Research Project Proposal: Deep Image Denoising

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CSE Track

POLITECNICO MILANO 1863

HONOURS PROGRAMME HP-SR in Information Technology

Outline

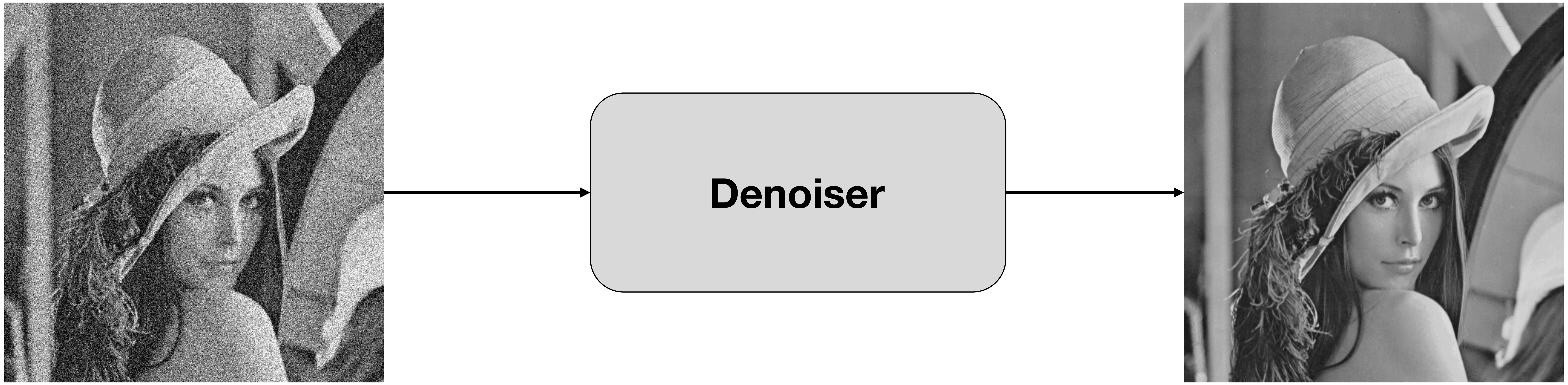
- **Introduction and Motivation**
- State of the Art
    - Classic methods
    - Neural networks
- Research Plan

Image denoising

- Subfield of image restoration
- Recover the original, clean image starting from a noisy image

$$\boldsymbol{y} = \boldsymbol{x} + \boldsymbol{\eta}$$

- The noise $\boldsymbol{\eta}$ can be a white noise (e.g. $\boldsymbol{\eta} \sim N(\mathbf{0}, \sigma^2 \boldsymbol{I})$) or follow more complex distributions (e.g. signal dependent, spatially correlated)



Applications of image denoising

- Provide the user with a pleasant and clean image
- Modular part for other image restoration tasks
- Preliminary step for high-level computer vision tasks and complex deep learning pipelines (e.g. autonomous driving)

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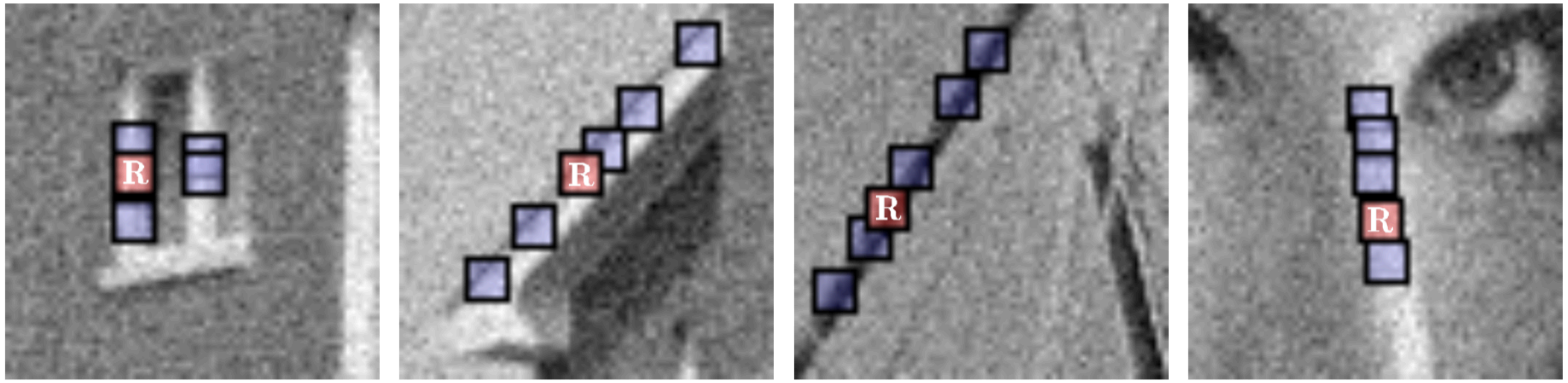
Classic methods

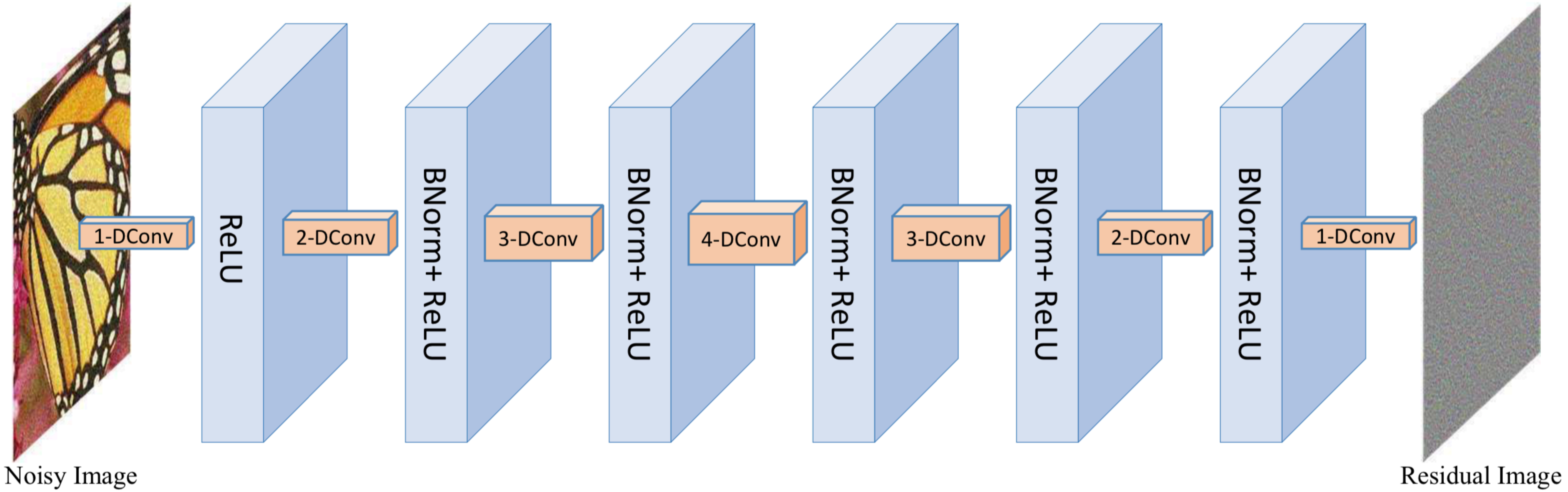
- Expert driven algorithms
- Exploit **self-similarity** between **non-neighbouring** pixels
- Computational intensive prediction
- Examples:
  - Non Local Means: weighted average of all pixels
  - BM3D: block matching and collaborative filtering



[Buades et al. CVPR 2005,
Dabov et al. IEEE Transactions on image processing 2007]

Principles of deep denoisers

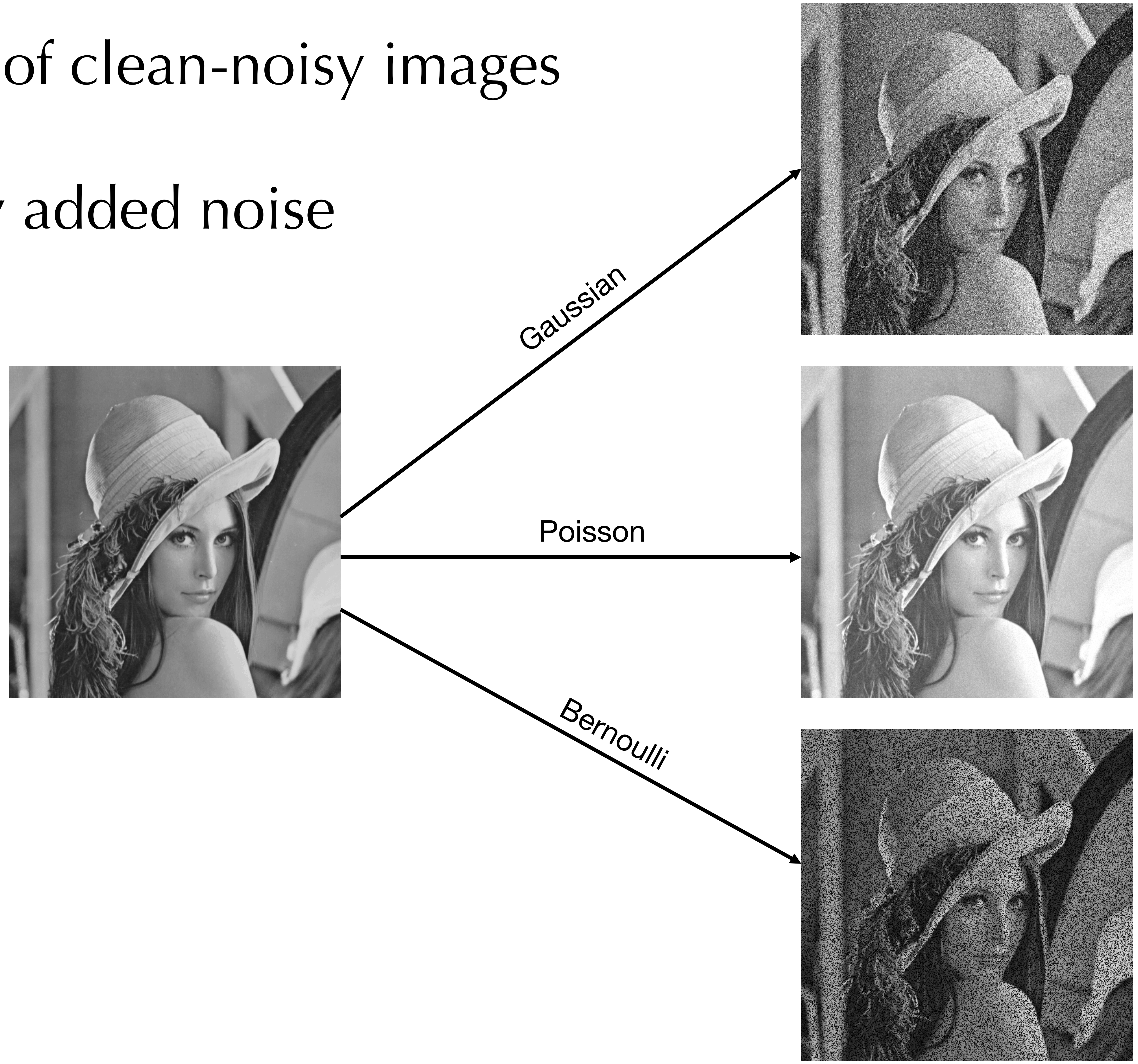
Pixelwise prediction and **residual learning**



[Zhang et al. CVPR 2017]

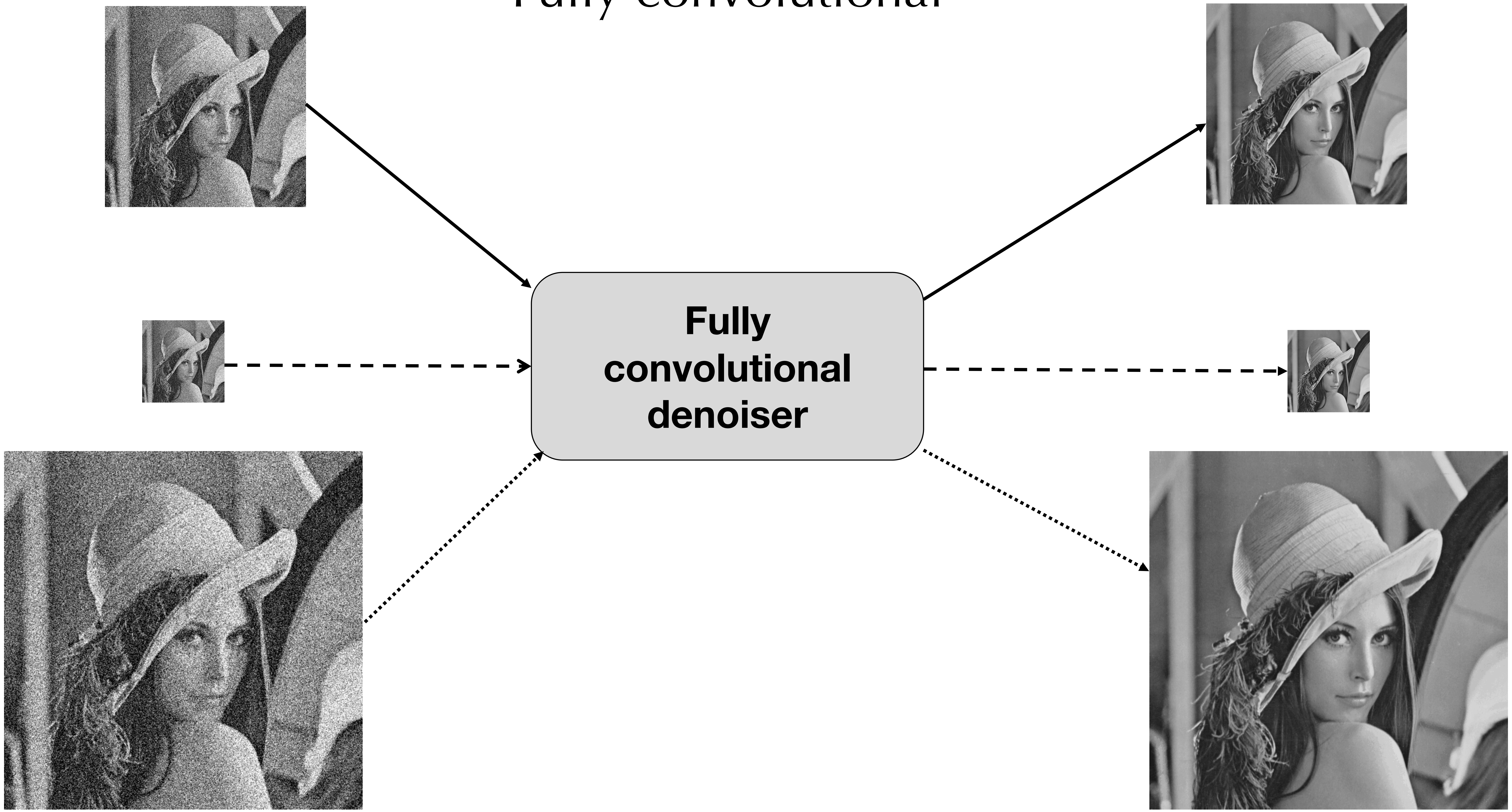
Principles of deep denoisers (2)

- Training with pairs of clean-noisy images
- Often, synthetically added noise



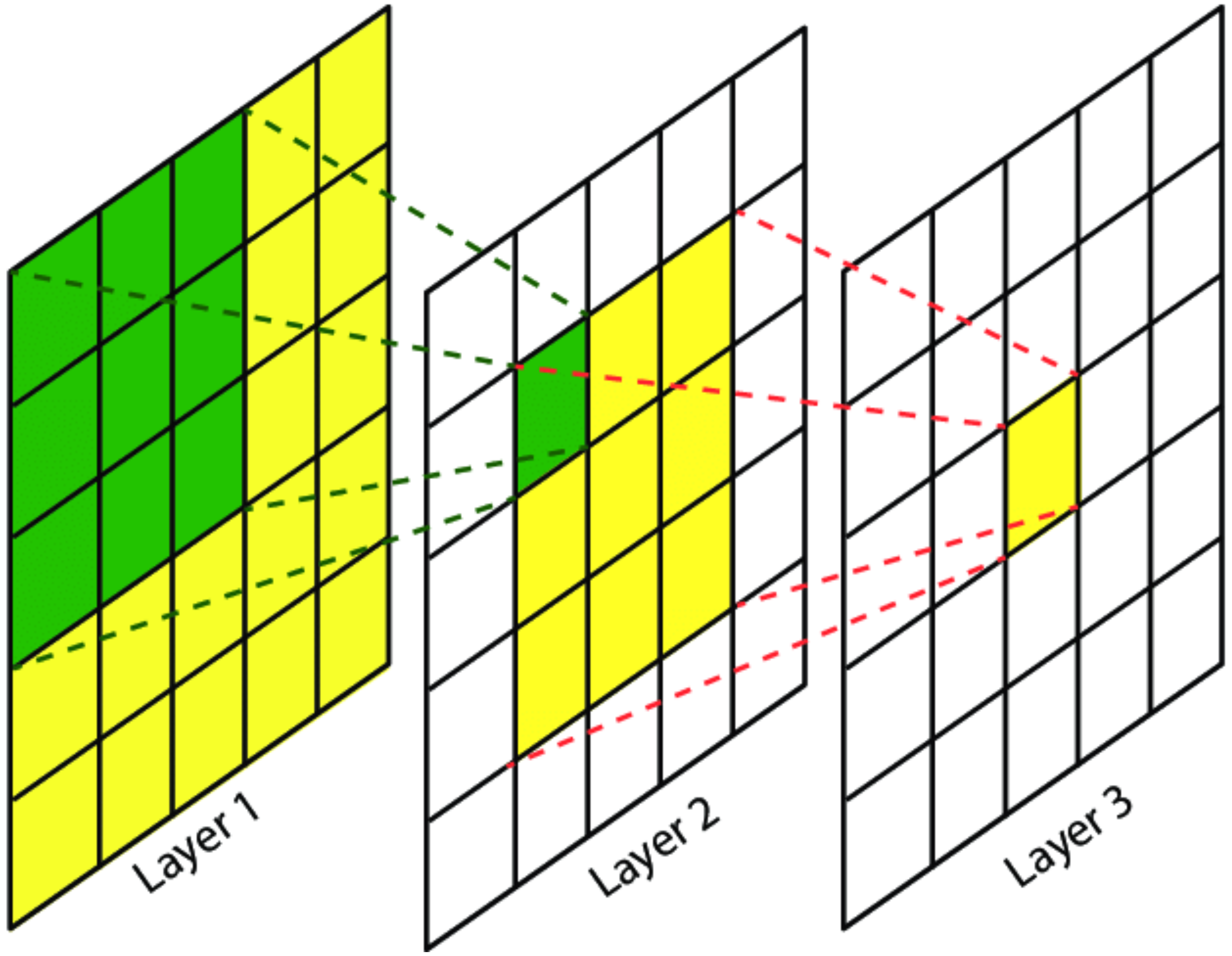
Principles of deep denoisers (3)

Fully convolutional



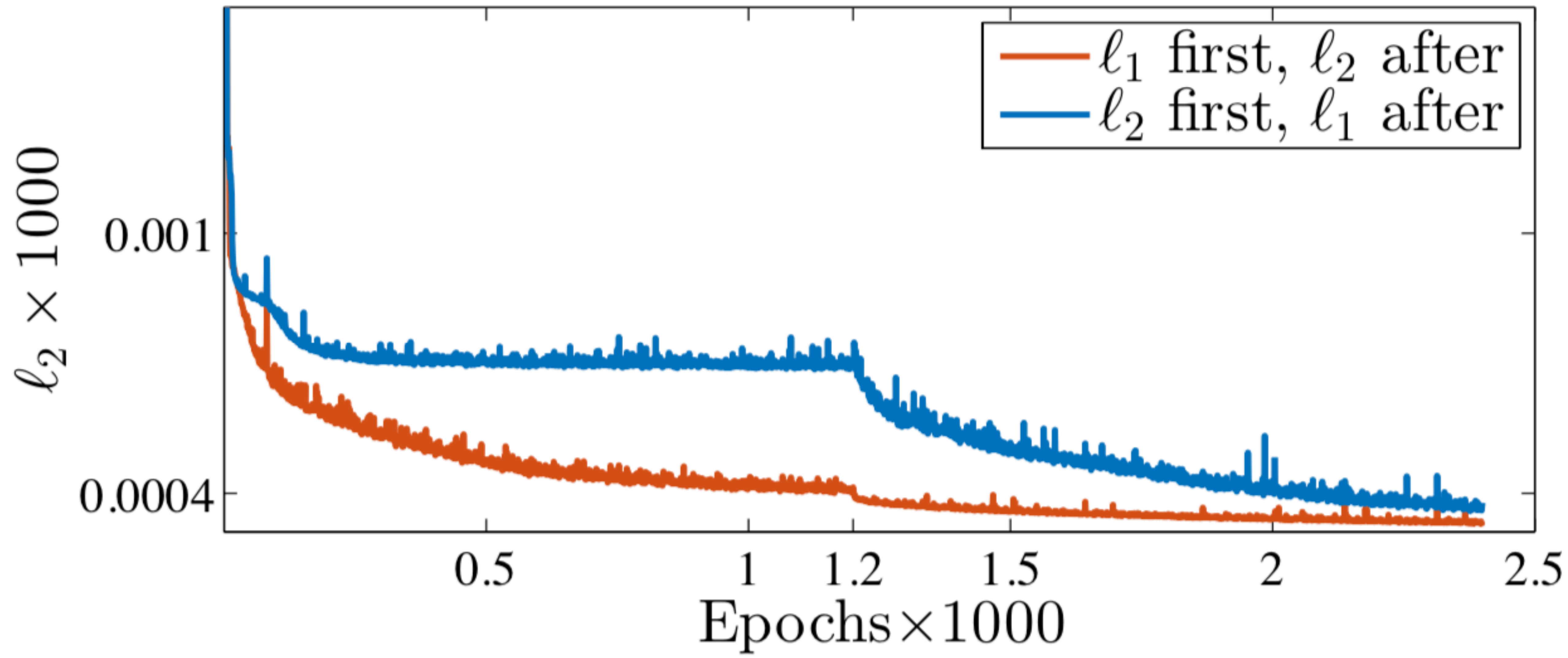
Principles of deep denoisers (4)

Wide receptive field



Loss functions for restoration

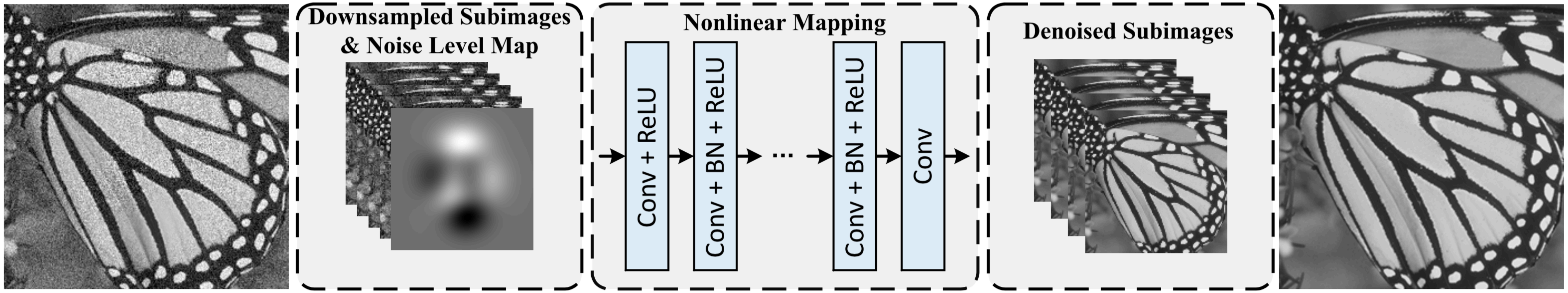
- ℓ_2 not the optimal choice
- **Perceptually** motivated loss functions
- Online swapping of loss functions to unstuck from local minima



[Zhao et al. IEEE Transactions on Computational Imaging 2016]

DnCNN and FFDNet

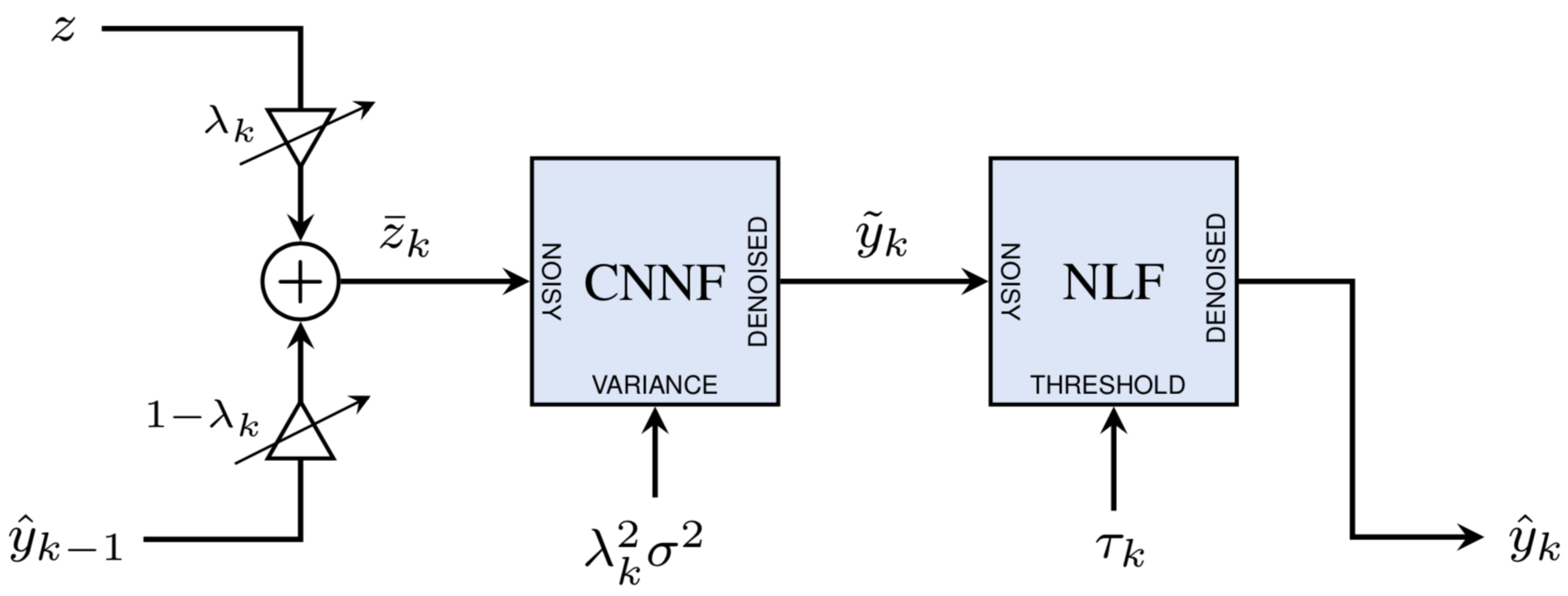
- Introduce **residual learning** and batch normalization
- Mainly designed for gaussian noise removal



[Zhang et al. IEEE Transactions on Image Processing 2017, Zhang et al. IEEE Transactions on Image Processing 2018]

NN3D

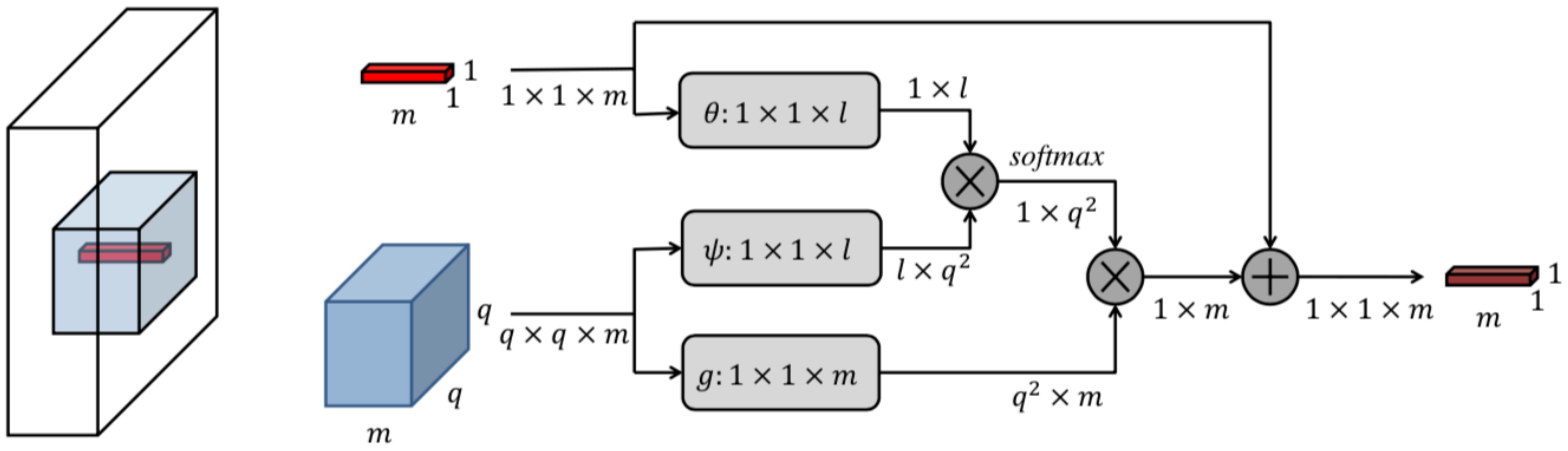
- **Iterative** application of a CNN and classic non-local filter (NLF)
- Increase the **receptive field**
- Good for images with structures



[Cruz et al. IEEE Signal Processing Letters 2018]

NLRN

- New module for **non-local** and learnable operations



[Liu et al. NIPS 2018]

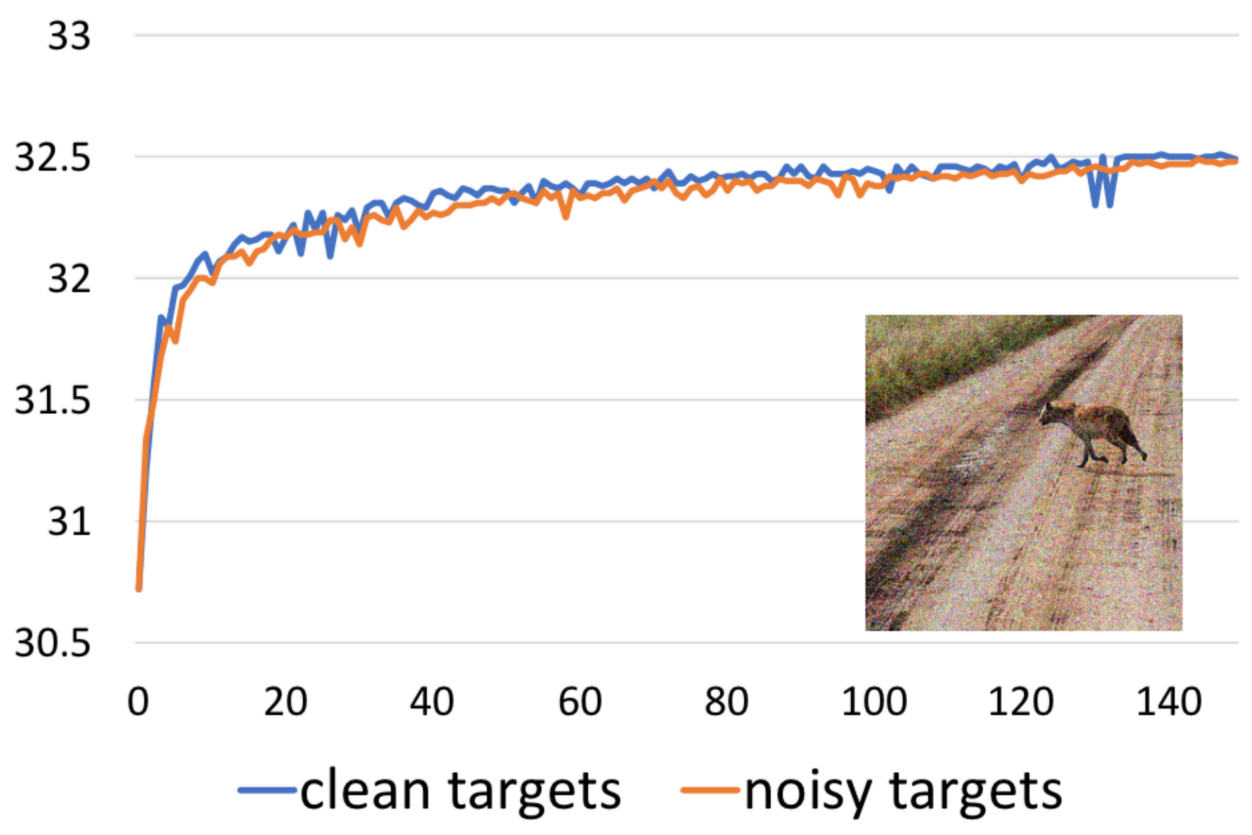
NLRN (2)

- **Recurrent neural network**
  - Recurrent state updated, with their non-local module, for T time steps
  - Output provided after T-th steps
  - Null input in the meanwhile
- Performance improvement for images with strong **self-similarity**

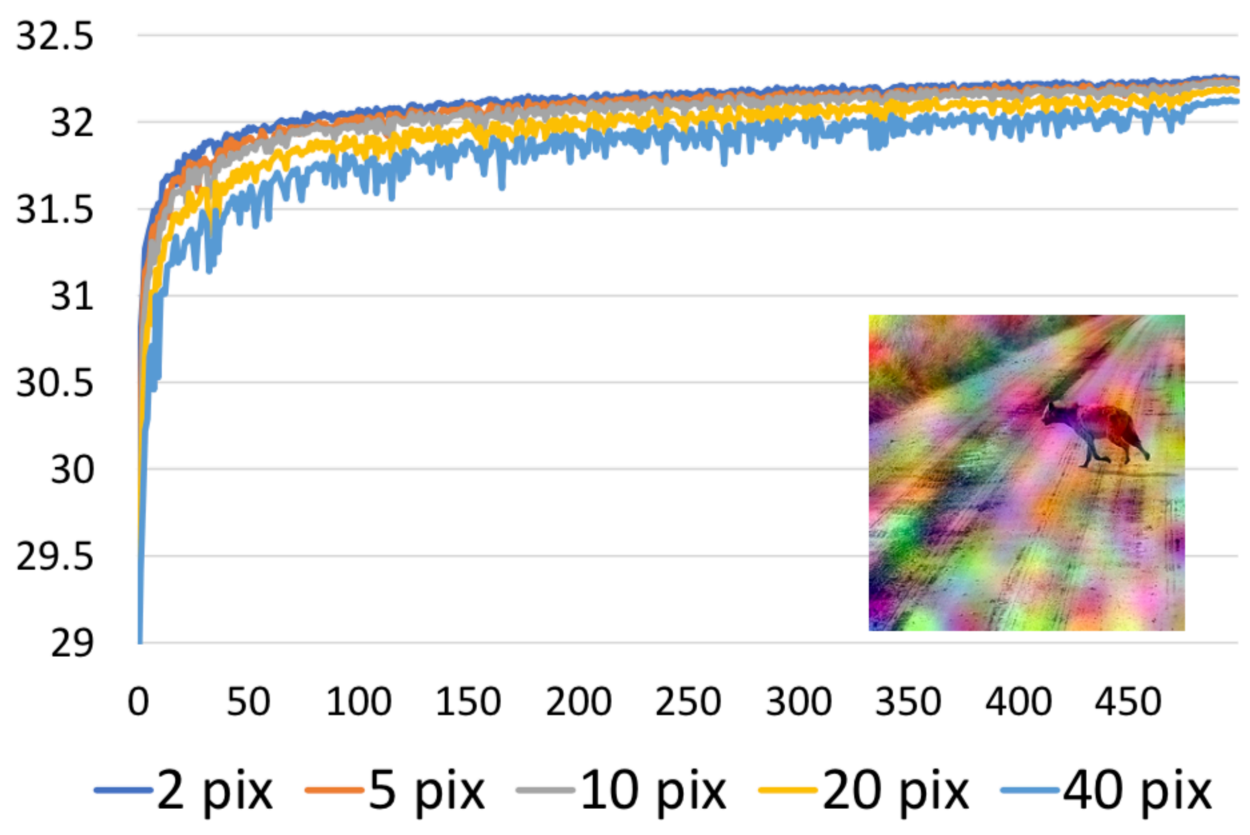
[Liu et al. NIPS 2018]

Noise2Noise

- It is possible to train a denoiser **without clean data**
- Using ℓ_2 as loss, the network learns to output the average of all plausible explanations
  - Add zero mean noise to target images



(a) White Gaussian, $\sigma = 25$

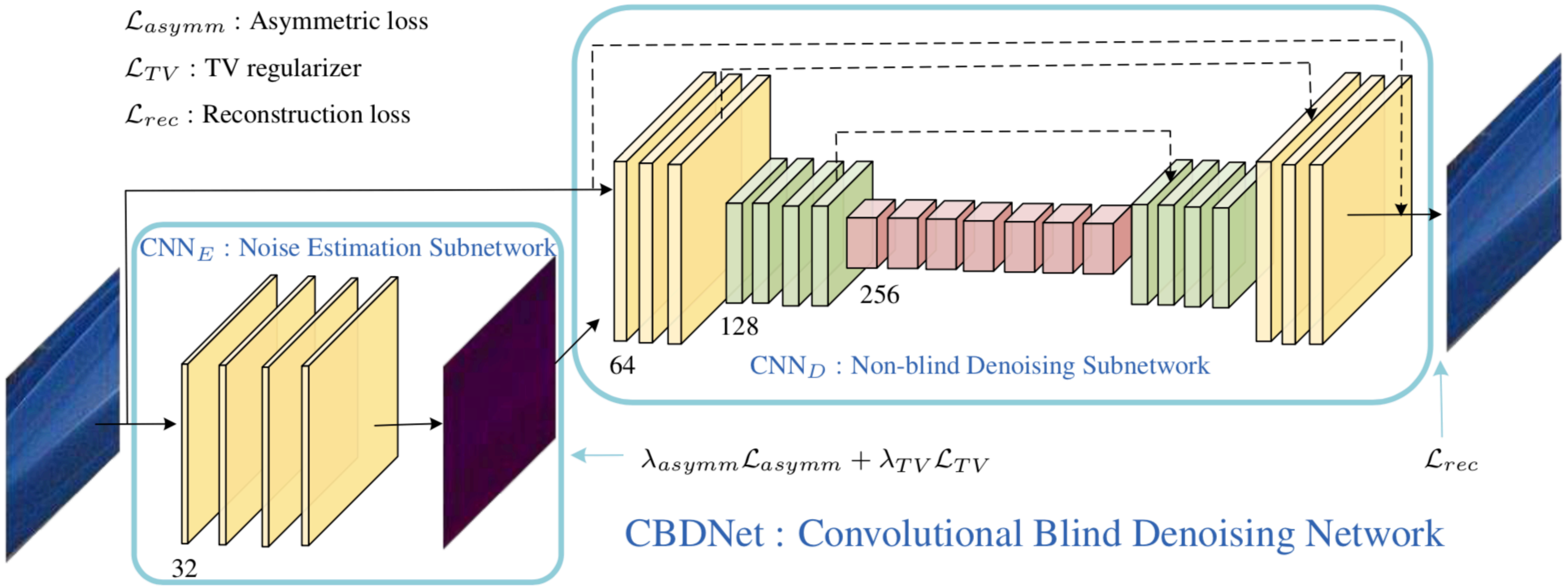


(b) Brown Gaussian, $\sigma = 25$

[Lehtinen et al. ICML 2018]

CBDNet

- They propose a more **realistic noise model**
  - Poisson-Gaussian for photon sensing and stationary disturbances
  - In-camera processing (demosaicing, gamma correction, compression)
- Good performance for **real photographs** denoising



[Guo et al. CVPR 2019]

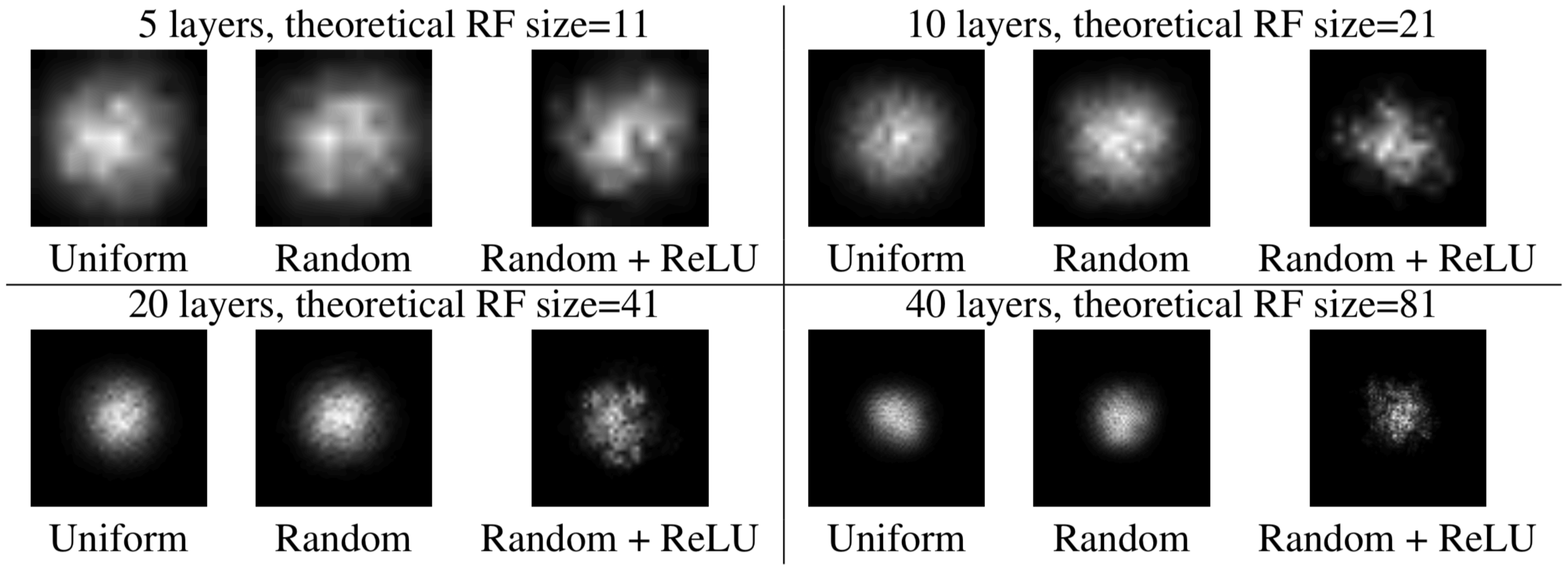
Summing up

- Deep learning models outperform classic methods
- Time consuming training
- Faster prediction
- Recent developments in DL denoising have been driven by:
    - **Practical considerations**, e.g. more realistic noise models and training without clean data
    - Transferring the **priors** at the foundation **of classic methods** into neural networks, e.g. non-local operations

Effective receptive field

- Classic methods effectively search for similarity in a window around the pixel

- Deep denoisers have the concept of **receptive field**
  - The **effective** receptive field is smaller than the **theoretical** receptive field



[Luo et al. NIPS 2016]

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Research directions

Goal: Investigate new network architectures and training procedures to

- Widen/control the effective receptive field of deep denoisers
- Promote translation/rotation equivariance

Research directions:

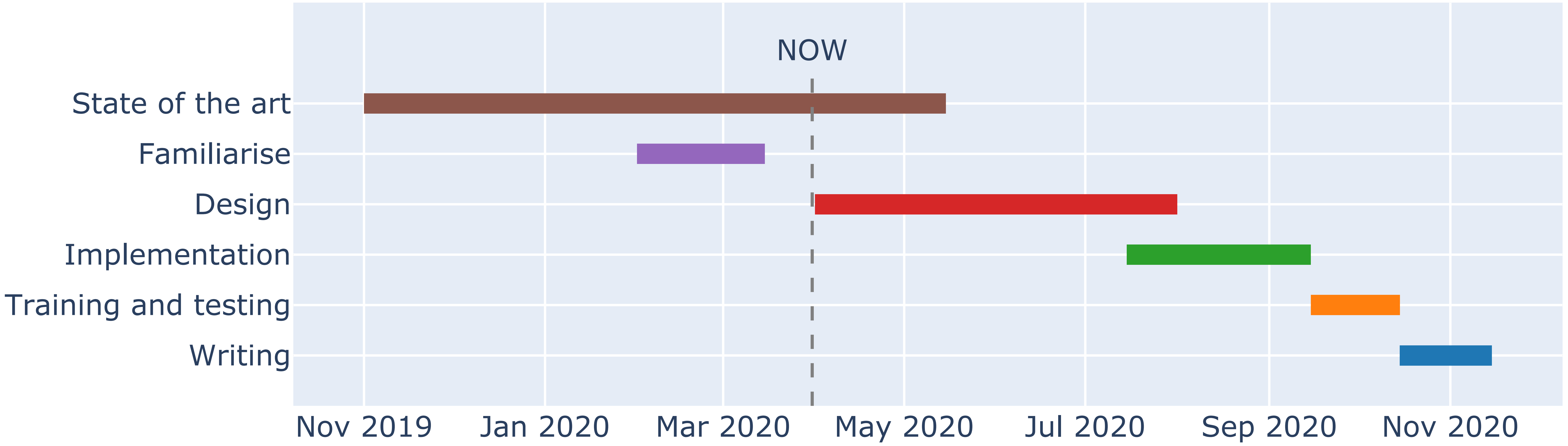
- Model the influence of the **effective receptive field** (ERF) on the denoising performance
- Design **RNN over shifted/rotated** version of the input image to
  - Increase the effective receptive field
  - Guarantee shift and rotation equivariance
- Adapt the modules in RotEqNet, which provides rotation invariance, equivariance and covariance for high-level vision tasks [Marcos et al. ICCV 2017]

Design and implementation

- Design of a new module/architecture
- Software implementation
- Training with common datasets

Testing and writing

- Testing with widely accepted benchmarks
- Comparison with state of the art methods
- Conference paper writing



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