Towards Versatile Image Restoration

Chen-Change LOY

Nanyang Technological University

Chinese University of Hong Kong

Homepage: http://www.ntu.edu.sg/home/ccloy/

Towards Versatile Image Restoration

Crafting a Toolchain for Image Restoration by Deep Reinforcement Learning, CVPR 2018

- https://github.com/yuke93/RL-Restore

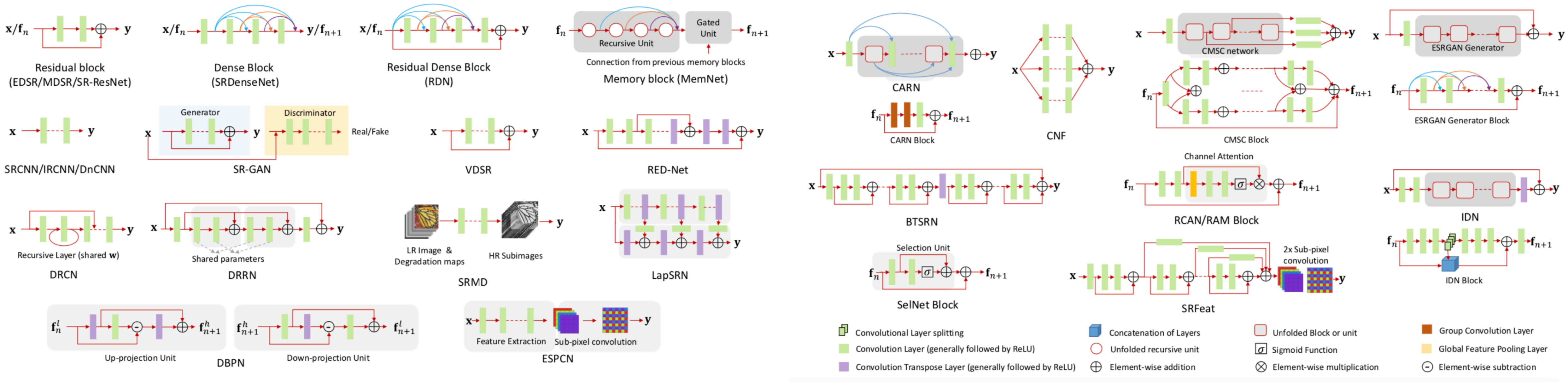
Path-Restore: Learning Network Path Selection for Image Restoration, arXiv:1804.03312

Ke Yu

Xintao Wang

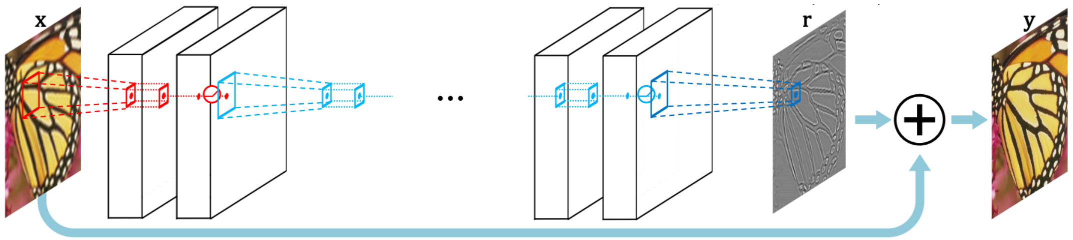
Chao Dong

Deep Networks for Image Restoration

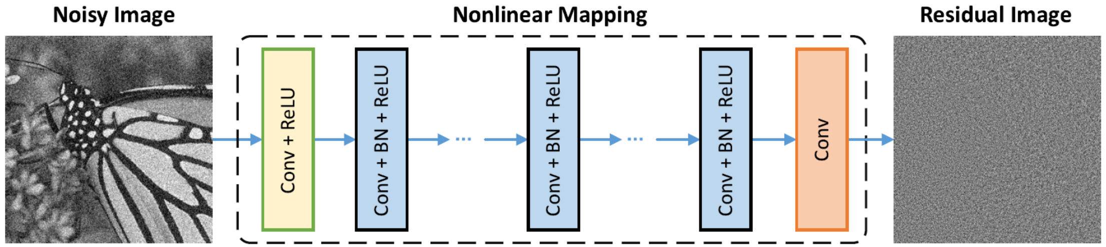


Saeed Anwar, Salman Khan, and Nick Barnes, A Deep Journey into Super-resolution: A Survey, 2019

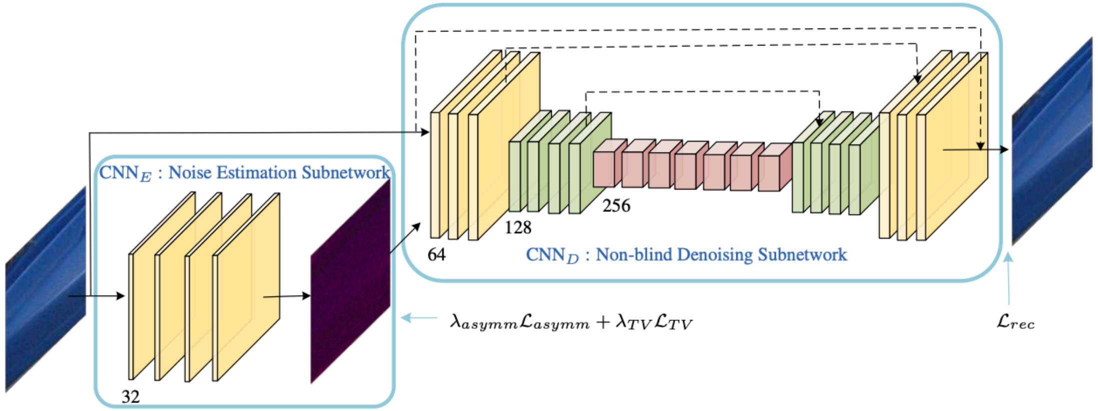
Deep Networks for Image Restoration



VDSR, CVPR 2016



DnCNN, TIP 2017

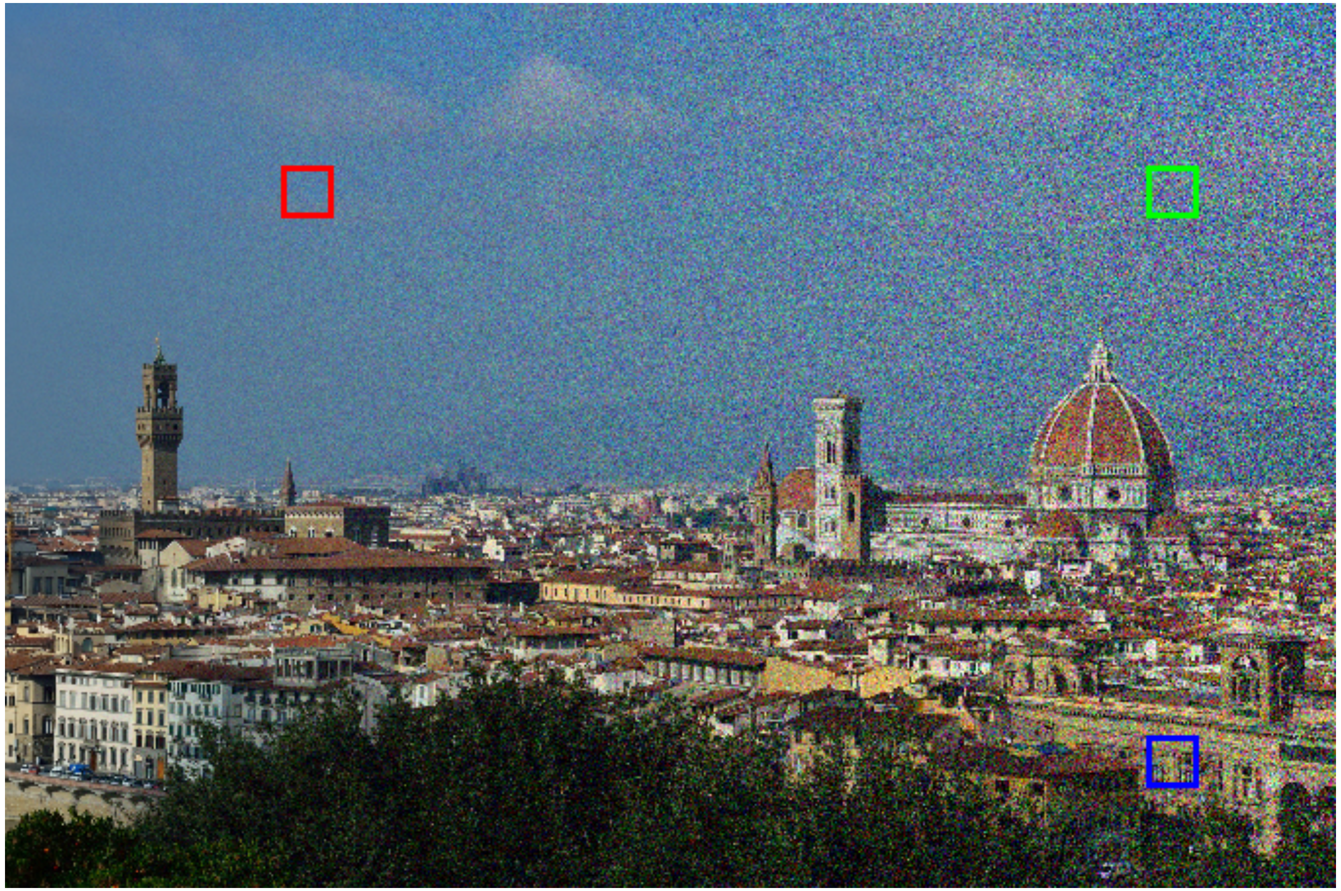


CBDNet, CVPR 2019

Towards solving more complicated distortions

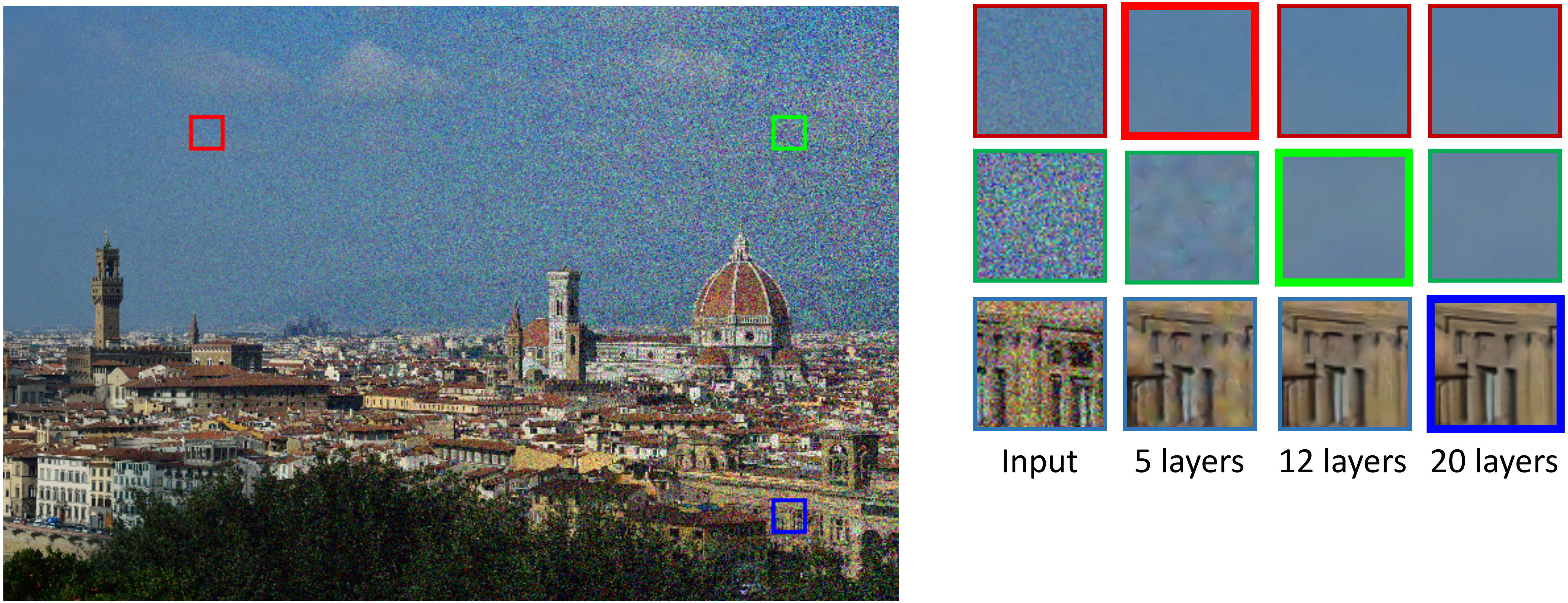
- Address multiple levels of degradation in one task, e.g., VDSR
- Address multiple individual tasks, e.g., DnCNN
- Address realistic noise, e.g., CBDNet

Deep Networks for Image Restoration



An illustrative example - different degradations in different regions

Deep Networks for Image Restoration



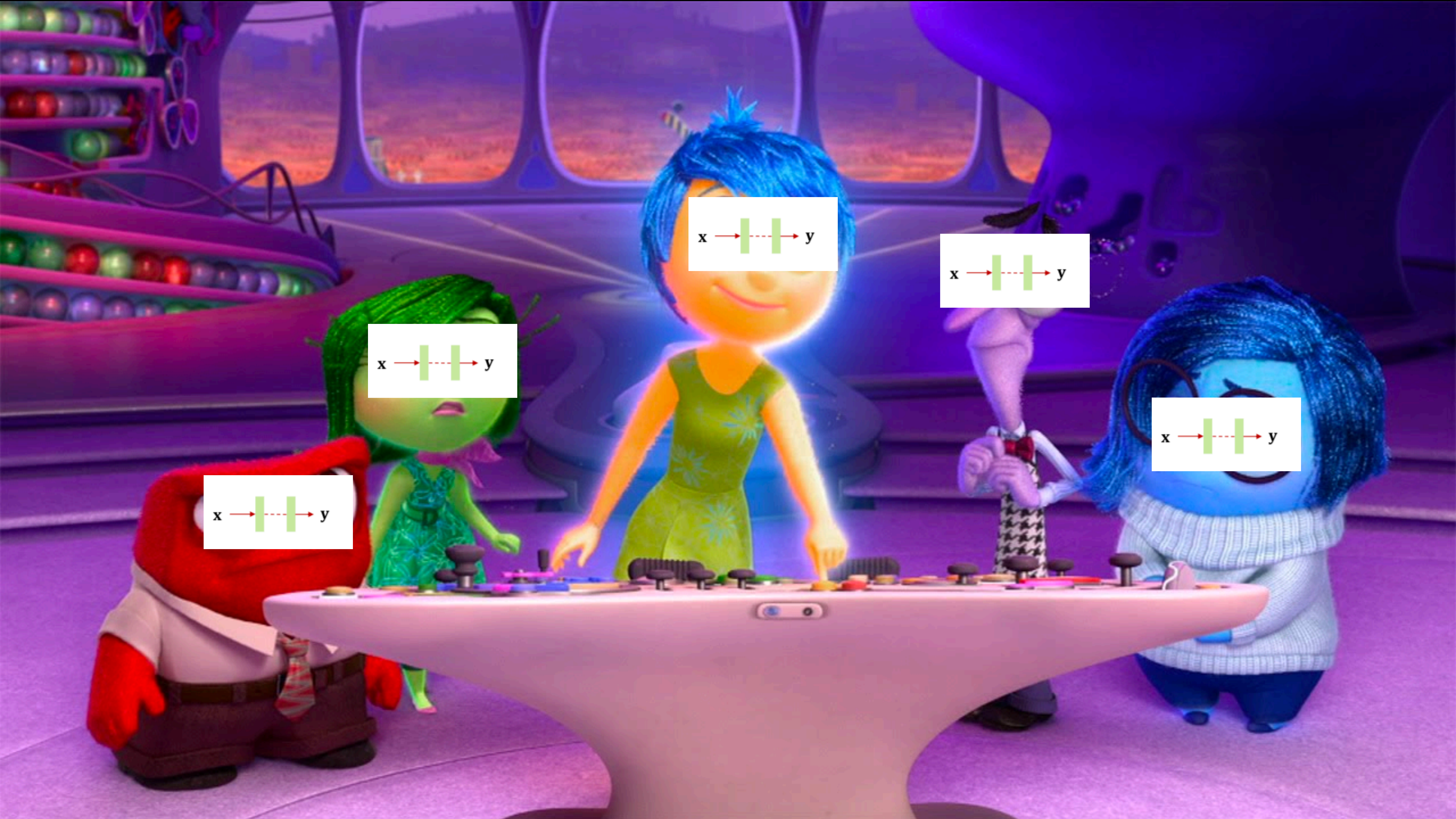
Deep Networks for Image Restoration

Using a single CNN to address multiple distortions

- *Inefficient*: Require a rather huge network to handle all possibilities
- *Inflexible*: All kinds of distorted images are processed with the same structure

Crafting a Toolchain

- Departs from the current philosophy that one would need a large-capacity CNN to solve a complex restoration task
- Have a set of tools (based on small CNNs) and learn to use them adaptively for solving the task at hand
- Handle images are potentially contaminated with a mix of distortions
- Efficient and transparent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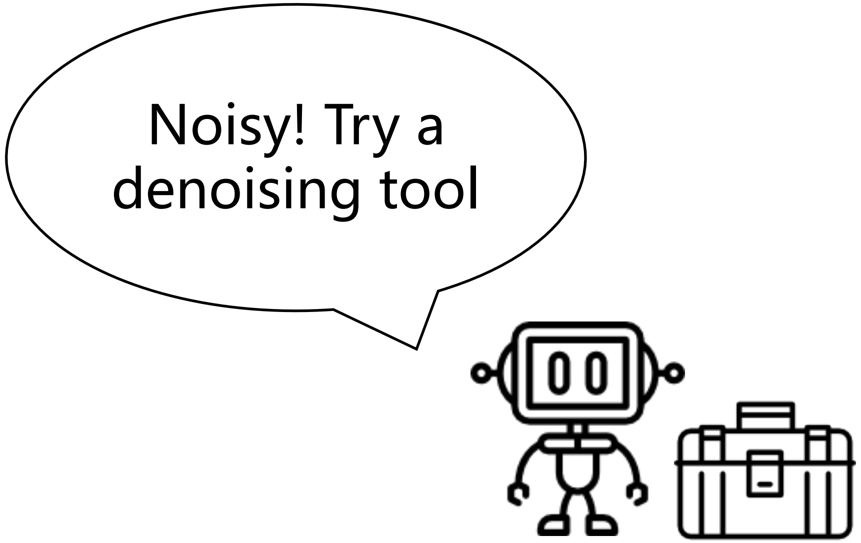
Crafting a Toolchain

- Progressively restore the image quality
- Treat image restoration as a **decision making** process



Yu et al. Crafting a Toolchain for Image Restoration by Deep Reinforcement Learning, CVPR 2018

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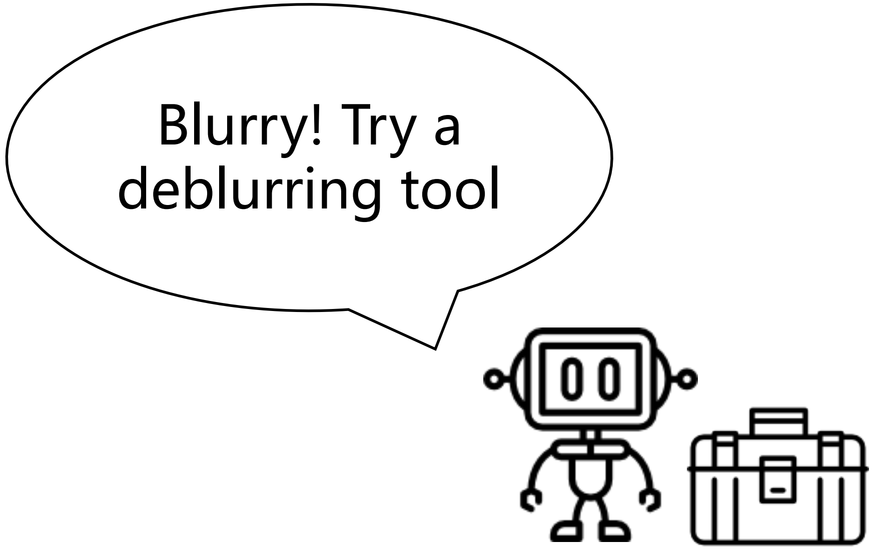

Yu et al. Crafting a Toolchain for Image Restoration by Deep Reinforcement Learning, CVPR 2018

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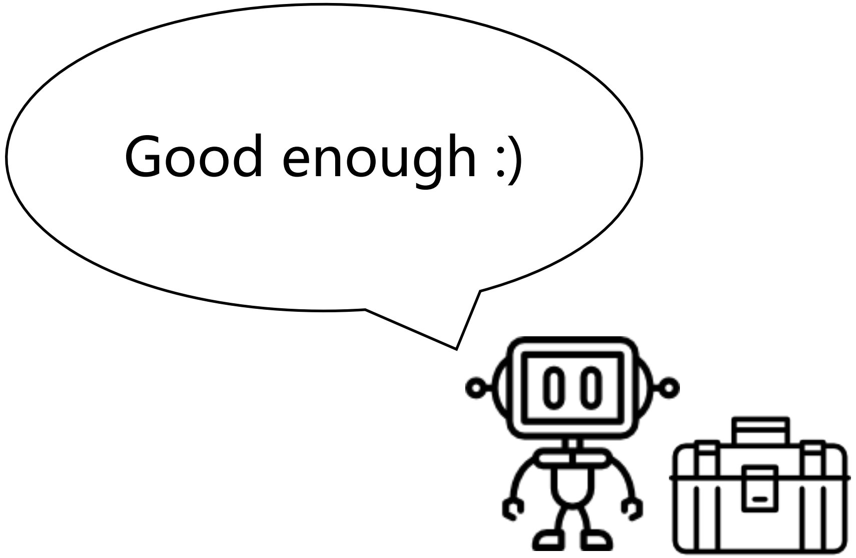

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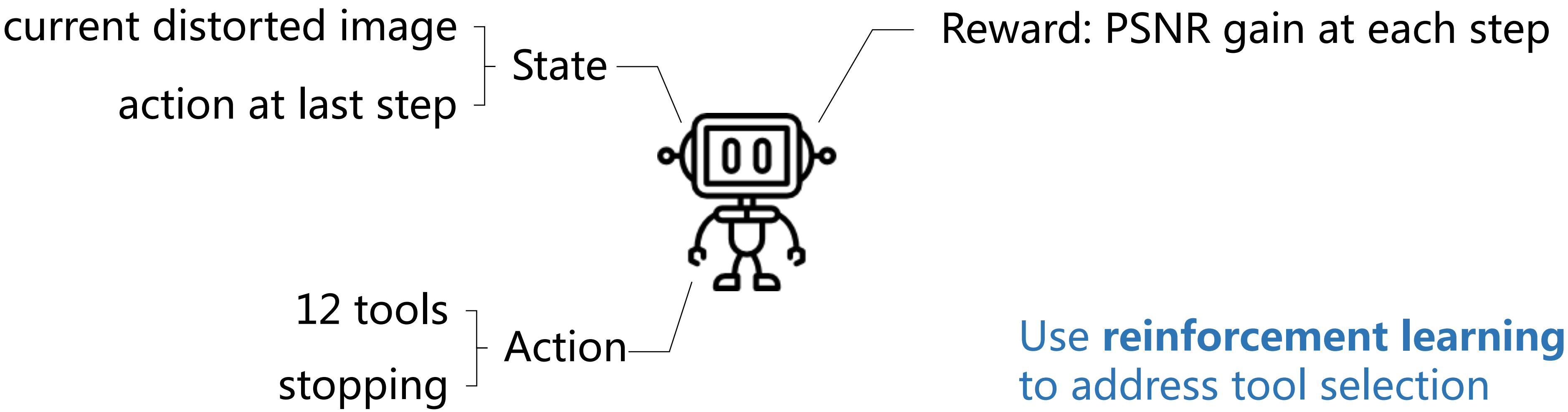
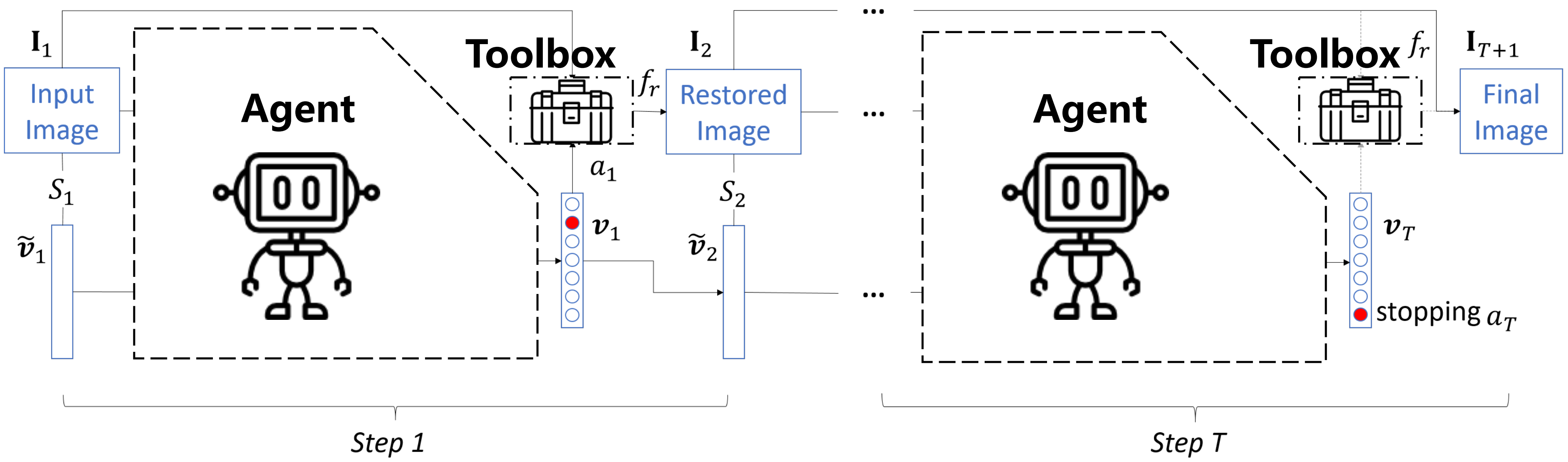
Crafting a Toolchain



Use **reinforcement learning** to address tool selection

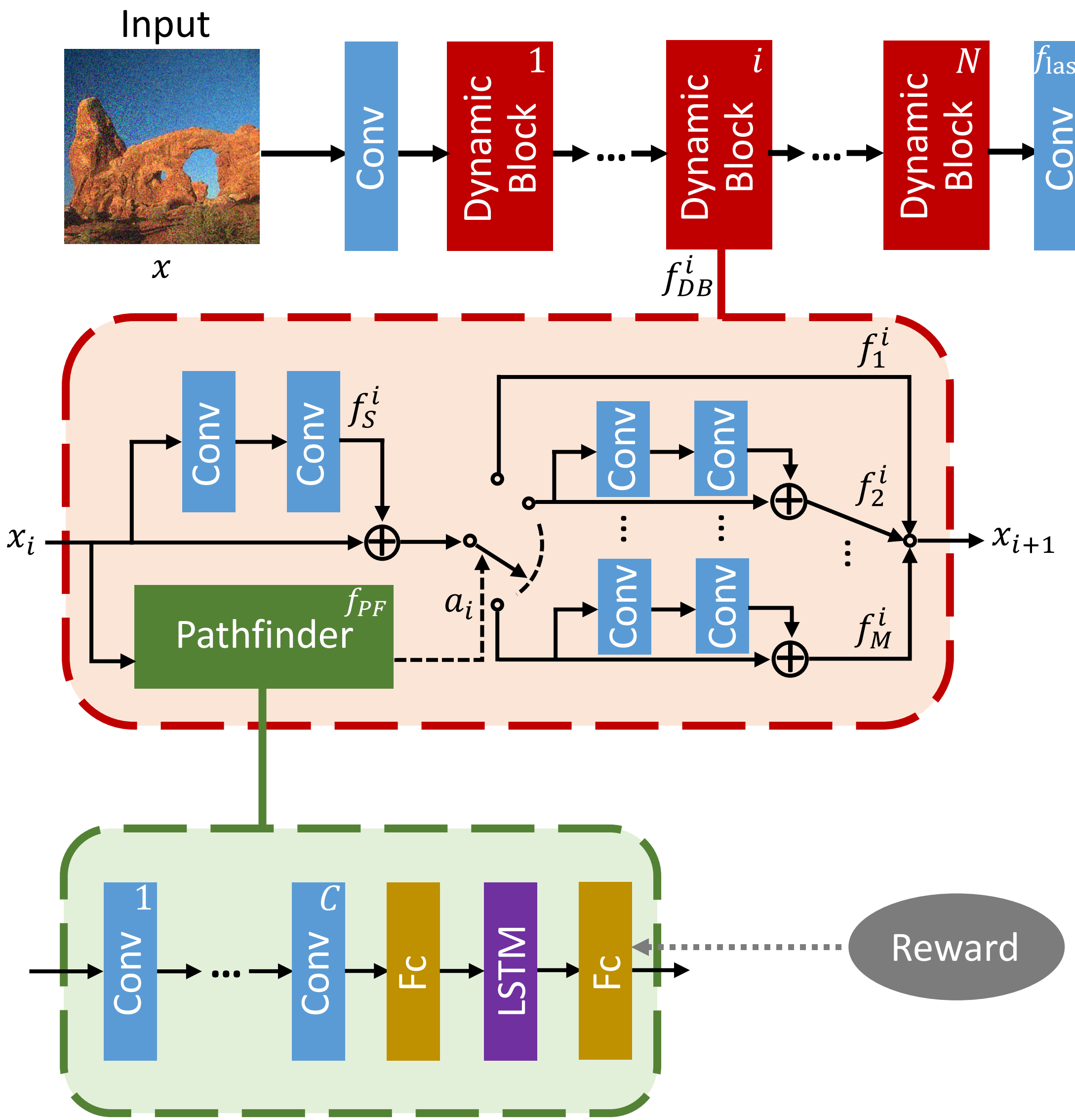
Yu et al. Crafting a Toolchain for Image Restoration by Deep Reinforcement Learning, CVPR 2018

Crafting a Toolchain



Yu et al. Crafting a Toolchain for Image Restoration by Deep Reinforcement Learning, CVPR 2018

Our Solution

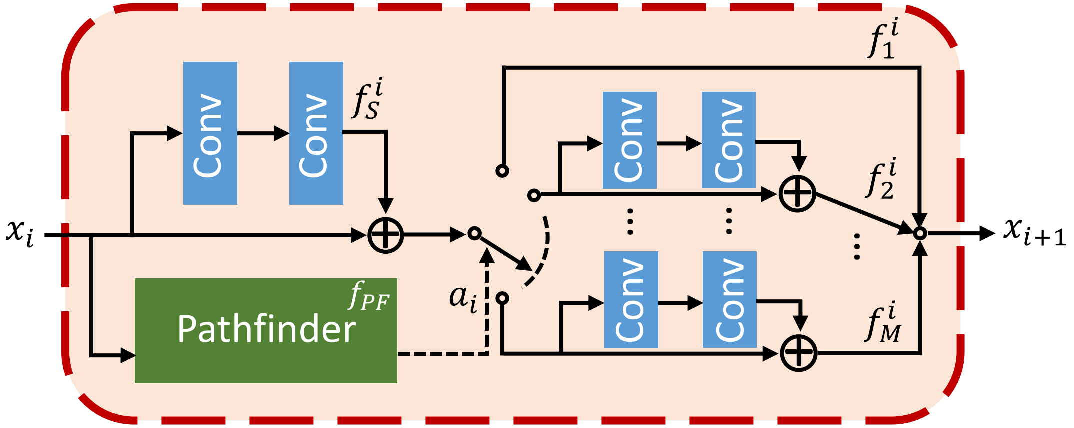


Dynamic Block
Allows flexible design on the number of path and path complexity

Pathfinder
Dispatches image regions based on diverse contents and distortions

Difficulty-Regulated Reward
Values performance gain of hard samples more than simple one

Dynamic Block



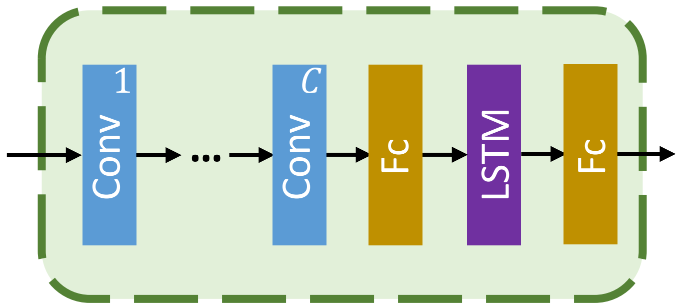
- Offer different options of complexity
- A path is activated according to the output of the pathfinder

$$x_{i+1} = f_{a_i}^i(f_S^i(x_i))$$

Selected dynamic path

Shared path

Pathfinder



- To achieve path selection
- LSTM to capture correlation of path selection in different dynamic blocks
- Less than 3% of the overall computations
- Path selection is non-differentiable – reinforcement learning for training
  - State – input feature and hidden state of LSTM, $s_i = \{x_i, h_i\}$
  - Action – the path index, $a_i \sim \pi(a|s_i)$

Difficulty Regulated Reward

- Learning a dispatch policy for different image regions that have diverse contents and distortions
- Consider performance, computation complexity, and difficulty of restoring an image region
- The reward at the *i*-th dynamic block

$$r_i = \begin{cases} -p \times (1 - \mathbf{1}_{\{1\}}(a_i)), & 1 \leq i < N, \\ -p \times (1 - \mathbf{1}_{\{1\}}(a_i)) + d \times (-\Delta L_2), & i = N, \end{cases}$$

Penalty for choosing a complex path
Smaller penalty encourages the pathfinder to select a longer path
Exception: No penalty for choosing a bypass connection

Difficulty
Proportional to MSE loss
Higher loss indicates higher difficulty
Penalize pathfinder from wasting computations on easy regions

Performance gain
The improvement of restoration in terms of L2 loss

Training and Testing

Training

- **Stage I**
  - Train the multi-path CNN with random policy of path selection for a good initialization

- **Stage II**
  - Train the pathfinder and the multi-path CNN simultaneously
  - Pathfinder is trained using the REINFORCE algorithm

Testing

- Each image is split into 63×63 regions with a stride 53.
- After processed by the multi-path CNN, all the regions are merged into a large image with overlapping pixels averaged

R. J. Williams. Simple statistical gradient-following algorithms for connectionist reinforcement learning.
Machine learning, 8(3-4):229–256, 1992

Comparison with DnCNN

Comparison with DnCNN

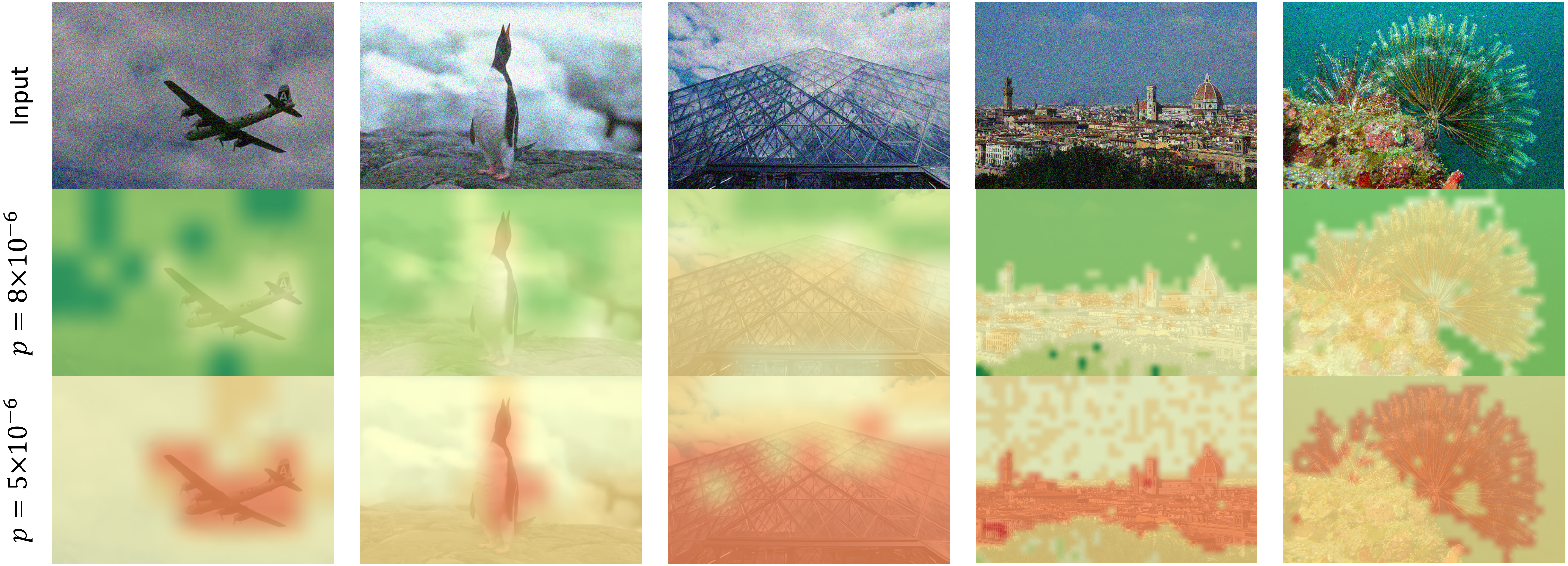
PSNR and average FLOPs of blind Gaussian denoising on CBSD68 and DIV2K-T50 datasets.

Dataset	CBSD68						DIV2K-T50					
Noise	uniform			spatially variant			uniform			spatially variant		
	σ=10	σ=50	FLOPs	linear	peaks	FLOPs	σ=10	σ=50	FLOPs	linear	peaks	FLOPs
DnCNN	36.07	27.96	5.31G	31.17	31.15	5.31G	37.32	29.64	5.31G	32.82	32.64	5.31G
Path-Restore	36.04	27.96	**4.22G**	31.18	31.15	**4.22G**	37.26	29.64	**4.20G**	32.83	32.64	**4.17G**

Path-Restore is consistently >25% faster than DnCNN
with comparable performance on different noise settings

CBSD68: Color images of BSD68 dataset
DIV2K-T50: Test set selected from NTIRE 2017 Challenge
DnCNN: K.Zhang et al. Beyond a gaussian denoiser: Residual learning of deep CNN for image denoising. TIP, 2017

Policy of Path Selection



Policy of Path Selection

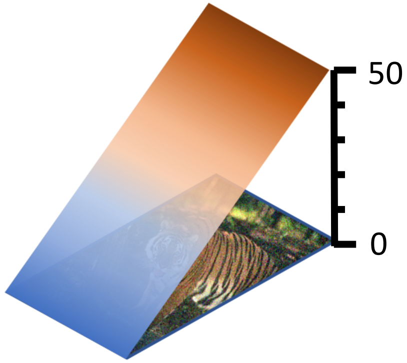
Input | Path selection

Input | Path selection

long

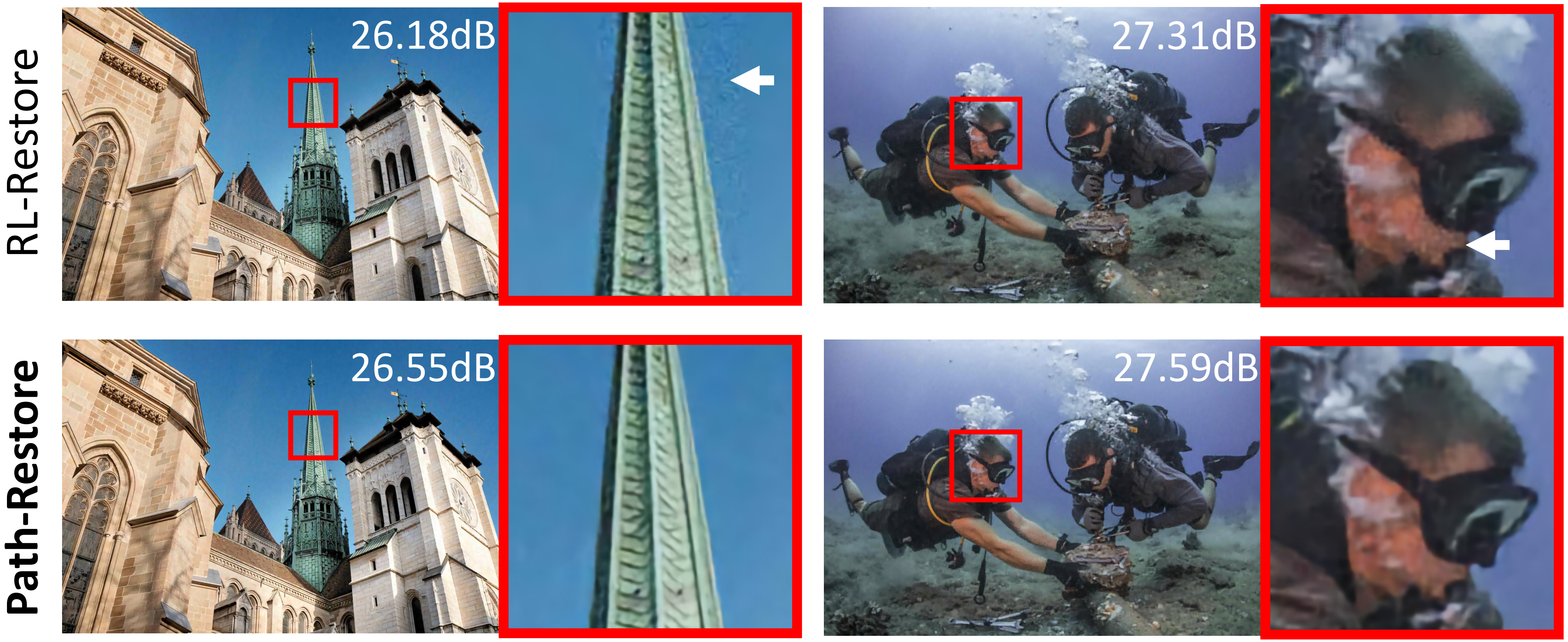
short

Noise distribution

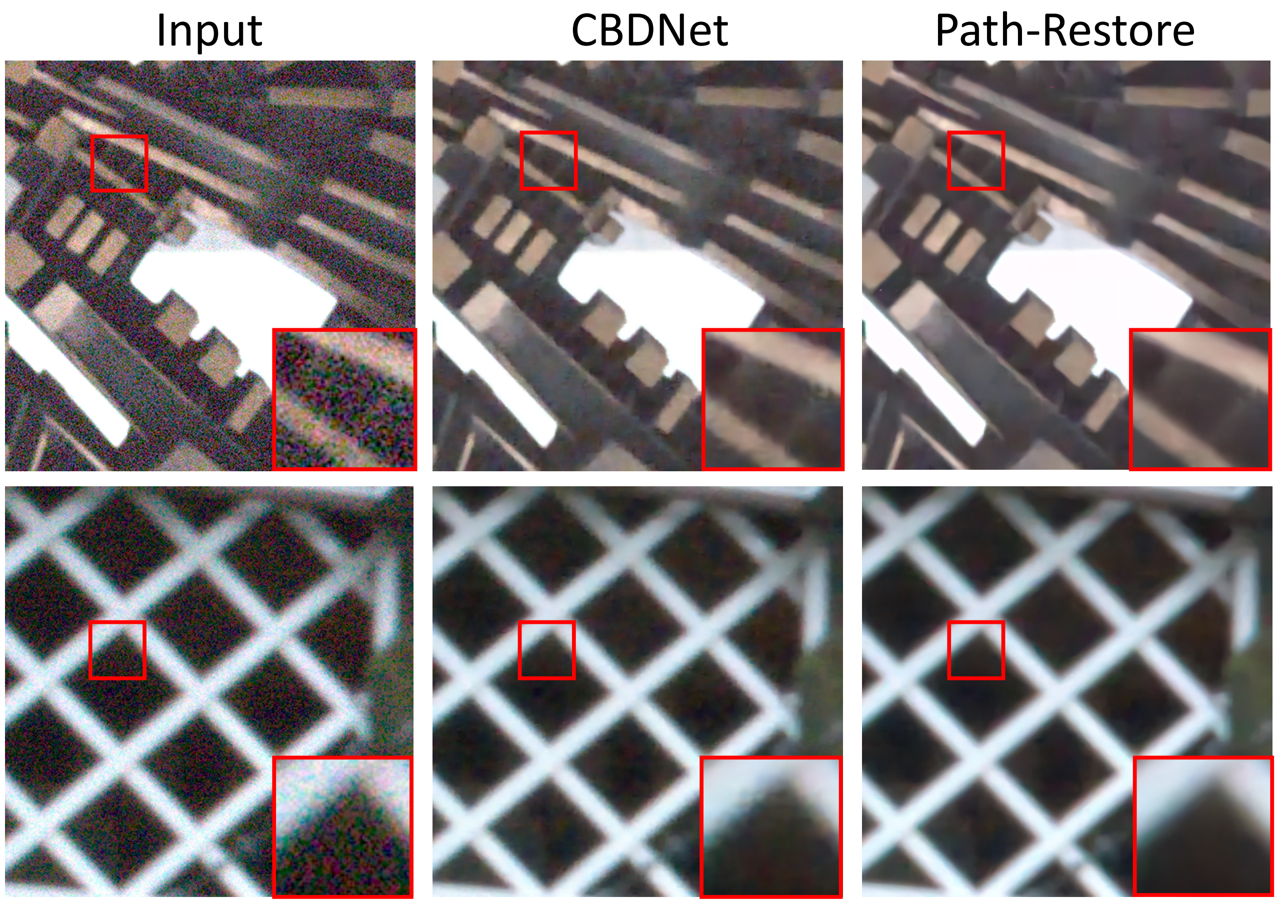


Mixed Distortions

An image is corrupted by different levels of Gaussian blur, Gaussian noise and JPEG compression simultaneously



Results on Darmstadt Noise Dataset



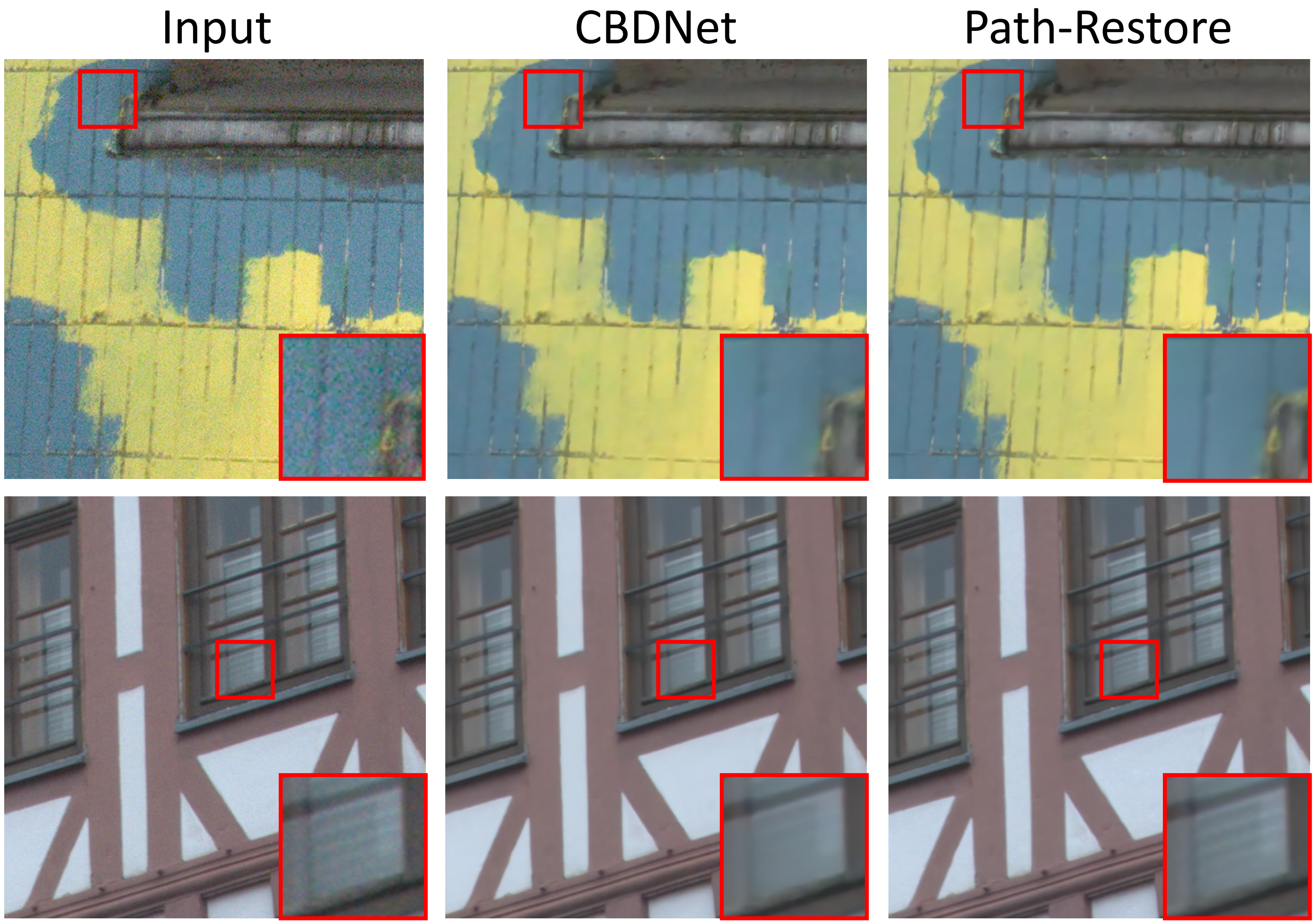
The DND contains 50 realistic high-resolution paired noisy and noise-free images, captured by four different consumer cameras

Method	PSNR / SSIM	FLOPs (G)	Time (s)
CBDNet [13]	38.06 / 0.9421	6.94	3.95
NLH*	38.81 / 0.9520	N/A	N/A
DRSR_v1.4*	39.09 / 0.9509	N/A	N/A
MLDN*	39.23 / 0.9516	N/A	N/A
RU_sRGB*	39.51 / 0.9528	N/A	N/A
Path-Restore	39.00 / 0.9542	**5.60**	**3.06**
Path-Restore-Ext	**39.72 / 0.9591**	22.6	12.6

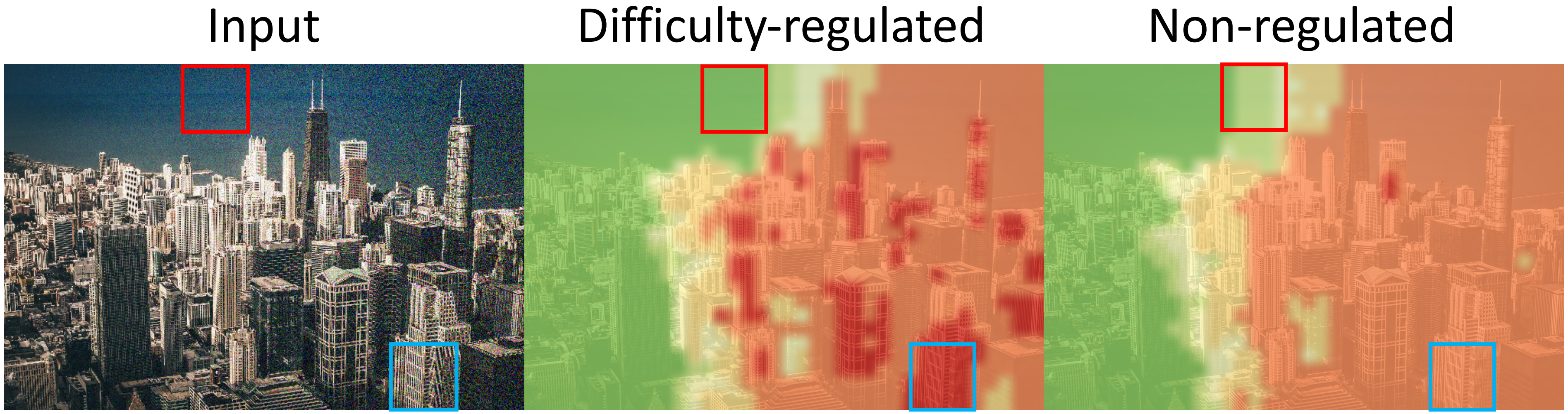
Unpublished works are denoted by "*"

T. Plotz and S. Roth. Benchmarking denoising algorithms with real photographs. CVPR 2017

Results on Darmstadt Noise Dataset

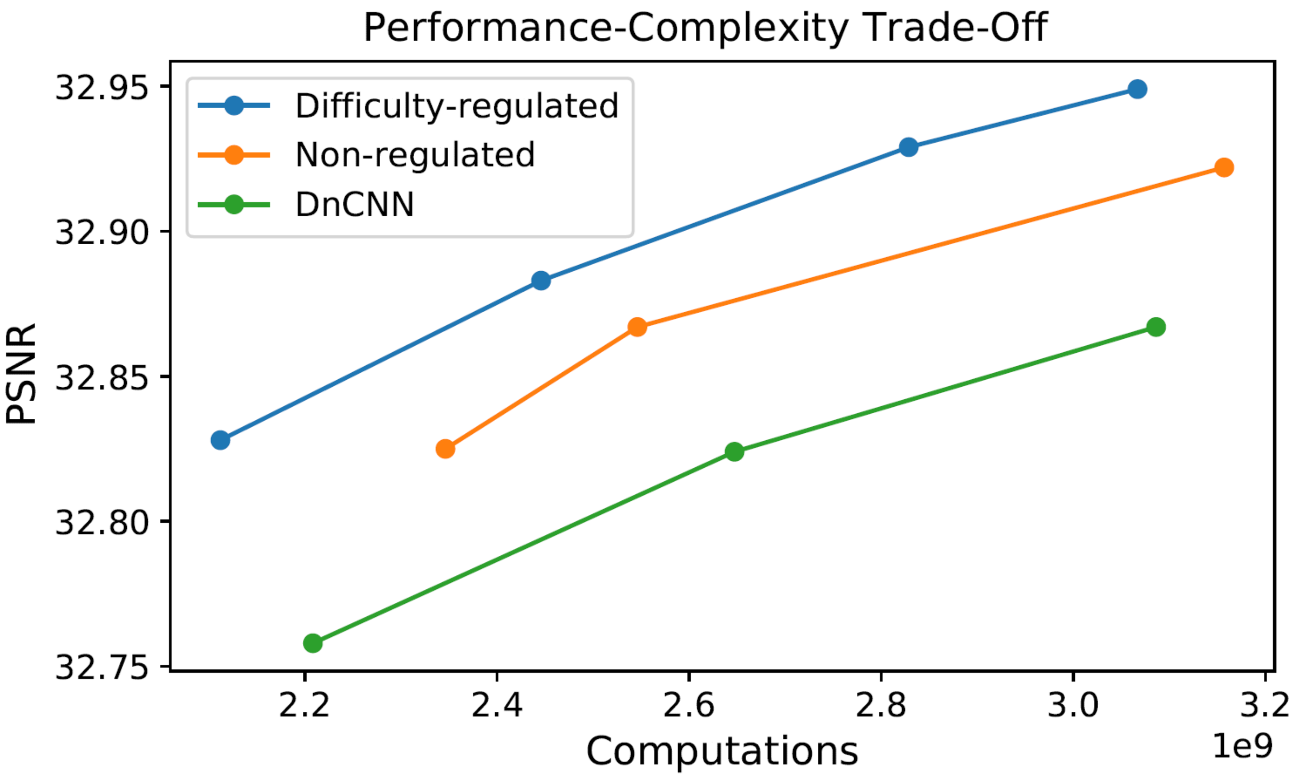


Difficulty-Regulated Award



Difficulty-regulated reward saves more computations when processing easy regions (*e.g.*, region in the red box), while using a longer path to process hard regions (*e.g.*, region in the blue box)

Performance-Complexity Trade-Off



Trade-off can be achieved by adjusting the reward penalty *p* while training

Towards Versatile Image Restoration

- **Task-adaptive**
  - Toolchain crafting
  - Dynamic network path selection
- **Human-controllable**
  - Deep network interpolation (CVPR 2019, Poster 171, 18 June morning)
- **Prior-driven**
  - Spatial feature transform (CVPR 2018)

Thanks