# Deep Learning based Super-Resolution


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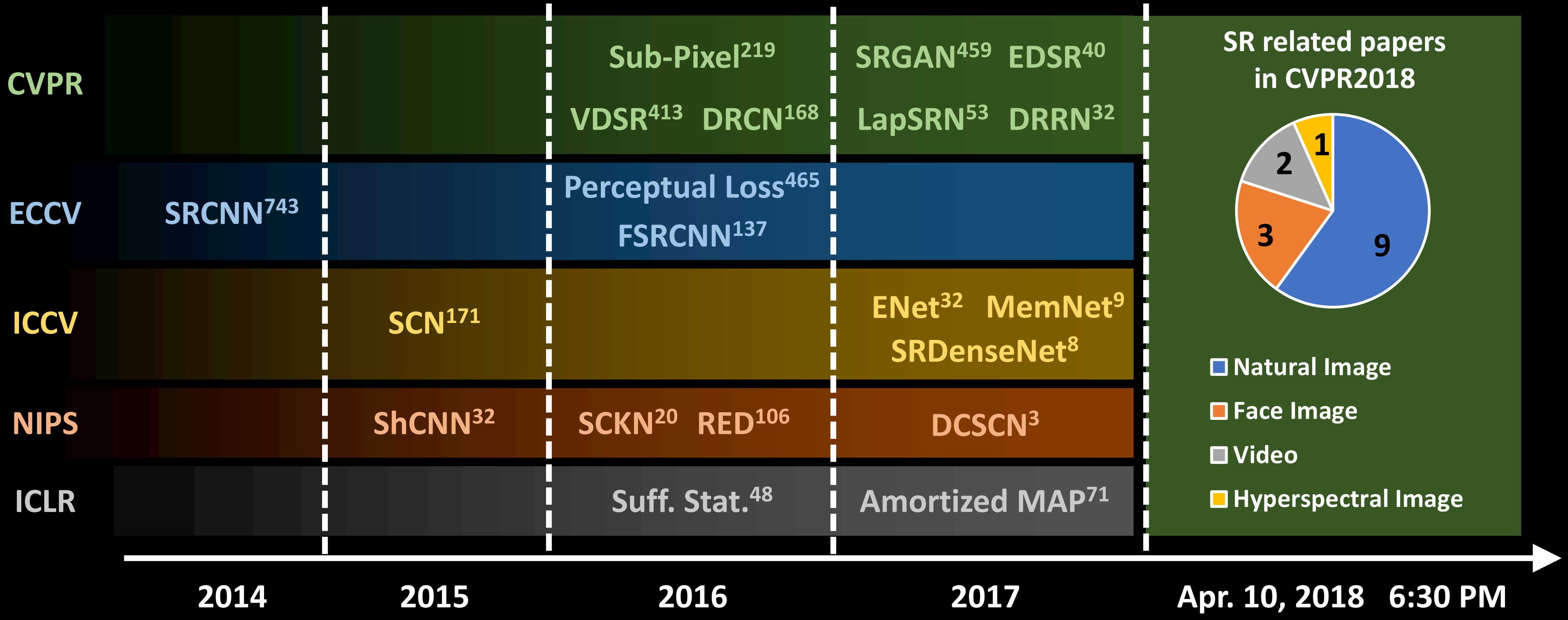
# Keywords

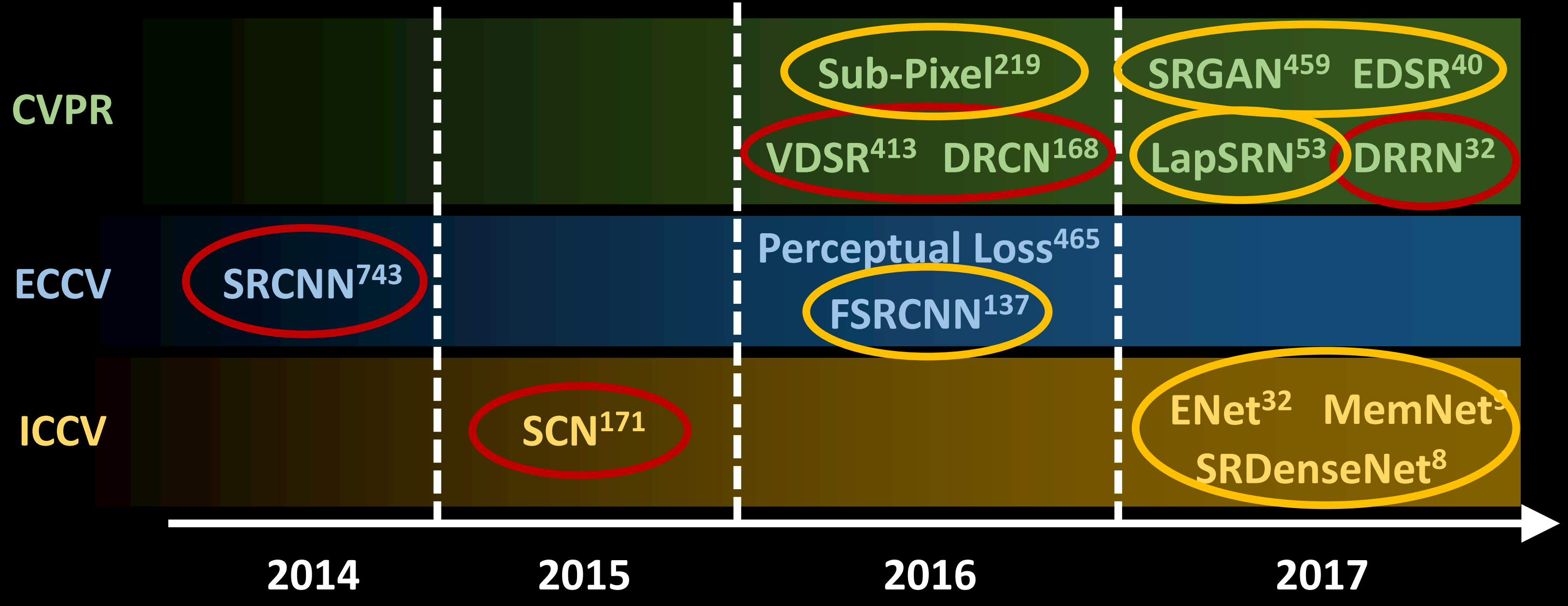
- Deep learning
- Super-resolution (SR)
- Natural images
- Top conferences, e.g.,
  - CVPR (held every year since 1985)
  - ECCV (held on even years since 1990)
  - ICCV (held on odd years since 1987)

# Brief Statistics and Milestones



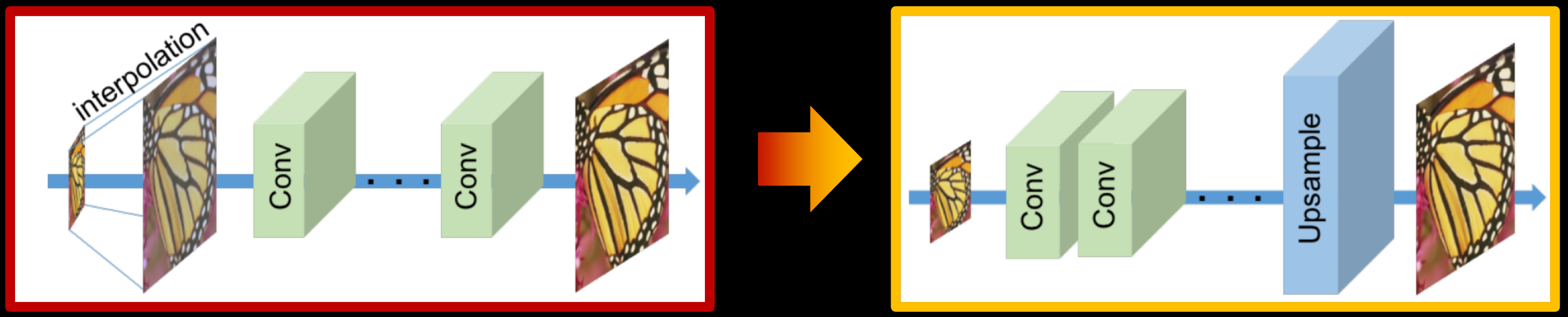

**Superscript: Number of citations from Google Scholar until Apr. 10, 2018 6:30PM.**

# Trend (1/4) --- Trained Upscaling

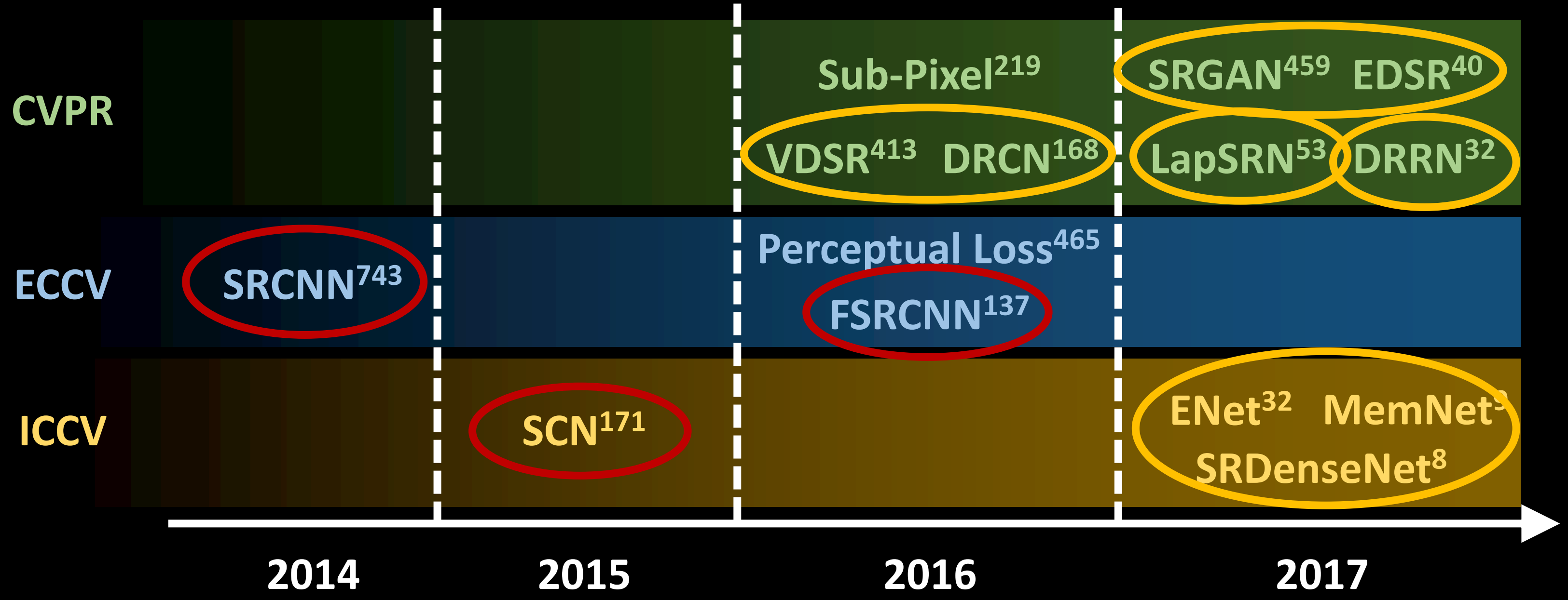



Directly start from low-resolution image:

- Faster
- Less parameters
- Learn the upscaling process

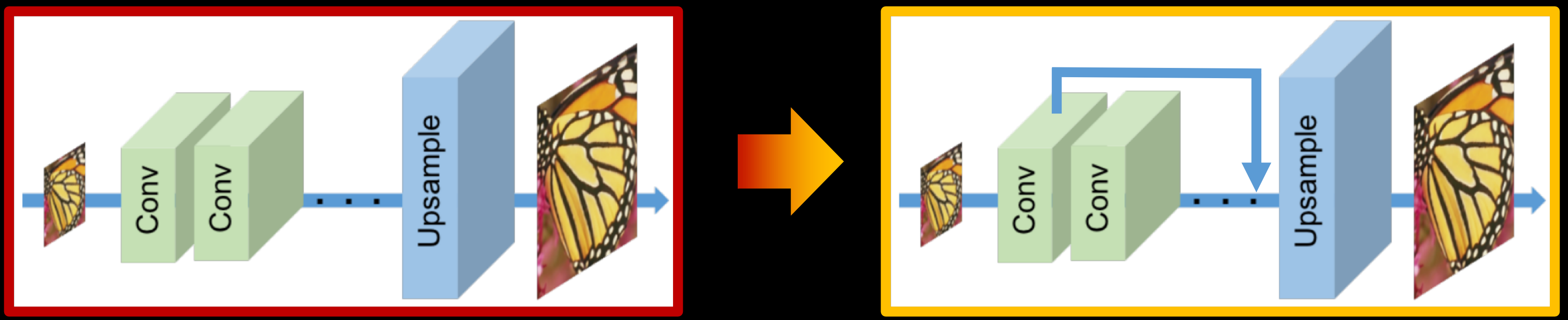


# Trend (2/4) --- Skip Connection (Residual Blocks)

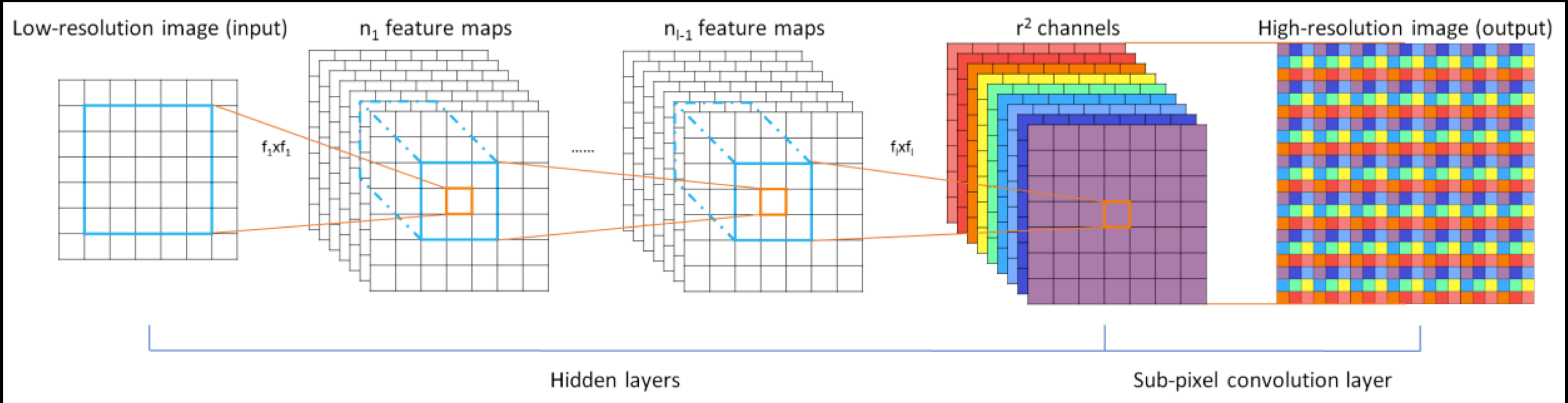



Skip low-level features to high-level layers:

- Assist identity mapping
- Alleviate vanishing gradient problem
- Finer texture



# Trend (3/4) --- Sub-Pixel for Upscaling




**The sub-pixel convolutional layer is faster than the deconvolution layer**

# Trend (4/4) --- Perceptual Loss

Original

SRCNN (L2 loss with 3-layer net)

SRResNet (L2 loss with deep ResNet)

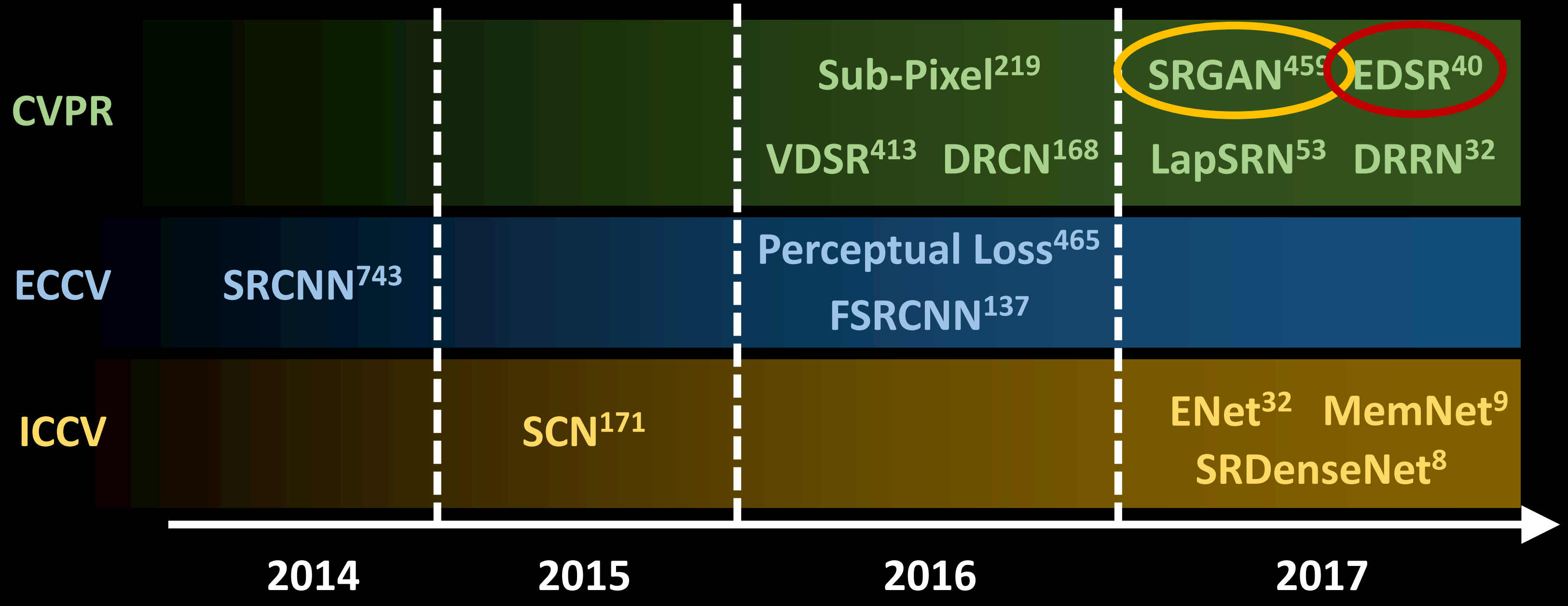
VGG feature loss

SRGAN (Adversarial loss)

Non-perceptual loss

Perceptual loss

# State-of-the-art Performance

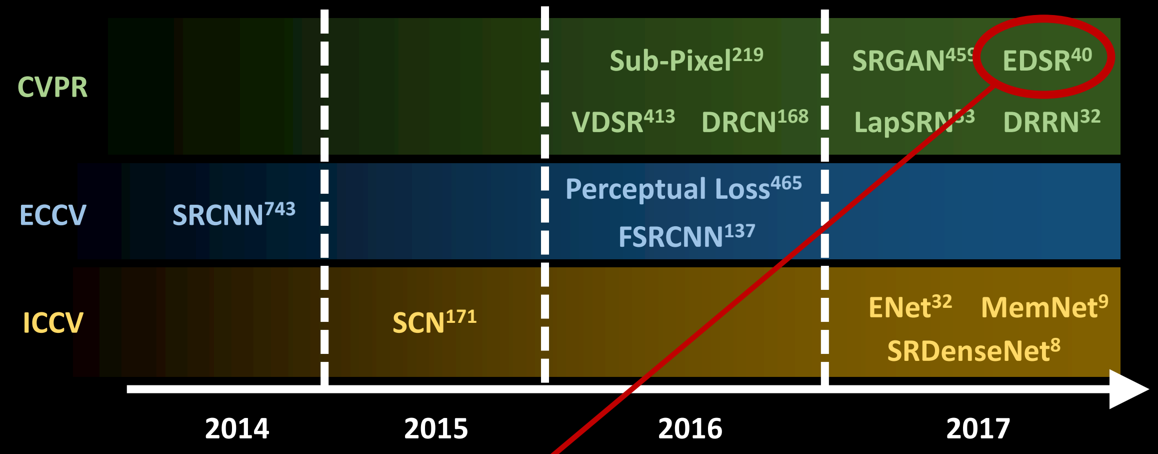


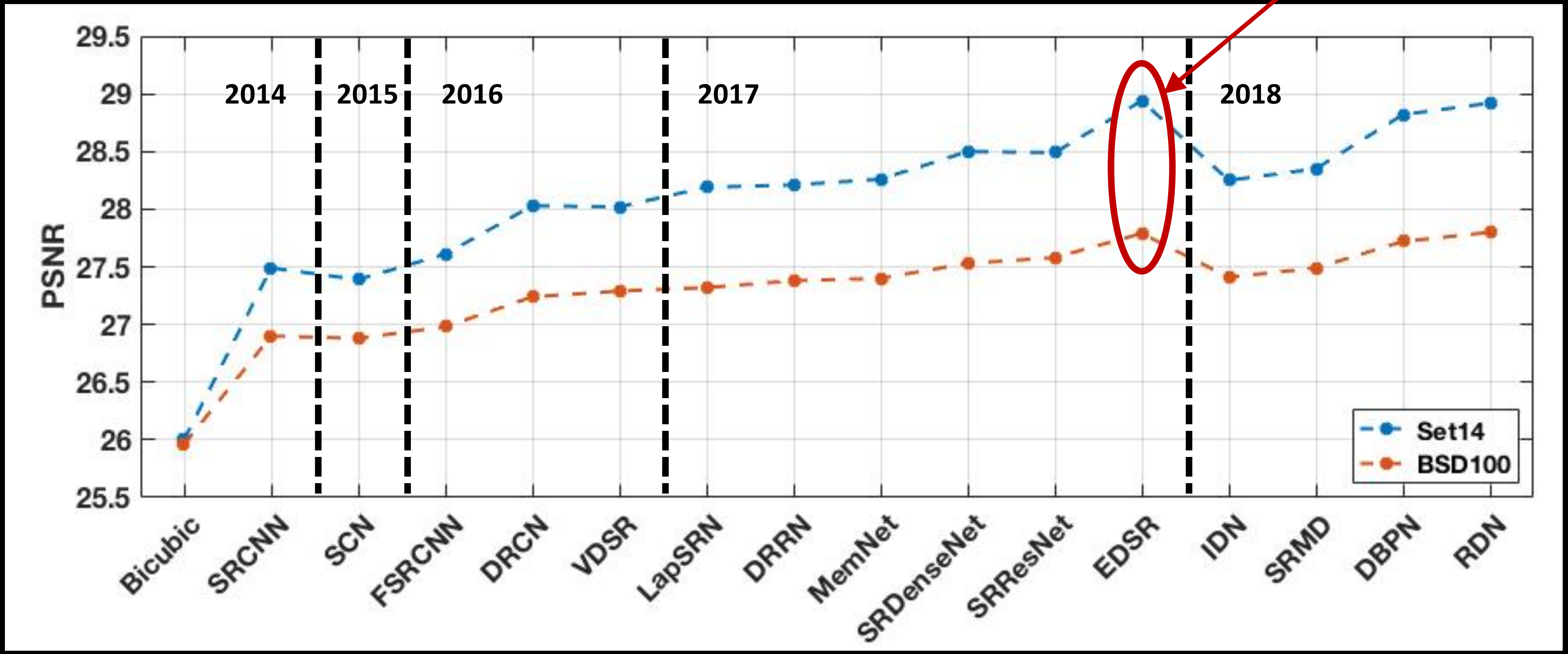

The state-of-art-work in visual quality, but with low PSNR

The state-of-art-work in PSNR, but visually blurry

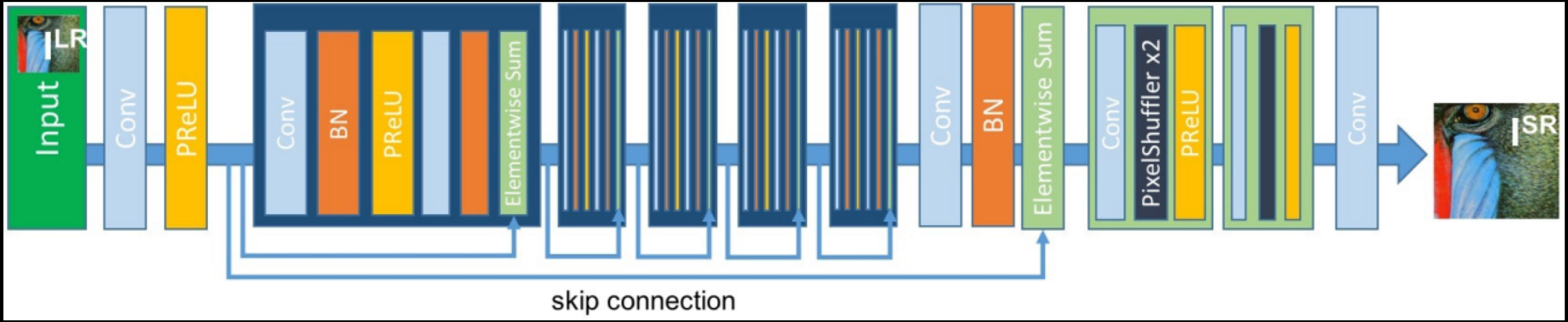
They share similar structure: res blocks, skip connection, and post upscaling

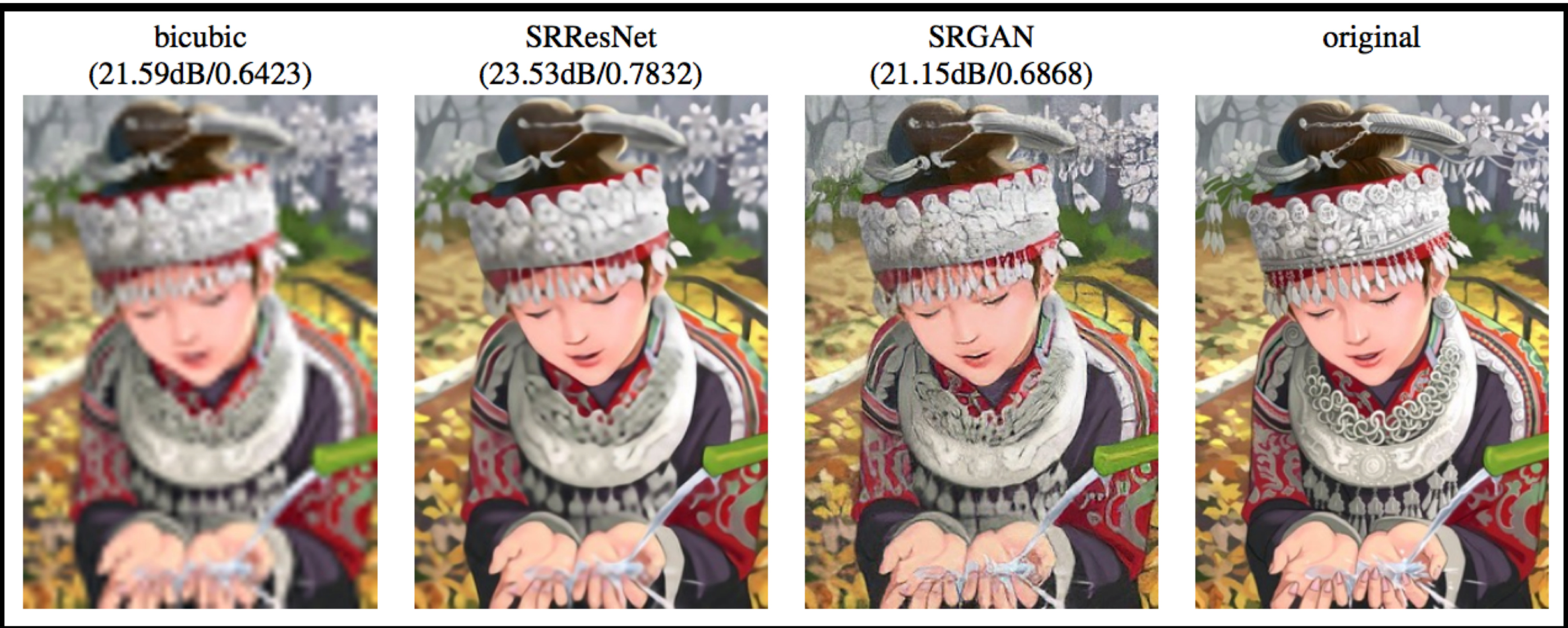
# State-of-the-art Performance



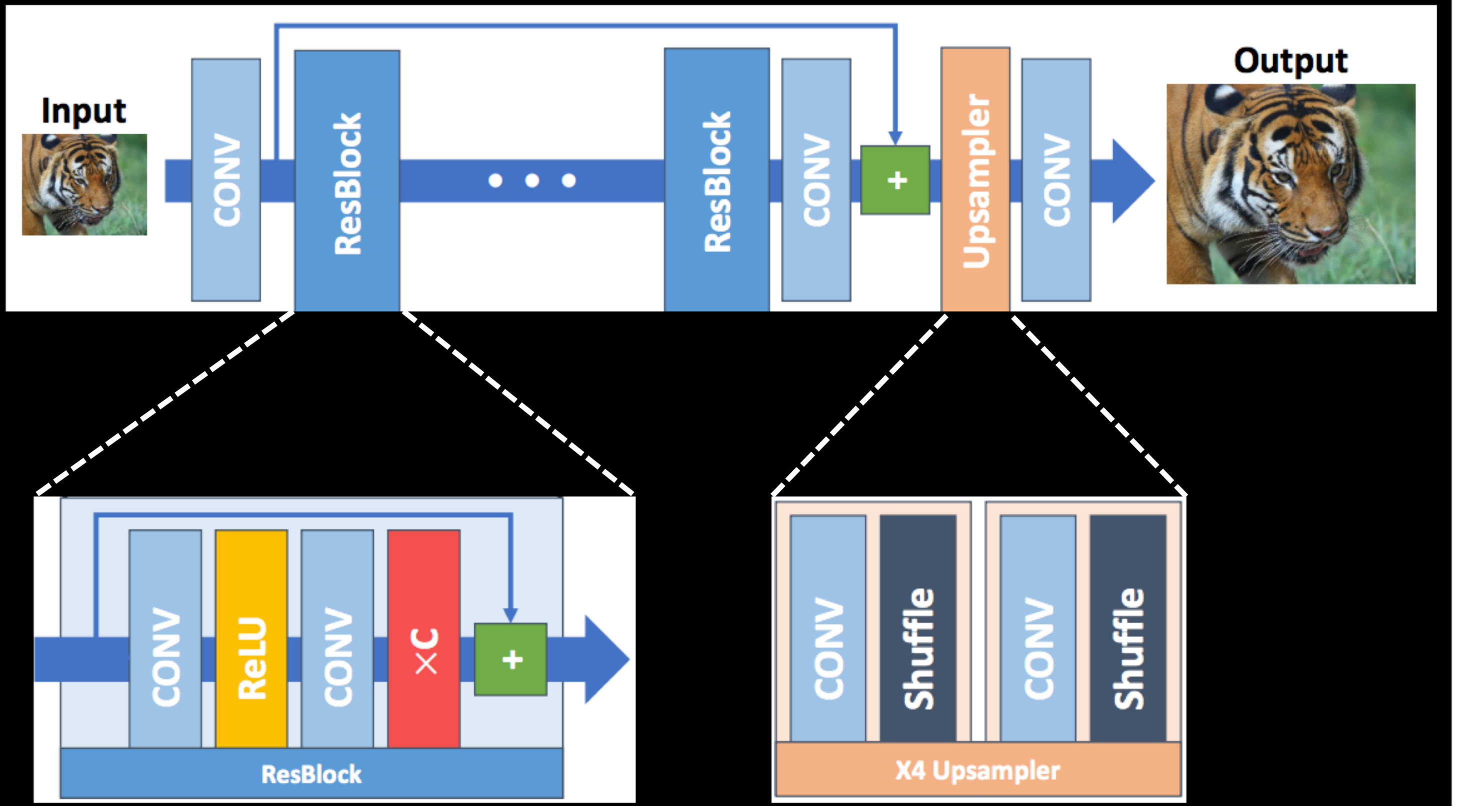
# SRGAN --- First Introduce GAN to SR

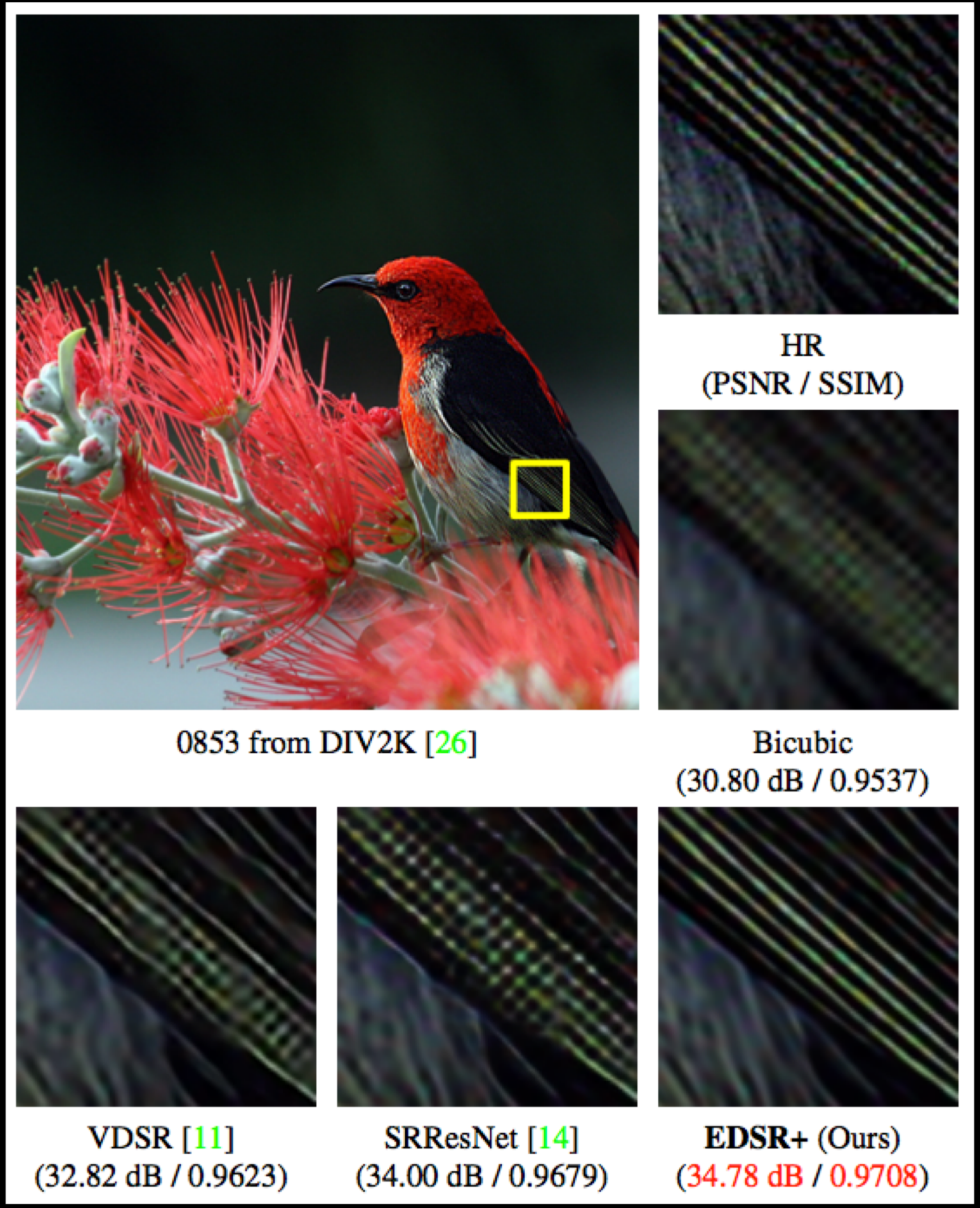


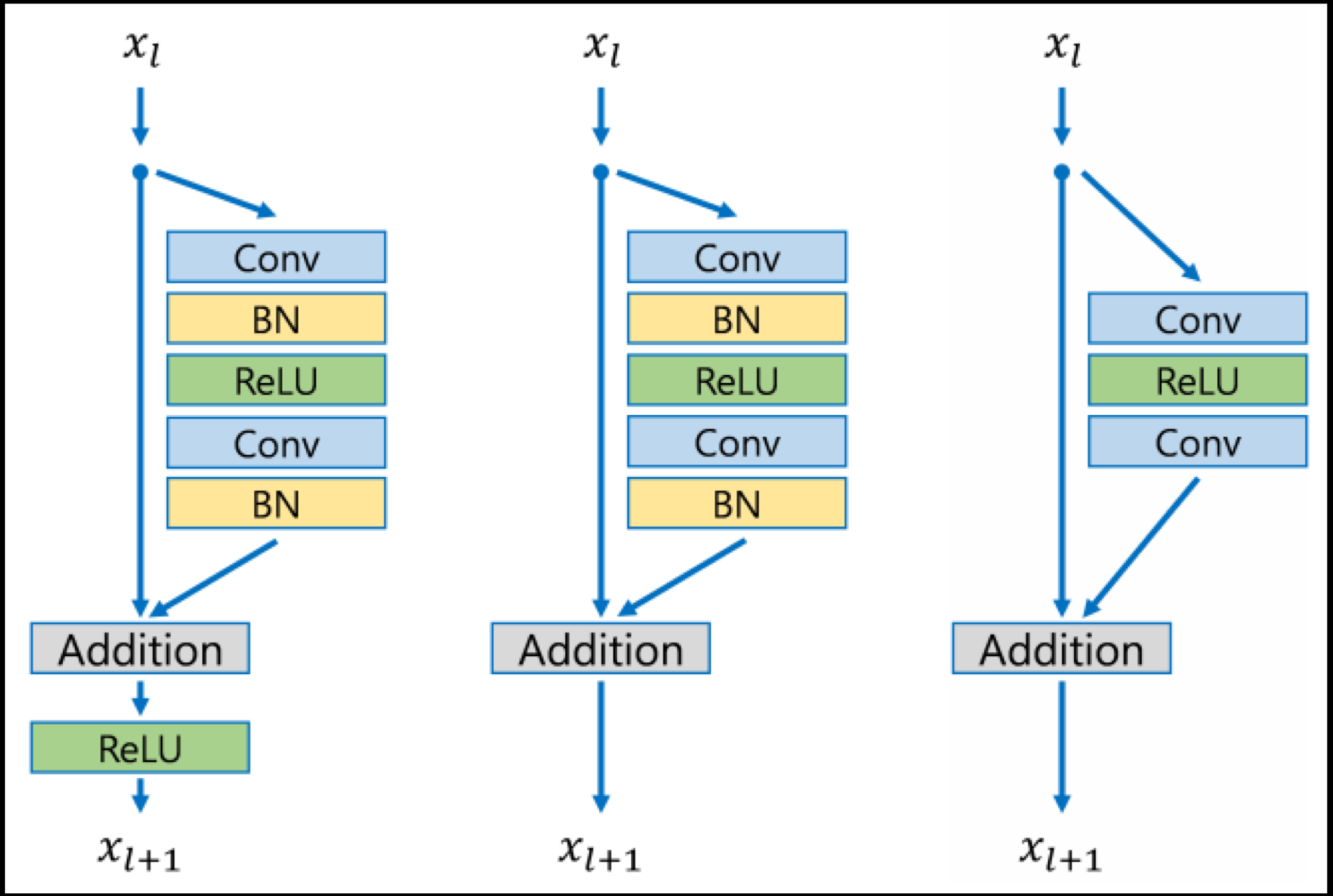
# EDSR --- Winner of NTIRE 2017

# EDSR --- Network Structure



# EDSR vs. SRGAN --- Residual Block




**Original** **SRGAN** **EDSR**

**Remove batch normalization:**

- **BN normalizes the features, it gets rid of range flexibility from networks by normalizing the features.**
- **Save approximately 40% of memory usage during training**

# Summary

**Current Trends:**
- Trained upscaling
- Skip connection
- Sup-pixel
- Perceptual loss

**Existing Problems:**
- Measurement metric, e.g., PSNR is not consistent to human evaluation
- Assumption on bicubic downscaling
- Lack of fine texture

It seems more and more difficult to make improvement to the traditional SR problem, especially in PSNR. It may be the time to explore new directions.

# Interesting Papers on Single Image SR in CVPR 2018

**Supervised learning → Unsupervised learning**

A. Shocher et al., "Zero-Shot" Super-Resolution using Deep Internal Learning

**Bicubic downscaling → Unknown downscaling**

K. Zhang et al., Learning a Single Convolutional Super-Resolution Network for Multiple Degradations

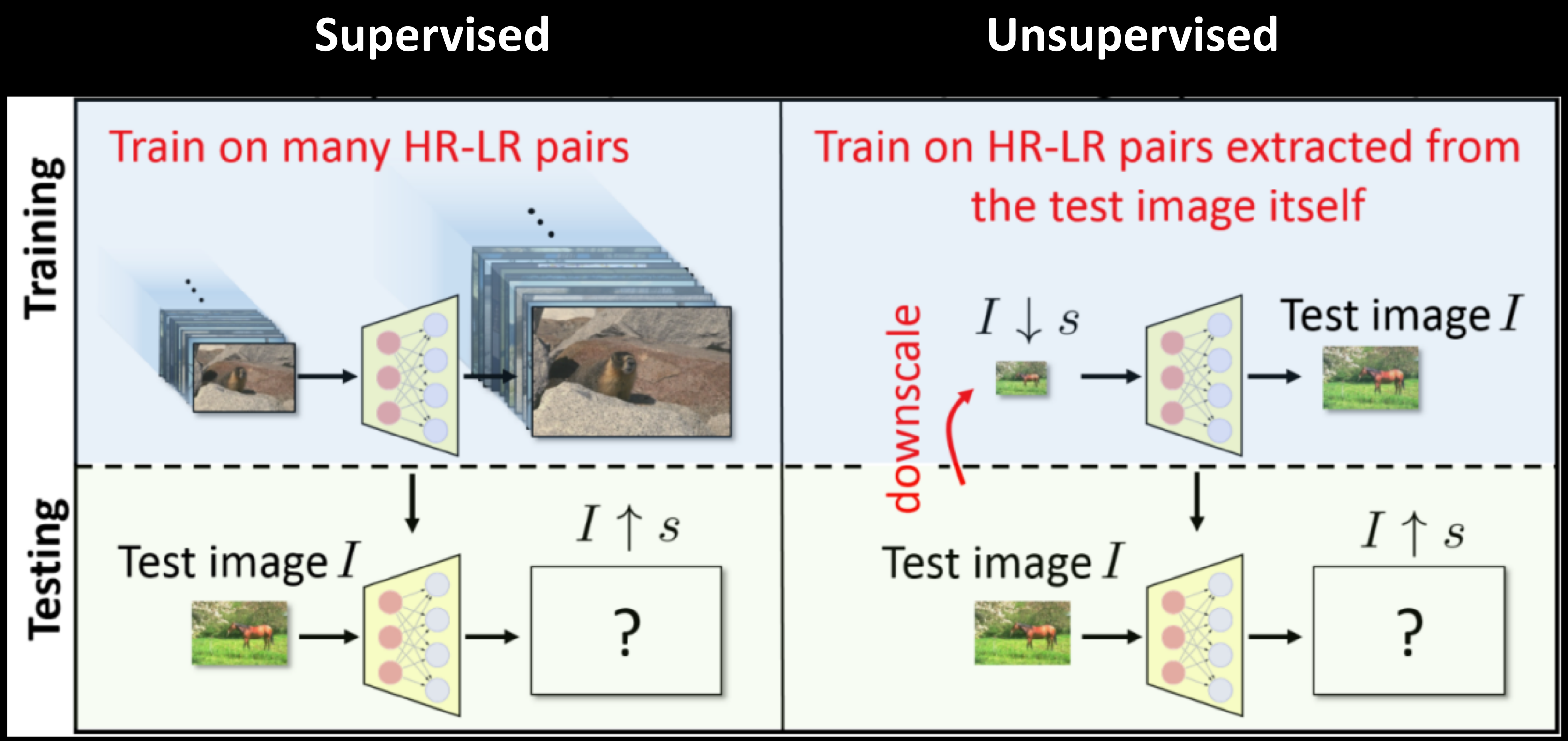
**One-way upscaling → Iterative up/downscaling**

M. Haris et al., Deep Back-Projection Networks For Super-Resolution

# Supervised learning → Unsupervised learning

A. Shocher et al., "Zero-Shot" Super-Resolution using Deep Internal Learning

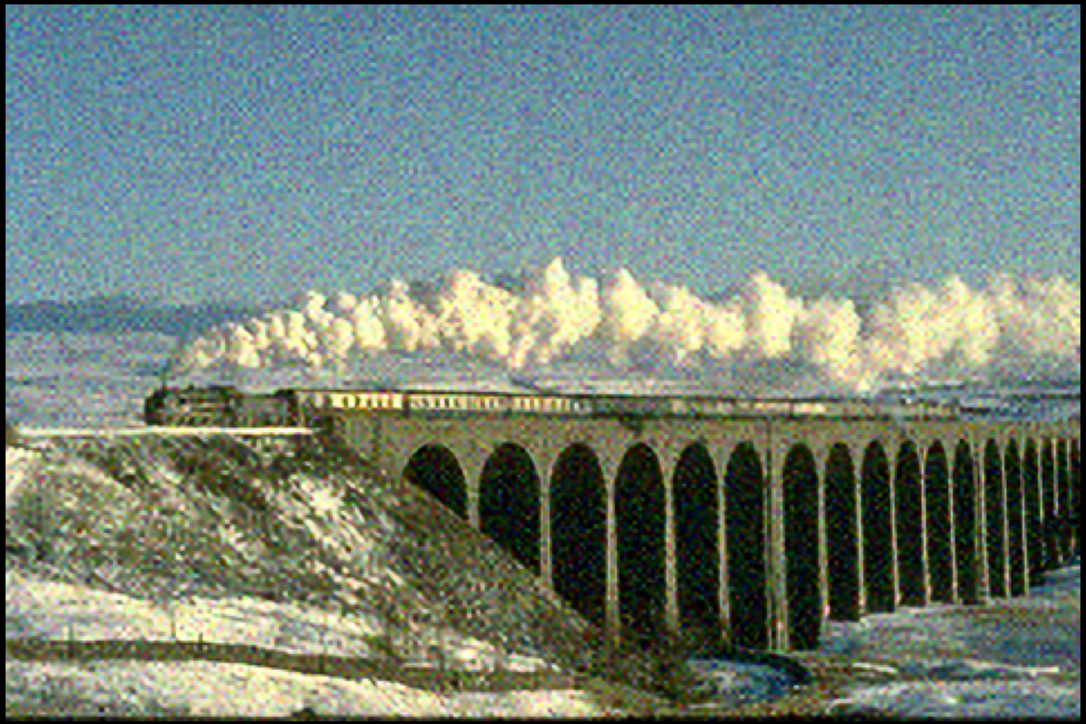
**Motivation :**
handling poor-quality low-resolution images, e.g., old photos, noisy images, biological data, and other images where the downscaling process is unknown or non-ideal.



# Supervised learning → Unsupervised learning

A. Shocher et al., "Zero-Shot" Super-Resolution using Deep Internal Learning

Low-resolution image



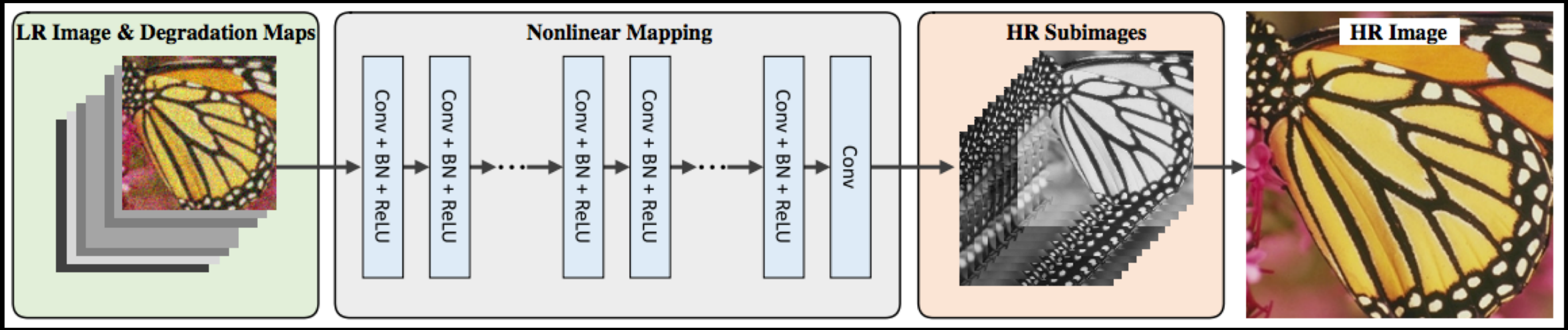
EDSR

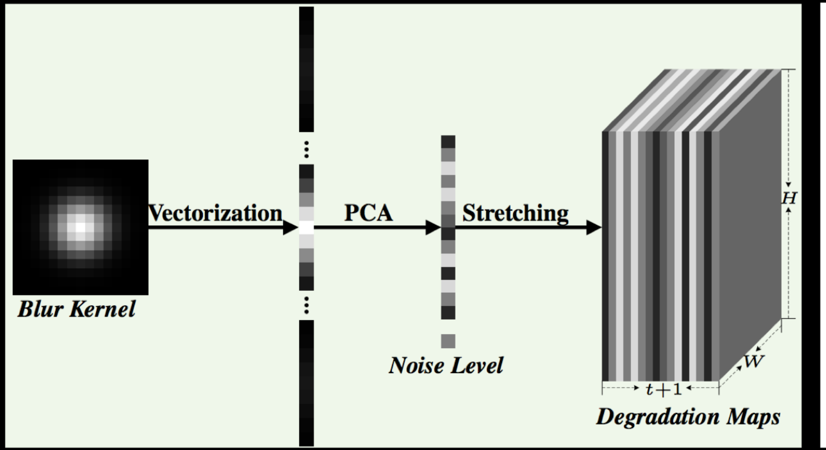
The proposed

# Bicubic downscaling → Unknown downscaling

K. Zhang et al., Learning a Single Convolutional Super-Resolution Network for Multiple Degradations

**Motivation ：**
**Just like the paper title, breaking the assumption that a low-resolution image is bicubicly downsampled from a high-resolution image.**

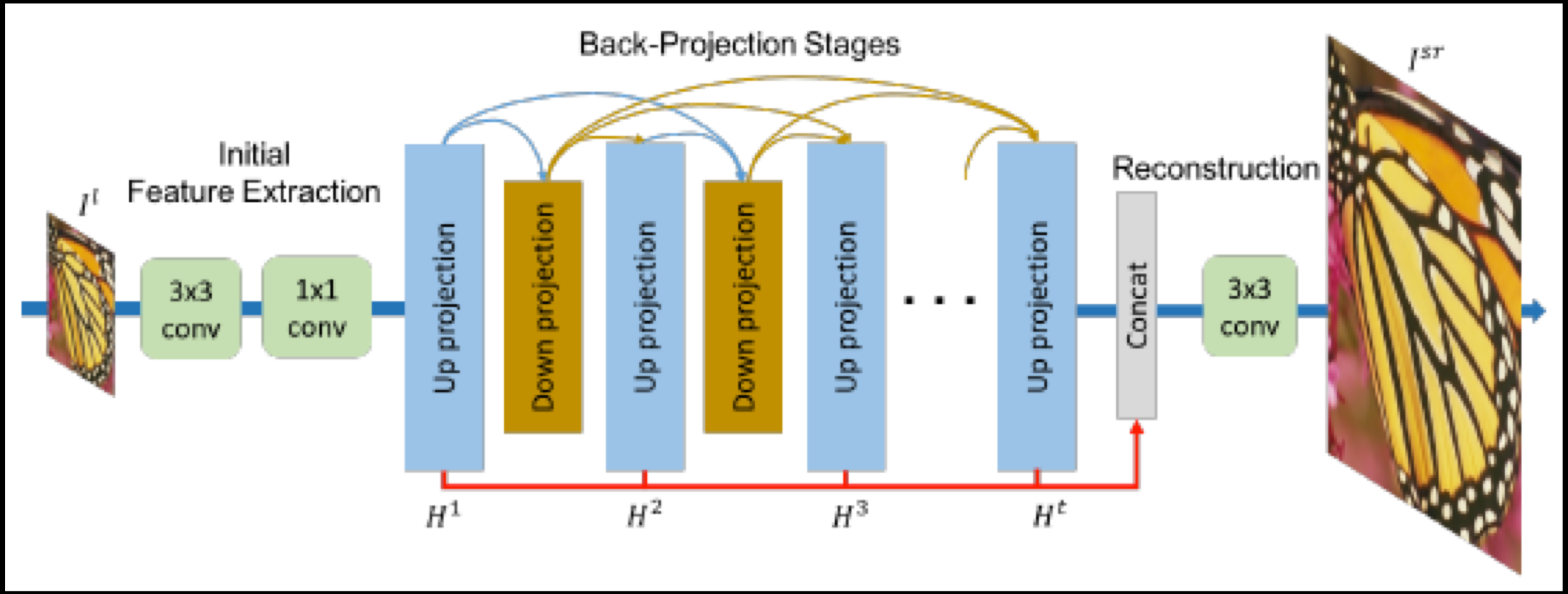



# Single upscaling → Iterative up/downscaling

M. Haris et al., Deep Back-Projection Networks For Super-Resolution

**Motivation :**
**Iterative error feedback by back-projection, addressing the mutual dependencies of low- and high-resolution images.**




**The dense inter-layer connections alleviate the vanishing gradient problem, produce improved feature, and encourage feature reuse.**

# Thank you