SINGLE IMAGE SUPER-RESOLUTION USING DEEP LEARNING

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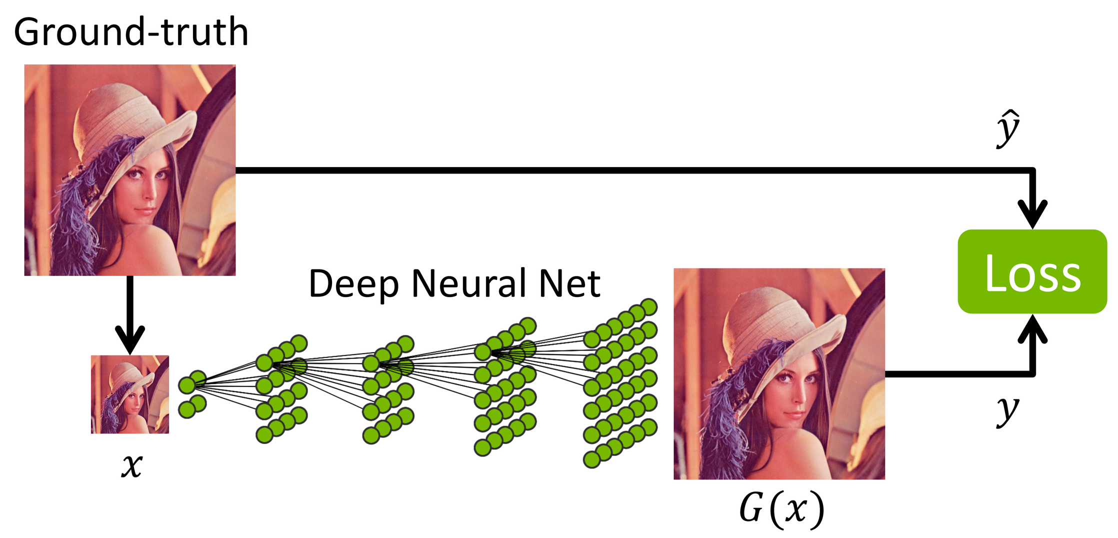
GOAL

Obtain high-resolution image by a given low-resolution image.

DEEP LEARNING APPROACH

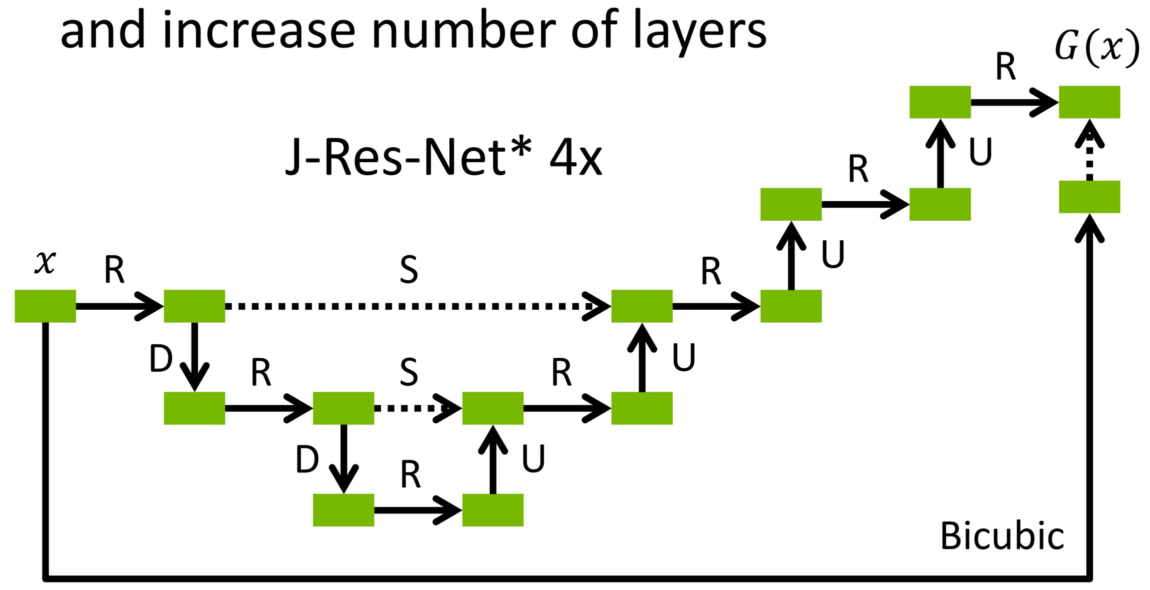
Our super-resolution model is based on deep neural network. It is trained in end-to-end fashion to produce high-resolution output from a given low-resolution input by minimizing a *distance* from the output to the ground-truth.



Deep learning approach exploits prior knowledge and statistics, extracted from training images.

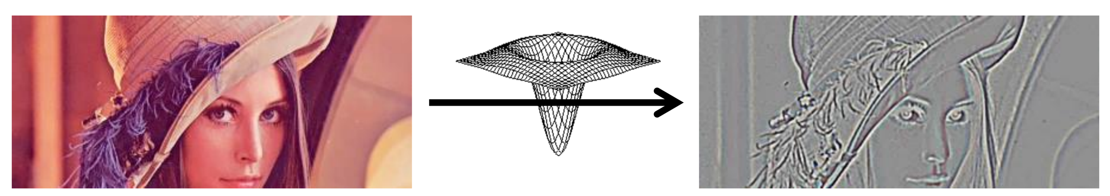
ARCHITECTURE

- G(x) = Bicubic(x) + DNN(x)
- Downscaling layers (D): to increase receptive field and capture more semantic features
- Skipped connections (S): to propagate low-level features and avoid loss of details after downscaling
- Residual blocks (R): to improve convergence and increase number of layers



LOSS FUNCTION

- **MSE** loss: corresponds to PSNR metric, which poorly represents perceptual image quality
- **HFENN** loss:
  - High-Frequency Error Norm (Normalized)
  - $HFENN = \|LoG(\hat{y} - y)\|^2 / const$



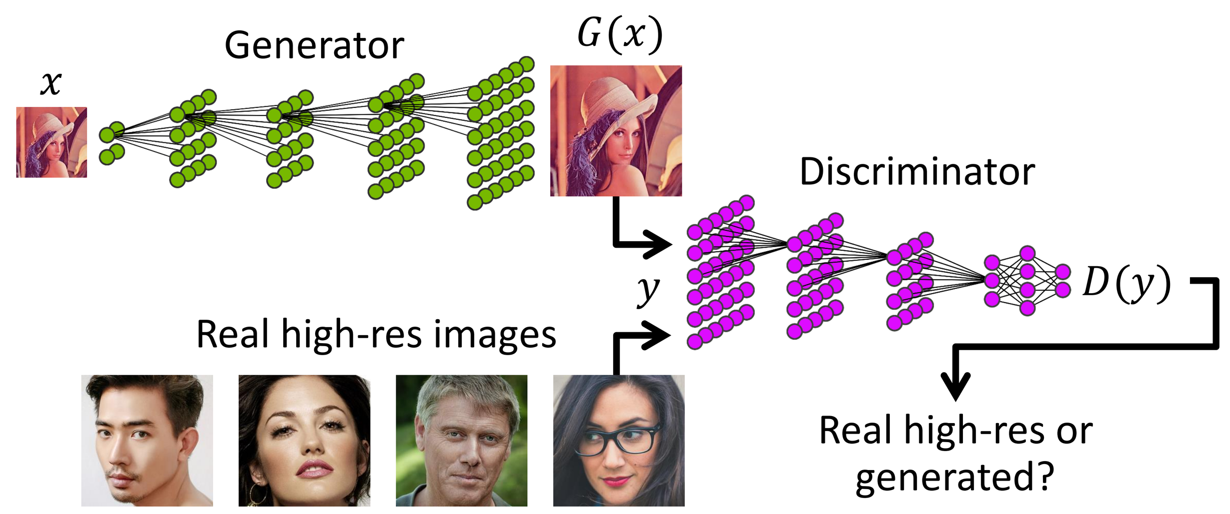
LoG (Laplacian of Gaussian)

  - Boosts reconstruction of high-frequency details
- **Composite** loss: $MSE + \alpha * HFENN$

GAN

Photorealistic image features could be boosted by means of Generative Adversarial Networks.

- **Generator**: our pretrained super-res model
- **Discriminator**: binary classifier to distinguish upscaled from real high-resolution images

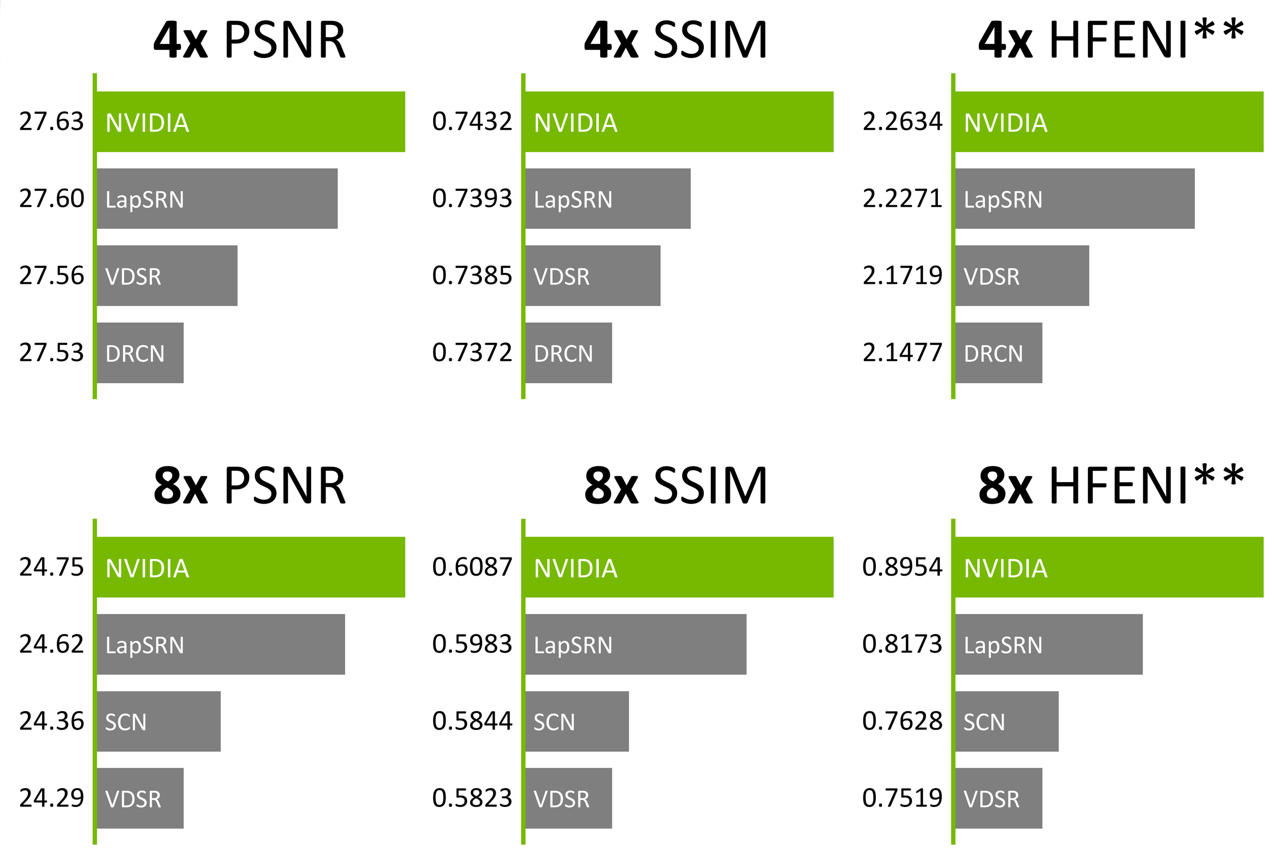


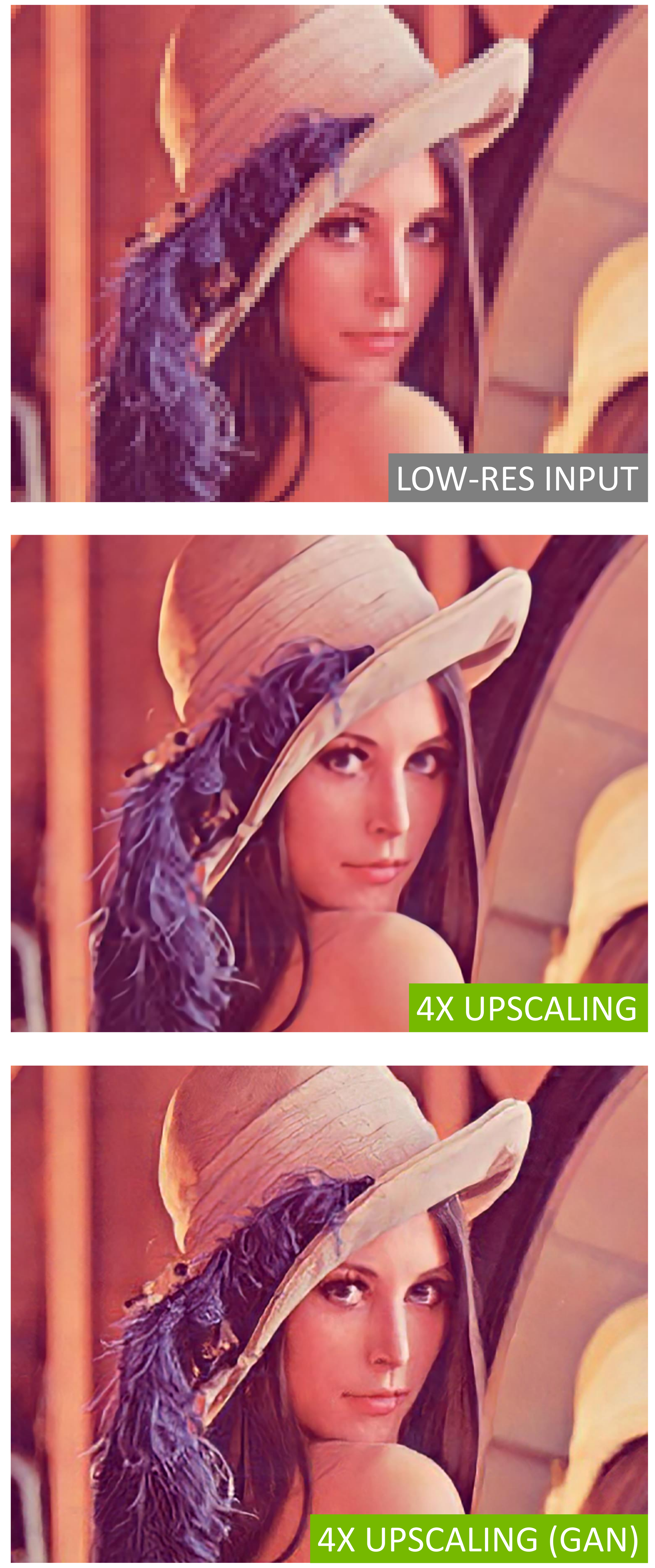
GAN loss = $-lnD(G(x))$

Total loss = Content loss + GAN loss

RESULTS

Mean values for Set5+Set14+BSDS100 datasets***





Super-resolution technology is released within NVIDIA GameWorks Materials & Textures service gwmt.nvidia.com

* J-Net: following U-Net notation idea (Ronneberger et al.)

** Inversed HFENN, suitable for evaluation of high-frequency details

*** Result images for other algorithms were taken from LapSRN work (Lai et al.)