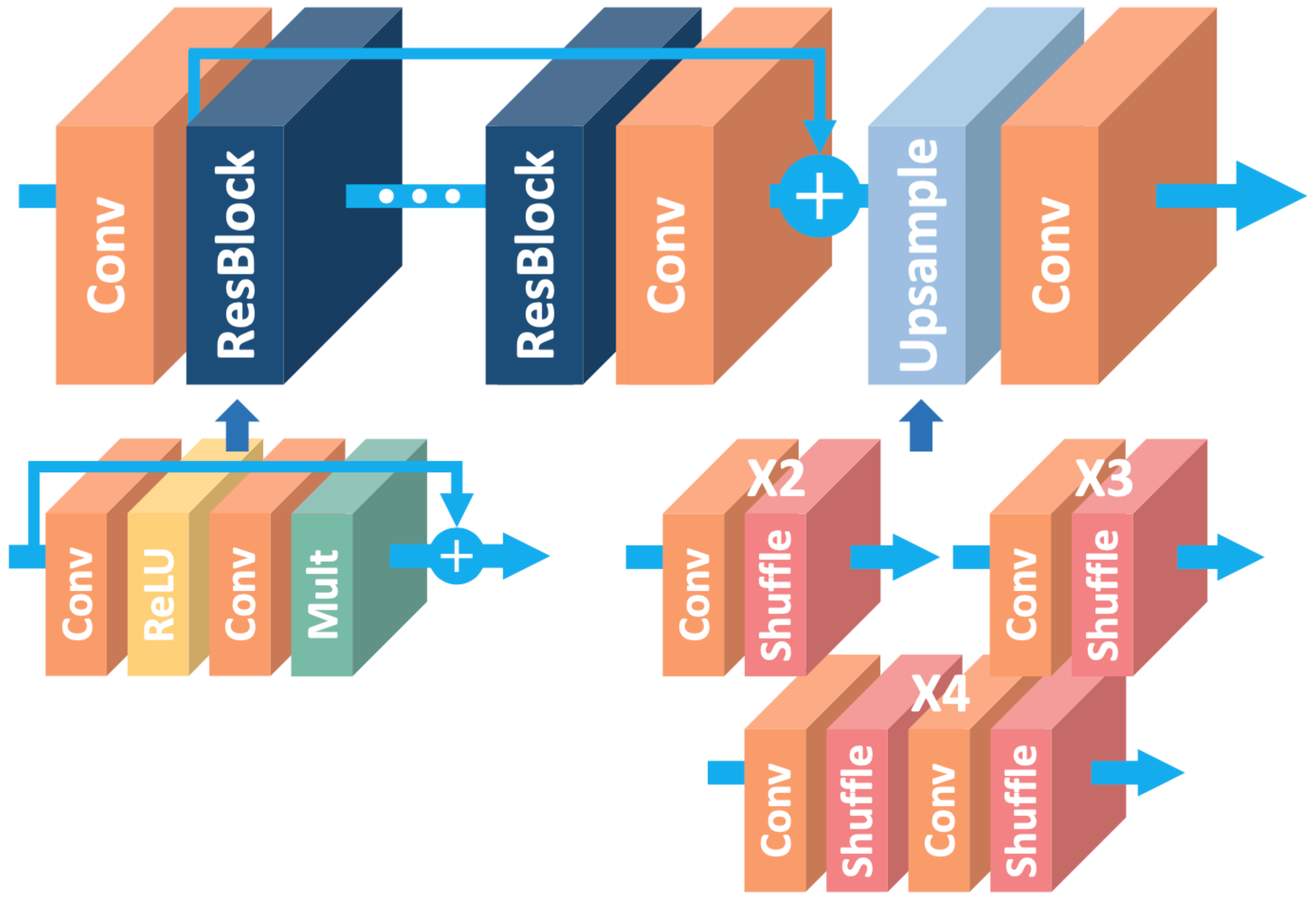
Zhang, Kai, et al. "Beyond a gaussian denoiser: Residual learning of deep cnn for image denoising." *IEEE Transactions on Image Processing* 26.7 (2017): 3142-3155.

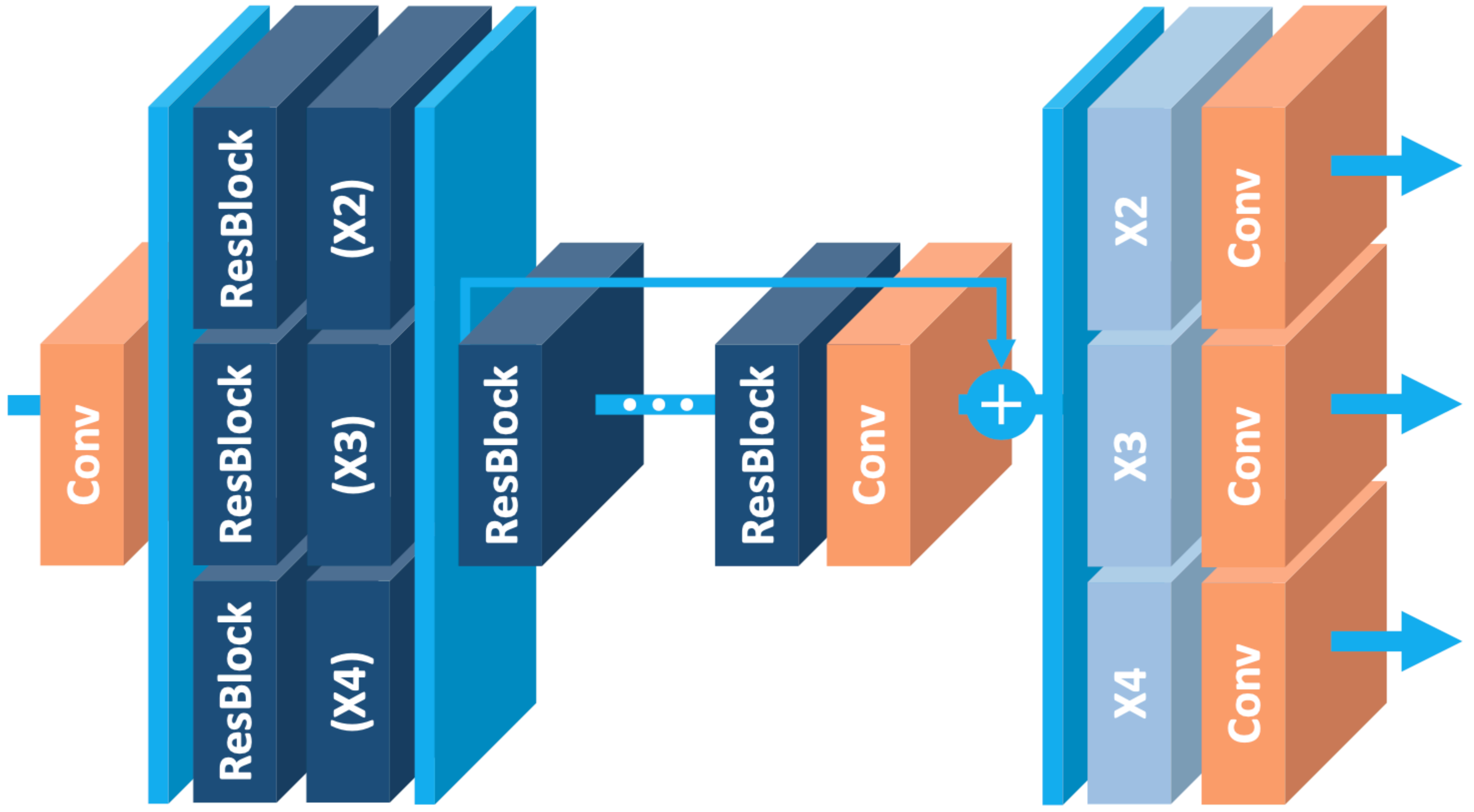
Enhanced Deep Residual Networks for Single Image Super-Resolution











Options	SRResNet [14] (reproduced)	Baseline (Single / Multi)	EDSR	MDSR
# Residual blocks	16	16	32	80
# Filters	64	64	256	64
# Parameters	1.5M	1.5M / 3.2M	43M	8.0M
Residual scaling	-	-	0.1	-
Use BN	Yes	No	No	No
Loss function	L2	L1	L1	L1

Lim, Bee, et al. "Enhanced deep residual networks for single image super-resolution." Proceedings of the IEEE conference on computer vision and pattern recognition workshops. 2017.

Deep Image Prior

Zero training data, zero validation data, and one test data!

$$x^* = \arg\min_x \|d(x) - x_0\|^2 + R(x)$$

$x^* \in \mathbb{R}^{rH\times rW\times C} \rightarrow$ super-resolved image

$x_0 \in \mathbb{R}^{H\times W\times C} \rightarrow$ low resolution image

$x \in \mathbb{R}^{rH\times rW\times C}$

$d : \mathbb{R}^{rH\times rW\times C} \rightarrow \mathbb{R}^{H\times W\times C}$

downsampling operator

$R(x) \rightarrow$ regularizer (e.g., total variation (TV) of the image)

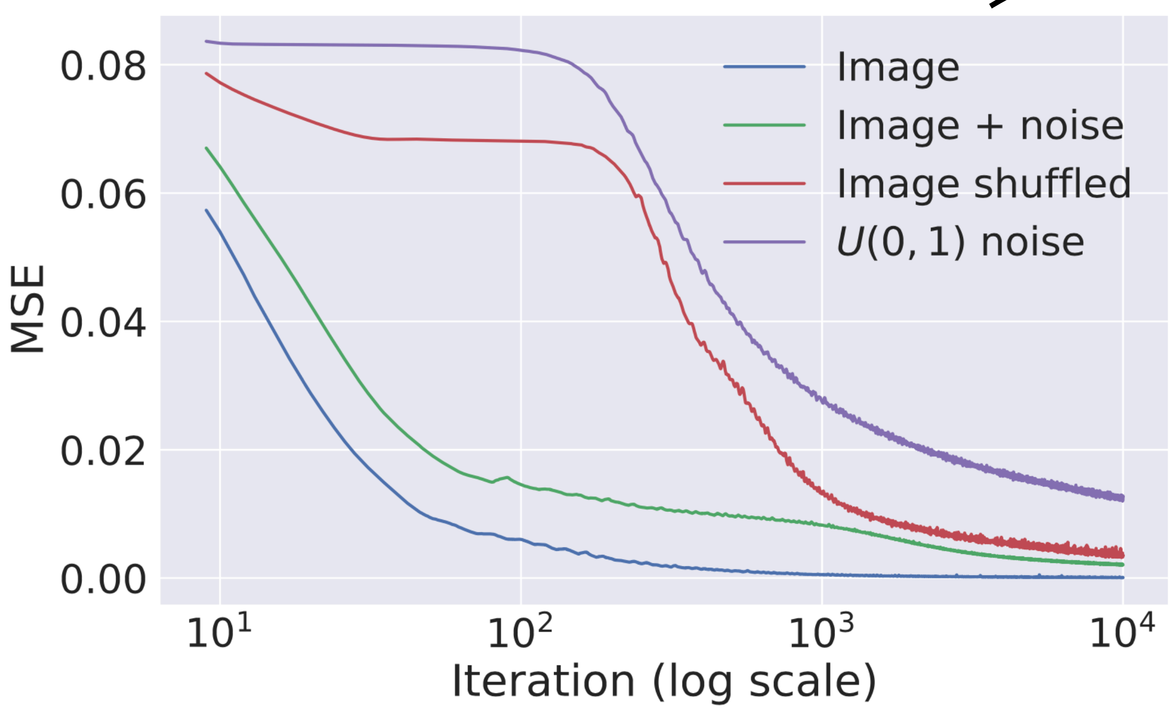
Use a CNN as the regularizer!

$R(x) = 0$ when $x = f_\theta(z)$ and $R(x) = +\infty$ otherwise

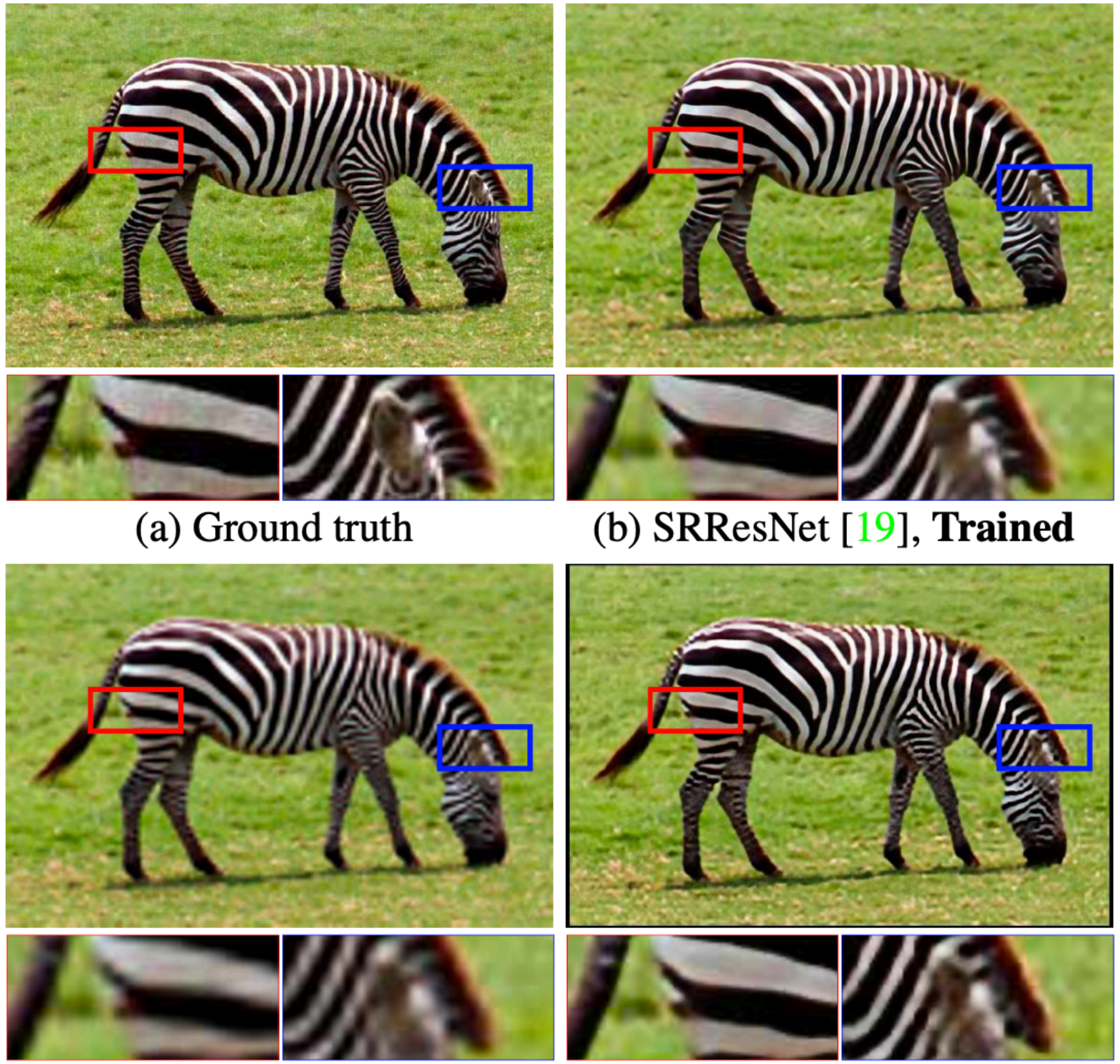
$z \rightarrow$ a vector filled with uniform noise (fixed)

$f_\theta \rightarrow$ CNN

$$\theta^* = \arg\min_\theta \|d(f_\theta(z)) - x_0\|^2 \qquad x^* = f_{\theta^*}(z)$$



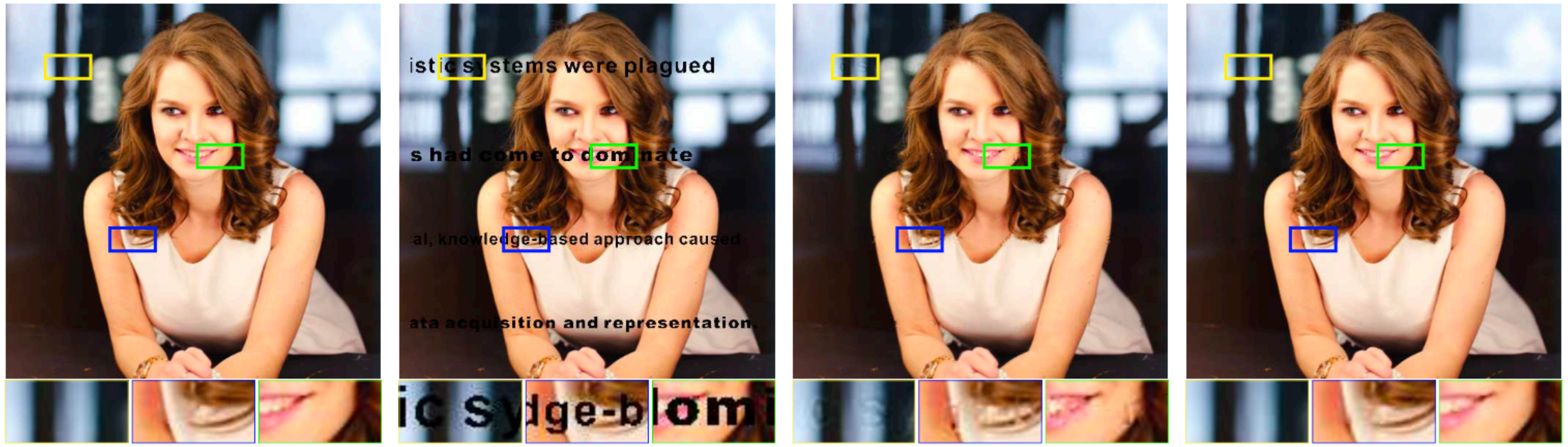
The network has a harder time overfitting noise than overfitting to natural images!



(a) Ground truth (b) SRResNet [19], **Trained**

(c) Bicubic, **Not trained** (d) Deep prior, **Not trained**

Inpainting

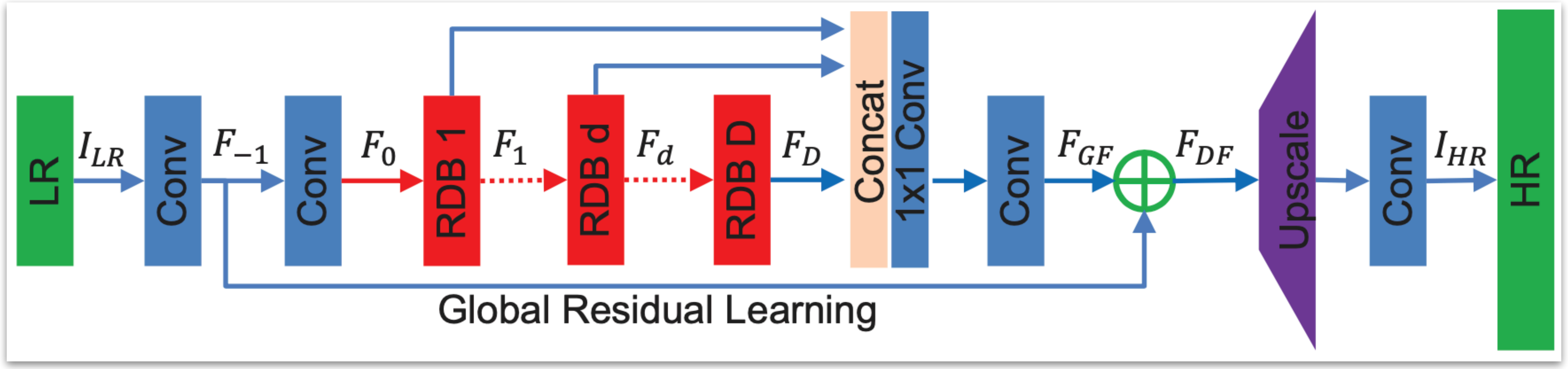


(a) Original image (b) Corrupted image (c) Shepard networks [27] (d) Deep Image Prior

Ulyanov, Dmitry, Andrea Vedaldi, and Victor Lempitsky. "Deep image prior." Proceedings of the IEEE conference on computer vision and pattern recognition. 2018.

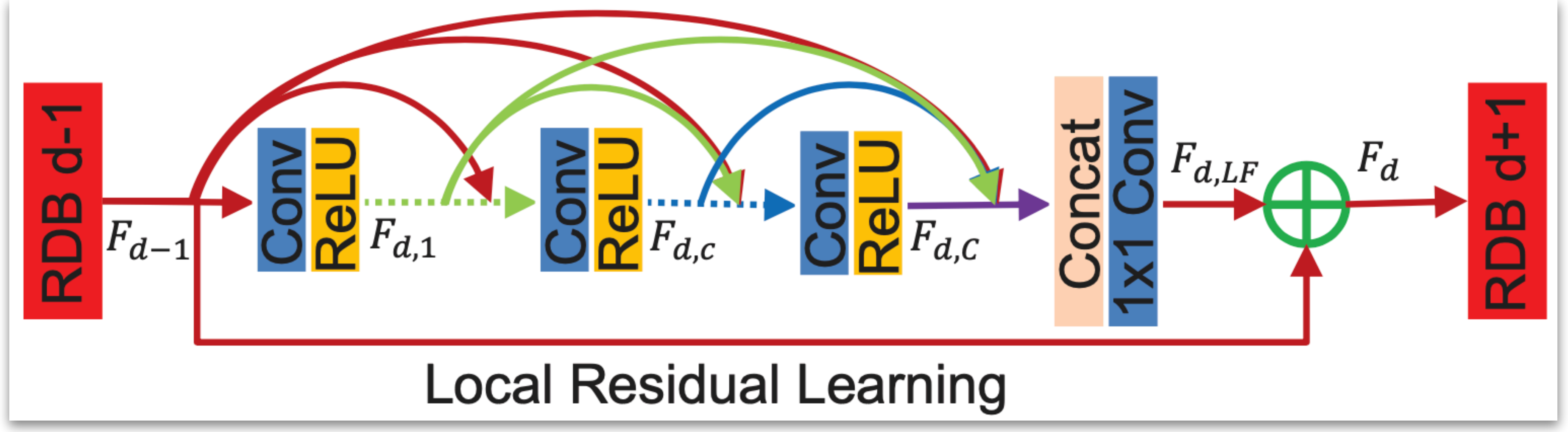
Residual Dense Network for Image Super-Resolution

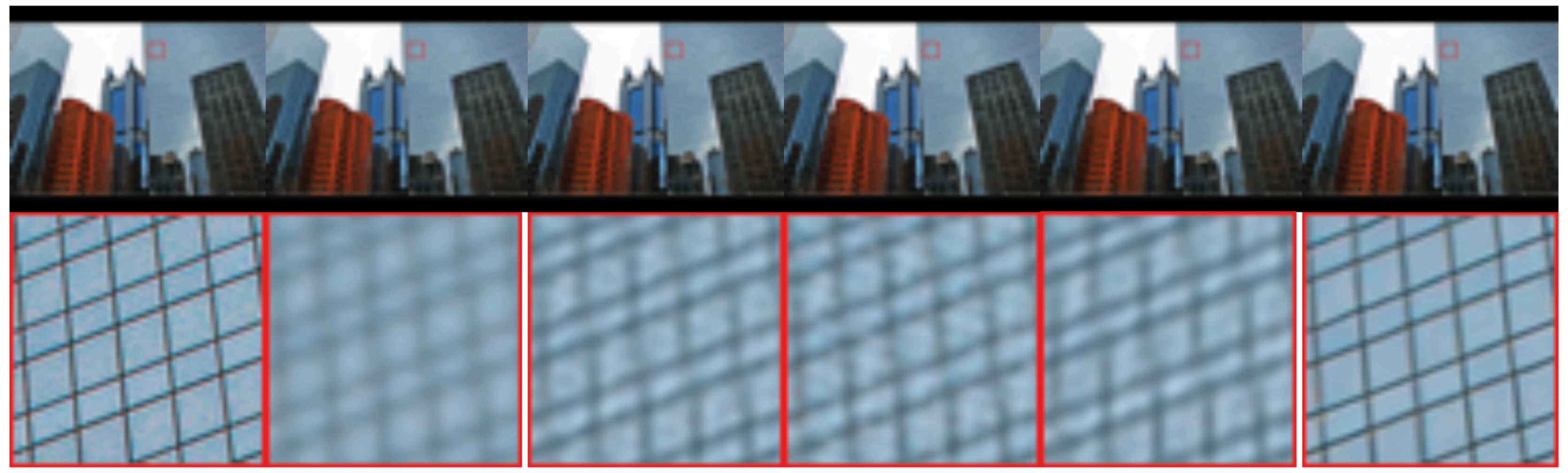
Residual Dense Network (RDN)



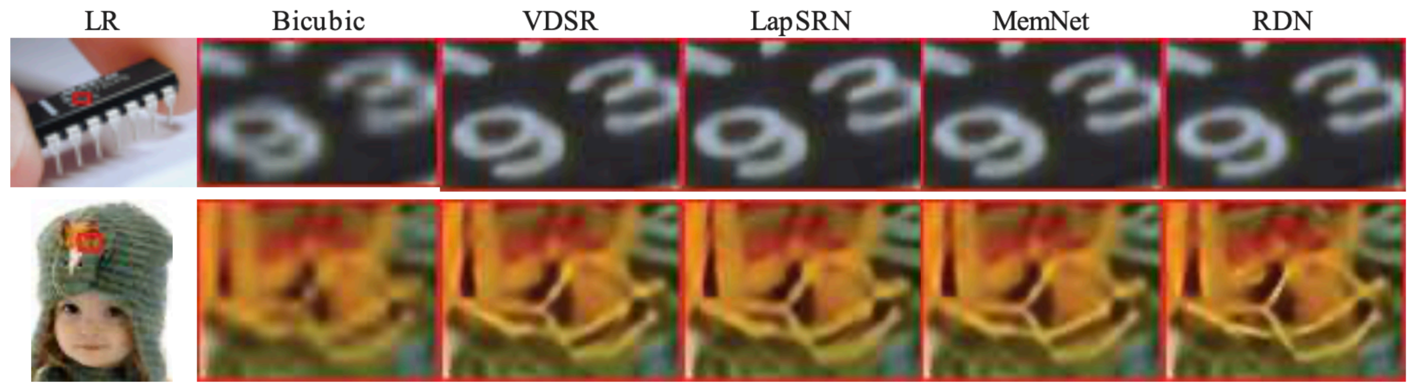
Dataset	Scale	Bicubic	SRCNN [3]	LapSRN [13]	DRRN [25]	SRDenseNet [31]	MemNet [26]	MDSR [17]	RDN (ours)	RDN+ (ours)
Set5	×2	33.66/0.9299	36.66/0.9542	37.52/0.9591	37.74/0.9591	-/-	37.78/0.9597	38.11/0.9602	38.24/0.9614	**38.30/0.9616**
	×3	30.39/0.8682	32.75/0.9090	33.82/0.9227	34.03/0.9244	-/-	34.09/0.9248	34.66/0.9280	34.71/0.9296	**34.78/0.9300**
	×4	28.42/0.8104	30.48/0.8628	31.54/0.8855	31.68/0.8888	32.02/0.8934	31.74/0.8893	32.50/0.8973	32.47/0.8990	**32.61/0.9003**
Set14	×2	30.24/0.8688	32.45/0.9067	33.08/0.9130	33.23/0.9136	-/-	33.28/0.9142	33.85/0.9198	34.01/0.9212	**34.10/0.9218**
	×3	27.55/0.7742	29.30/0.8215	29.79/0.8320	29.96/0.8349	-/-	30.00/0.8350	30.44/0.8452	30.57/0.8468	**30.67/0.8482**
	×4	26.00/0.7027	27.50/0.7513	28.19/0.7720	28.21/0.7721	28.50/0.7782	28.26/0.7723	28.72/0.7857	28.81/0.7871	**28.92/0.7893**
B100	×2	29.56/0.8431	31.36/0.8879	31.80/0.8950	32.05/0.8973	-/-	32.08/0.8978	32.29/0.9007	32.34/0.9017	**32.40/0.9022**
	×3	27.21/0.7385	28.41/0.7863	28.82/0.7973	28.95/0.8004	-/-	28.96/0.8001	29.25/0.8091	29.26/0.8093	**29.33/0.8105**
	×4	25.96/0.6675	26.90/0.7101	27.32/0.7280	27.38/0.7284	27.53/0.7337	27.40/0.7281	27.72/0.7418	27.72/0.7419	**27.80/0.7434**
Urban100	×2	26.88/0.8403	29.50/0.8946	30.41/0.9101	31.23/0.9188	-/-	31.31/0.9195	32.84/0.9347	32.89/0.9353	**33.09/0.9368**
	×3	24.46/0.7349	26.24/0.7989	27.07/0.8272	27.53/0.8378	-/-	27.56/0.8376	28.79/0.8655	28.80/0.8653	**29.00/0.8683**
	×4	23.14/0.6577	24.52/0.7221	25.21/0.7553	25.44/0.7638	26.05/0.7819	25.50/0.7630	26.67/0.8041	26.61/0.8028	**26.82/0.8069**
Manga109	×2	30.80/0.9339	35.60/0.9663	37.27/0.9740	37.60/0.9736	-/-	37.72/0.9740	38.96/0.9769	39.18/0.9780	**39.38/0.9784**
	×3	26.95/0.8556	30.48/0.9117	32.19/0.9334	32.42/0.9359	-/-	32.51/0.9369	34.17/0.9473	34.13/0.9484	**34.43/0.9498**
	×4	24.89/0.7866	27.58/0.8555	29.09/0.8893	29.18/0.8914	-/-	29.42/0.8942	31.11/0.9148	31.00/0.9151	**31.39/0.9184**

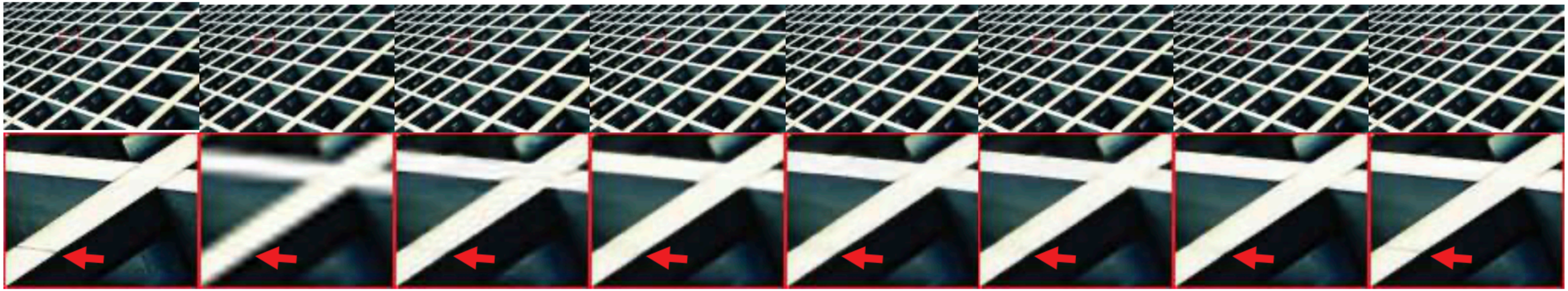
Residual Dense Block (RDB)





PSNR/SSIM 22.88/0.6248 24.50/0.7477 25.03/0.7500 25.36/0.7859 29.20/0.8880



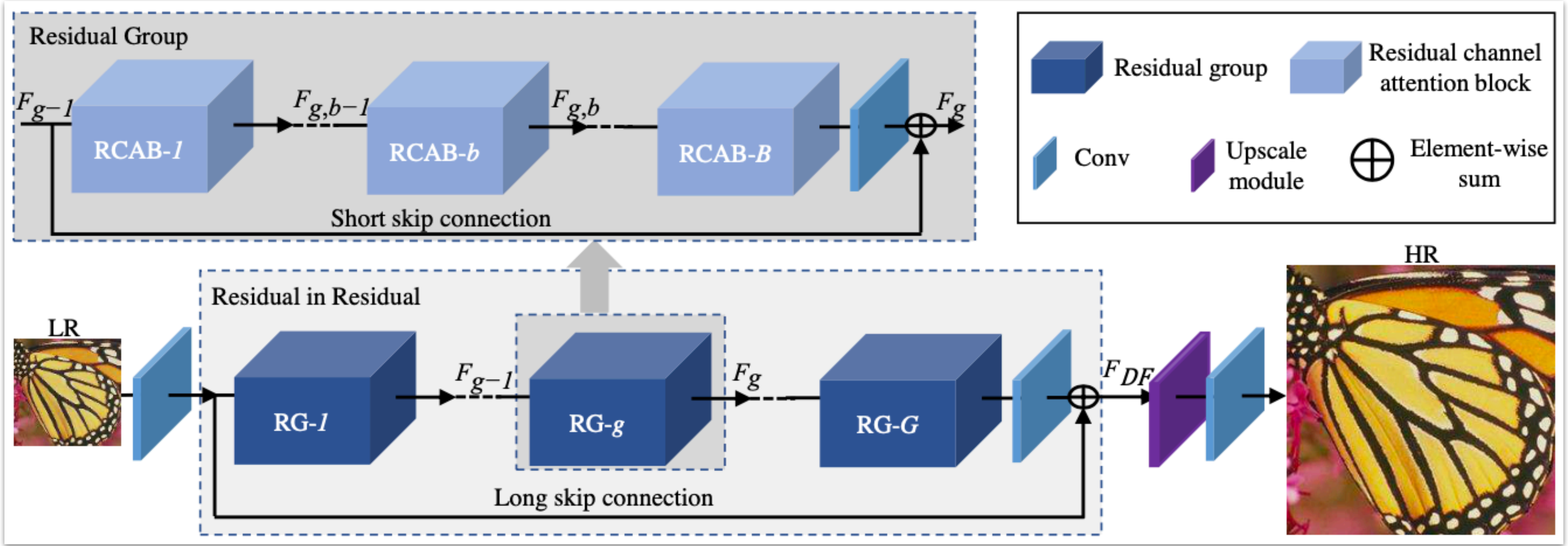


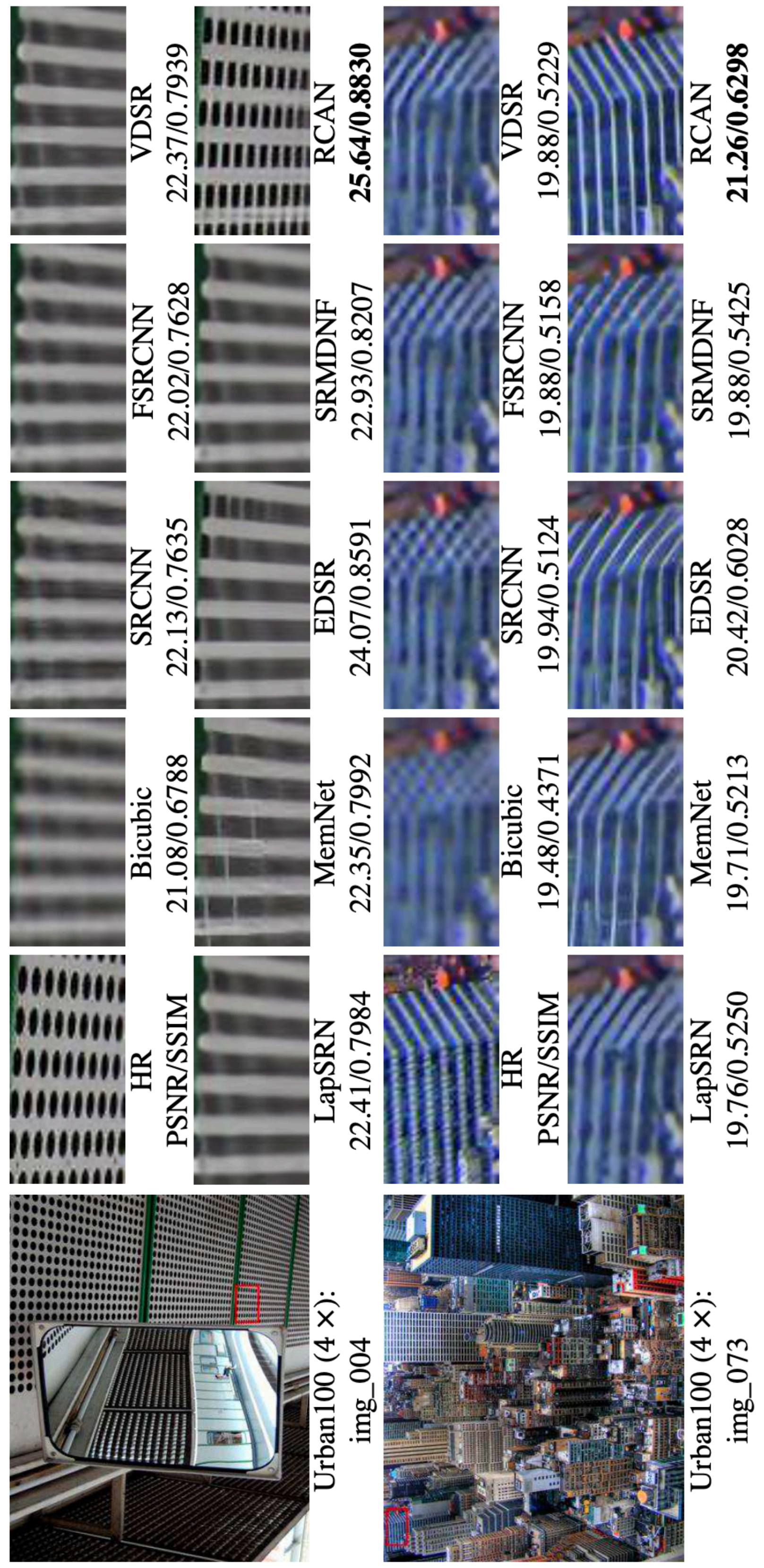
PSNR/SSIM 22.09/0.7856 28.27/0.8854 30.05/0.9226 31.30/0.9278 31.48/0.9294 33.78/0.9431 34.66/0.9458

Zhang, Yulun, et al. "Residual dense network for image super-resolution." Proceedings of the IEEE conference on computer vision and pattern recognition. 2018.

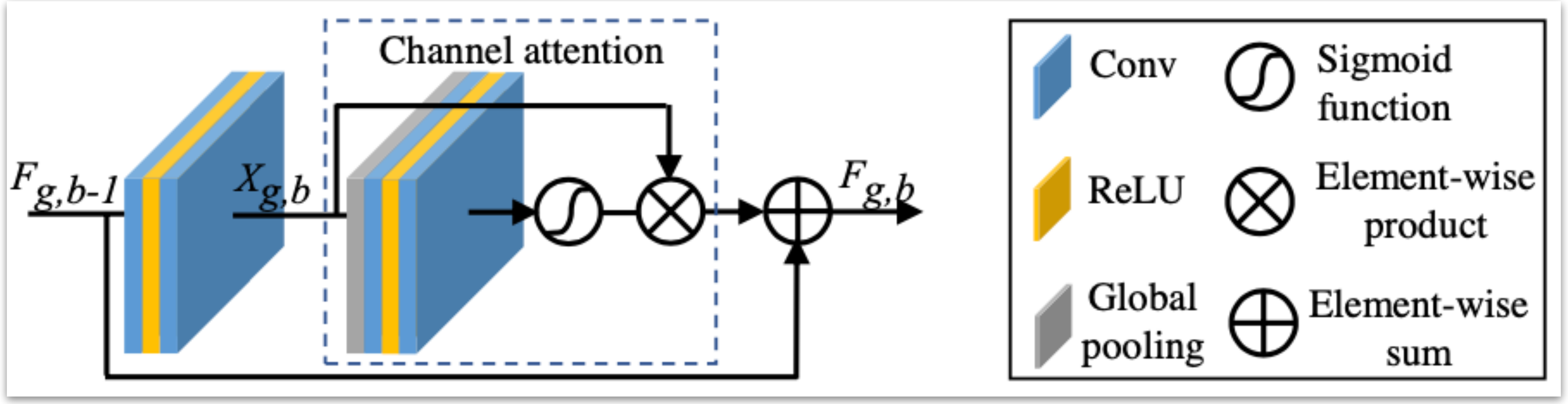
Image Super-Resolution Using Very Deep Residual Channel Attention Networks

Residual Channel Attention Network (RCAN)

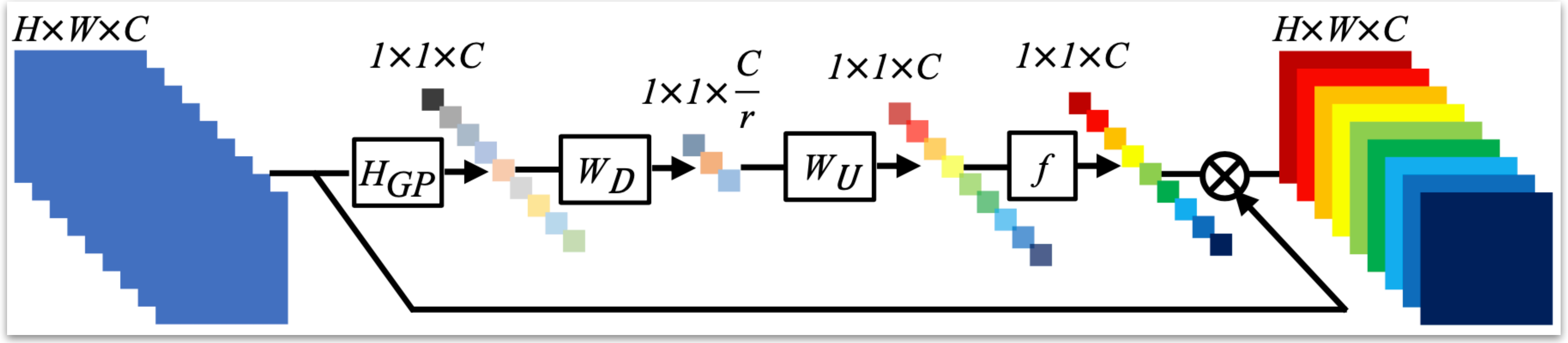




Residual Channel Attention Block (RCAB)



Channel Attention (CA)

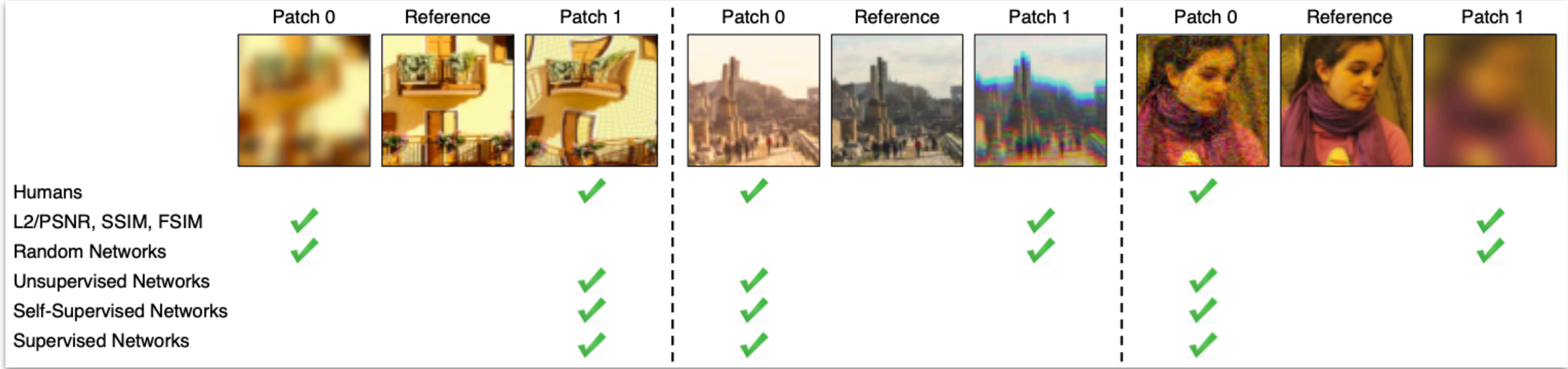


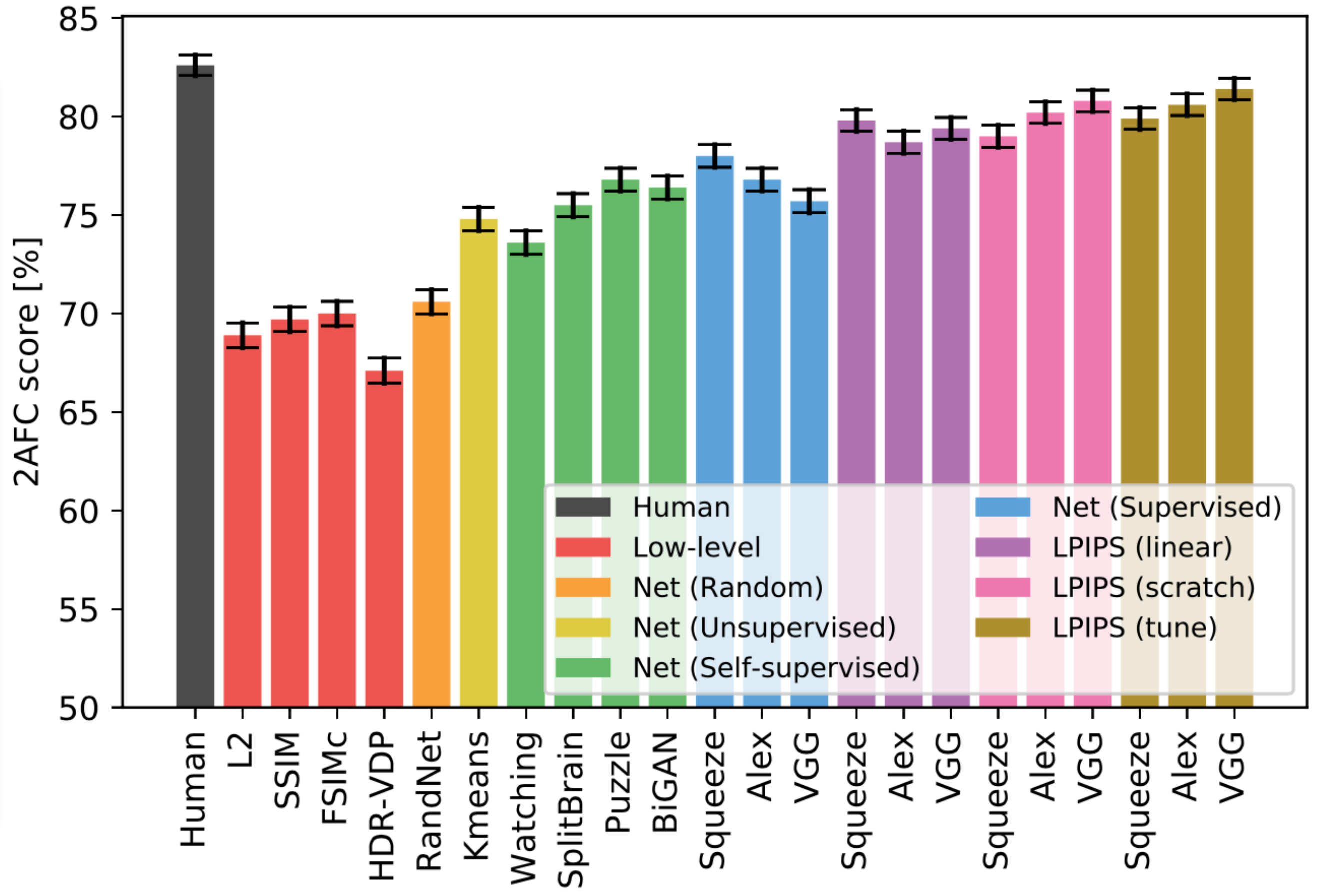
Zhang, Yulun, et al. "Image super-resolution using very deep residual channel attention networks." *Proceedings of the European conference on computer vision (ECCV)*. 2018.

Boulder

The Unreasonable Effectiveness of Deep Features as a Perceptual Metric

Which patch (left or right) is “closer” to the middle patch in these examples?





Distortions

Red: Perceptual Distance: Is a red circle more similar to a red square or to a blue circle?

Berkeley-Adobe Perceptual Patch Similarity (BAPPS) Dataset

– Two Alternative Forced Choice (2AFC): Which of two distortions is more similar to a reference?

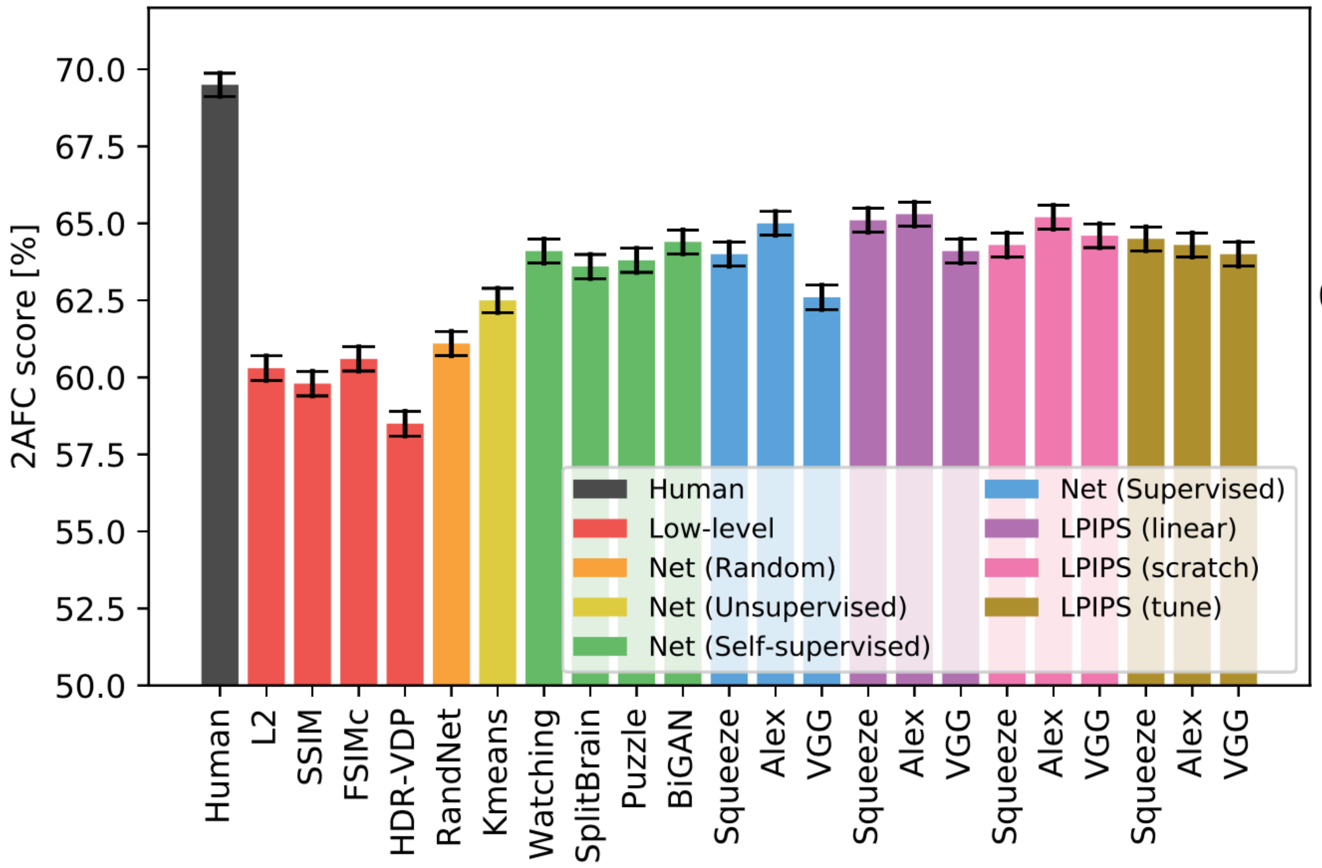
$x \rightarrow$ randomly selected image patch

$x_0, x_1 \rightarrow$ distorted patches

$h \in \{0, 1\} \rightarrow$ response of a human (which one is closer to the original patch?)

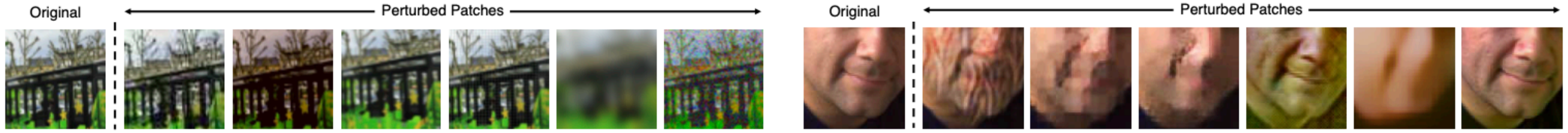
$\mathcal{T} \rightarrow$ dataset of patch triplets (x, x_0, x_1, h)

– Just Noticeable Difference (JND): Are two patches (one reference and one distorted) the same?



Real algorithms

Superresolution
Frame interpolation
Video deblurring
Colorization



(a) **Traditional** (b) **CNN-based**

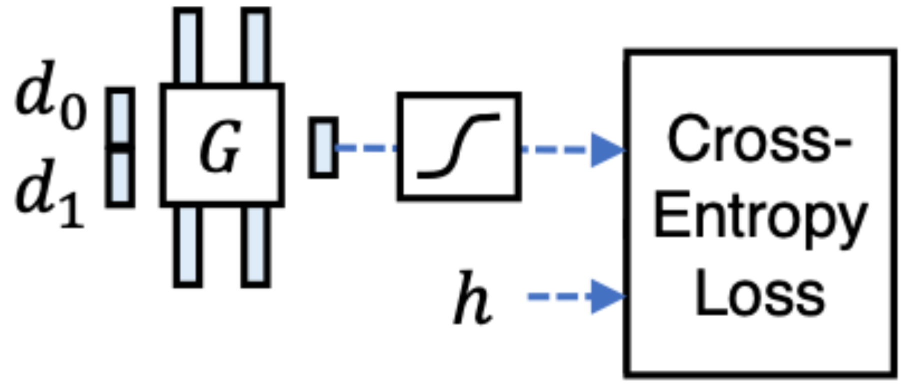
Learned Perceptual Image Patch Similarity (LPIPS) metric

Distance between reference and distorted patches x, x_0 with network $\mathcal{F}$:

$$d(x, x_0) = \sum_l \frac{1}{H_l W_l} \sum_{h,w} ||w_l \odot (\hat{y}^l_{hw} - \hat{y}^l_{0hw})||_2^2$$

$\hat{y}^\ell, \hat{y}^\ell_0 \in \mathbb{R}^{H_\ell \times W_\ell \times C_\ell}$ for layer ℓ $\quad w^\ell \in \mathbb{R}^C \rightarrow$ scaling factor

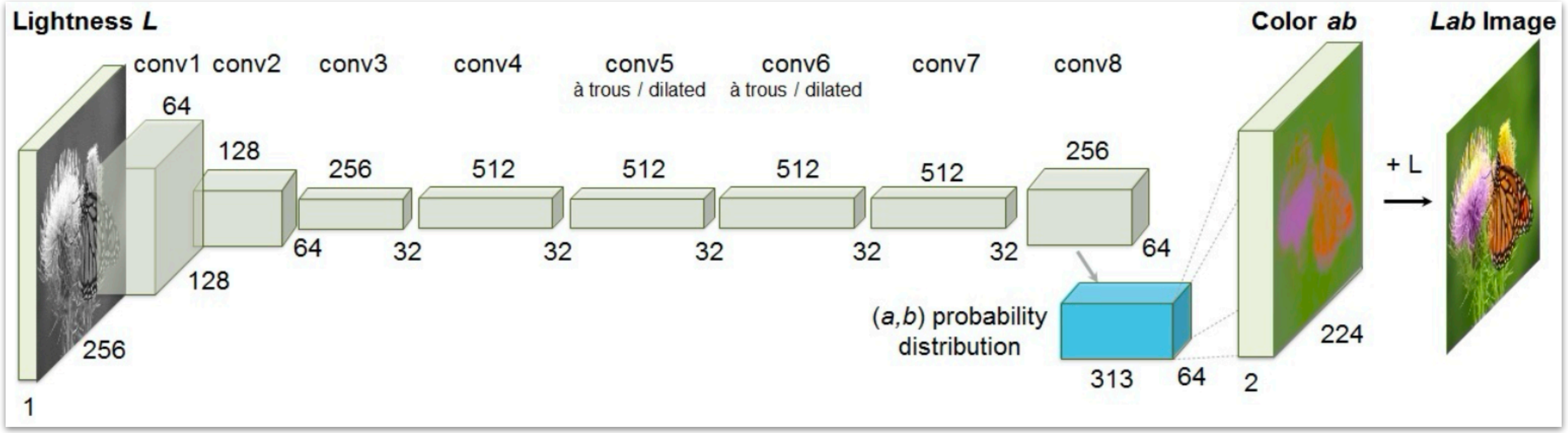
$||\hat{y}^\ell|| = ||\hat{y}^\ell_0|| = 1 \rightarrow$ unit normalized in the channel dimension



Predicting Perceptual Judgement

Zhang, Richard, et al. "The unreasonable effectiveness of deep features as a perceptual metric." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2018.

Colorful Image Colorization



$L_{\mathrm{cl}}(\hat{Z}, Z) = -\sum_{h,w} v(Z_{h,w}) \sum_q Z_{h,w,q} \log(\hat{Z}_{h,w,q})$

$v(Z_{h,w}) \rightarrow$ weighting term used to rebalance the loss based on color-class rarity

$\hat{Y} = H(\hat{Z}) \rightarrow$ class probabilities to point estimates

$H(Z_{h,w}) = \mathbb{E}[f_T(Z_{h,w})]$

$f_T(z) = \dfrac{\exp(\log(z)/T)}{\sum_q \exp(\log(z_q)/T)}$

$T = 0.38$

$X \in \mathbb{R}^{H\times W\times 1} \rightarrow$ input lightness channel

$Y \in \mathbb{R}^{H\times W\times 2} \rightarrow$ two associated color channels

$\hat{Y} = F(X) \in \mathbb{R}^{H\times W\times 2} \rightarrow$ mapping (to be learned)

Distances in CIE *Lab* color space model perceptual distances

$$L_2(\hat{Y}, Y) = \frac{1}{2}\sum_{h,w} \|Y_{h,w} - \hat{Y}_{h,w}\|_2^2$$

Not robust to the inherent ambiguity and multimodal nature of the colorization problem. For example, an apple is typically red, green, or yellow, but unlikely to be blue or orange. Quantize the $ab \in [-110, 110]^2$ output space into bins with grid size 10 and keep the $Q = 313$ values which are in-gamut.

$\hat{Z} = G(X) \in [0,1]^{H\times W\times Q} \rightarrow$ probability distribution over colors

$Z = H_{\mathrm{gt}}^{-1}(Y) \rightarrow$ converts ground truth color Y to vector Z, using a soft-encoding scheme

Find the 5-nearest neighbors to $Y_{h,w}$ in the output space and weight them proportionally to their distance from the ground truth using a Gaussian kernel with $\sigma = 5$.

Class Rebalancing

$p \in \Delta^Q \rightarrow$ empirical probability of colors in the quantized ab space

$\tilde{p} \in \Delta^Q \rightarrow$ smoothed empirical distribution (smoothed version of p using Gaussian kernel G_σ)

$w \propto ((1-\lambda)\tilde{p} + \lambda/Q)^{-1} \in \mathbb{R}^Q \rightarrow$ weight factor

$1/Q \rightarrow$ uniform distribution

$\mathbb{E}[w] = \sum_q \tilde{p}_q w_q = 1 \rightarrow$ normalization constraint

$q^* = \arg\max_q Z_{h,w,q} \rightarrow$ closest ab bin

$v(Z_{h,w,q}) = w_{q^*}$

Colorization as a pretext task for representation learning

Acting as a cross-channel encoder!

PASCAL classification, detection, and segmentation

Zhang, Richard, Phillip Isola, and Alexei A. Efros. "Colorful image colorization." *European conference on computer vision*. Springer, Cham, 2016.

Questions?