DEEP IMAGE PRIOR

DMITRY ULYANOV • ANDREA VEDALDI • VICTOR LEMPITSKY

SUPERVISOR: Dr. Pascal Peter

PRESENTER: Harsh Agarwal

BACKGROUND

- Deep Learning generally comprises of
  - Network
  - Dataset
  - Learning Procedure

- While Deep Image Prior comprises of
  - Network
  - Learning Procedure

OVERVIEW

NOISING & DE-NOISING

x – *Clean Image*

Degradation

$\hat{x}$ – *Degraged Image*

Restoration

x^* – *Restored Image*

$$x^* = argmax_x \ p(x|\hat{x}) \quad [MAP]$$

$$p(x|\hat{x}) = \frac{p(\hat{x}|x).p(x)}{p(\hat{x})} \propto \underbrace{p(\hat{x}|x)}_{\text{Likelihood}}.\underbrace{p(x)}_{\text{Prior}}$$

NOISING & DE-NOISING

x – *Clean Image*

Degradation

$\hat{x}$ – *Degraged Image*

Restoration

x^* – *Restored Image*

$$\hat{x} = x + \epsilon, \epsilon \sim N(0, \sigma^2)$$

$$p(\hat{x}|x) = N(\hat{x}; x, \sigma^2)$$

$$x^* = argmax_x p(x|\hat{x})$$

$$x^* = argmax_x\, p(\hat{x}|x)p(x)$$

NOISING & DE-NOISING

$x - Clean\ Image$ $\hat{x} - Degraged\ Image$ $x^* - Restored\ Image$

$$x^* = argmax_x p(x|\hat{x}) = argmax_x p(\hat{x}|x).p(x)$$

Assuming we do not need any Prior:

$$x^* = argmax_x p(\hat{x}|x) = argmax_x N(\hat{x}; x, \sigma^2) = \hat{x}$$

DEGRADATION & RESTORATION

x $- \; Clean\ Image$

$\hat{x}$ $- \; Degraged\ Image$

x^* $- \; Restored\ Image$

$$x^* = argmax_x p(x|\hat{x}) = argmax_x p(\hat{x}|x)p(x)$$

$$= argmin_x\big(-\log(p(\hat{x}|x)) - \log\big(p(x)\big)\big)$$

Expressing this as an Energy Minimization Problem:

$$x^* = argmin_x \underbrace{E(x,\hat{x})}_{\text{Task-Dependent Term}} + \underbrace{R(x)}_{\text{Prior}}$$

TASK DEPENDENT DATA TERM

x $-$ *Clean Image*

$\hat{x}$ $-$ *Degraged Image*

x^* $-$ *Restored Image*

m $-$ *Binary Image Mask*

$$x^* = argmin_x E(x, \hat{x})$$

Denoising $E(x, \hat{x}) = ||x - \hat{x}||^2$

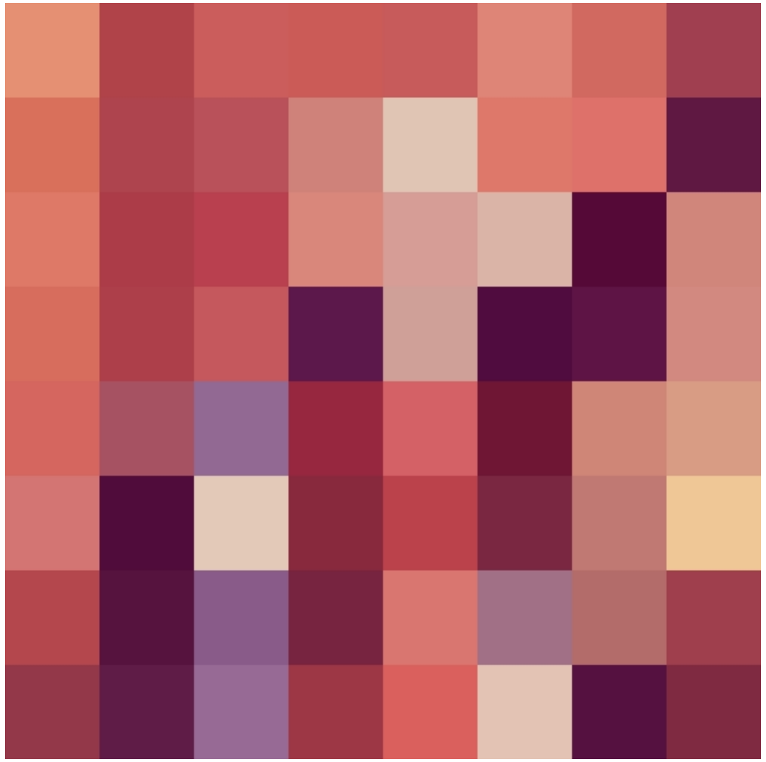
Super-Resolution $E(x, \hat{x}) = ||d(x) - \hat{x}||^2$

Inpainting $E(x, \hat{x}) = ||(x - \hat{x}) \cdot m||^2$

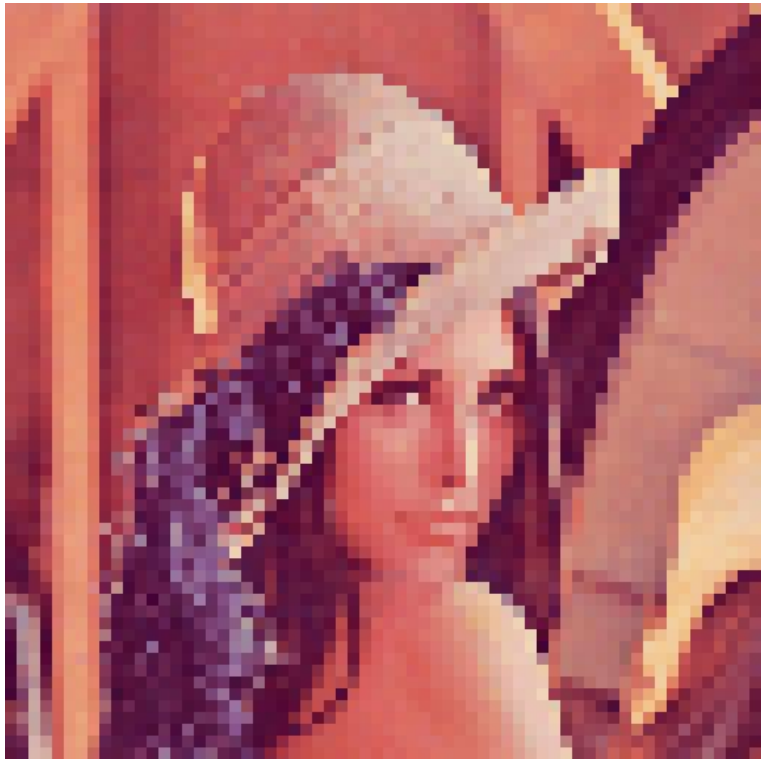
OVERVIEW

1. Mathematically: What is Prior?
2. Intuitively: What is a Prior?
3. Implicit and Explicit Prior
4. Deep Image Prior
5. Results
6. Conclusion

USE OF PRIOR



(8 x 8)

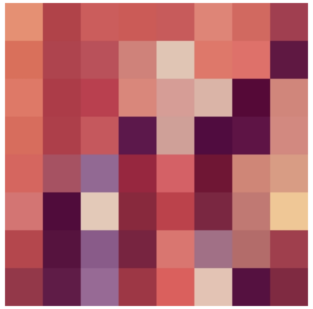


(64 x 64)

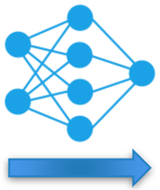
https://en.wikipedia.org/wiki/Lenna

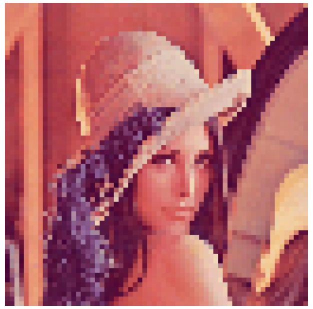
TYPES OF PRIORS

Learned Prior



Low-Resolution Images





High-Resolution Images

Explicit Prior

$$\min_{x} \; ||d(x) - \hat{x}\,||$$

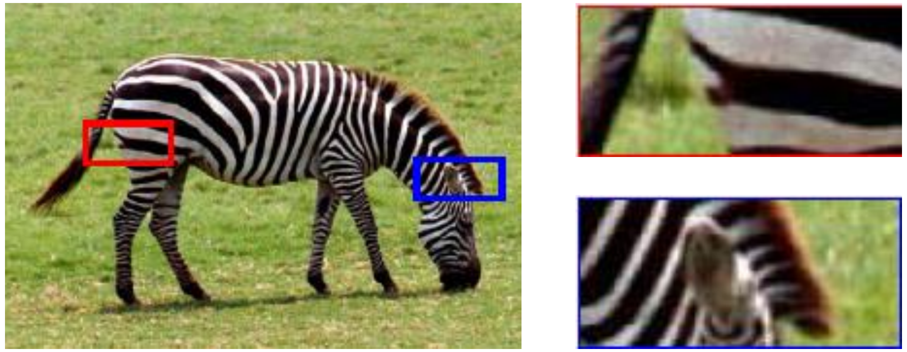
Given, x is a woman's face shot in natural lighting

Deep Image Prior

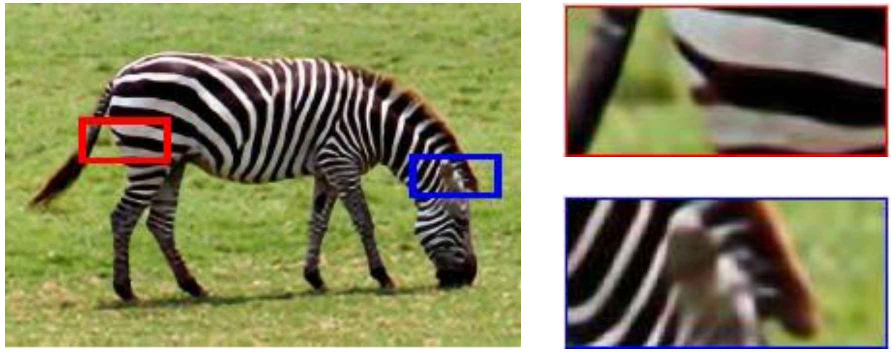
$$\min_{x} \; ||d(x) - \hat{x}\,||$$

Here, x is the output of a Deep Learning Network

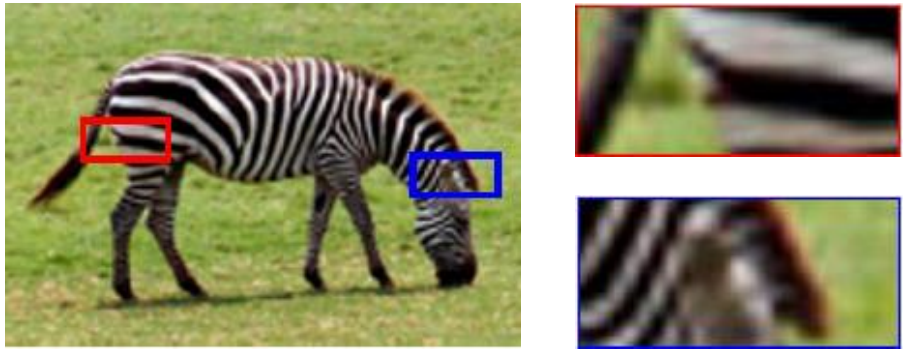
RESULTS



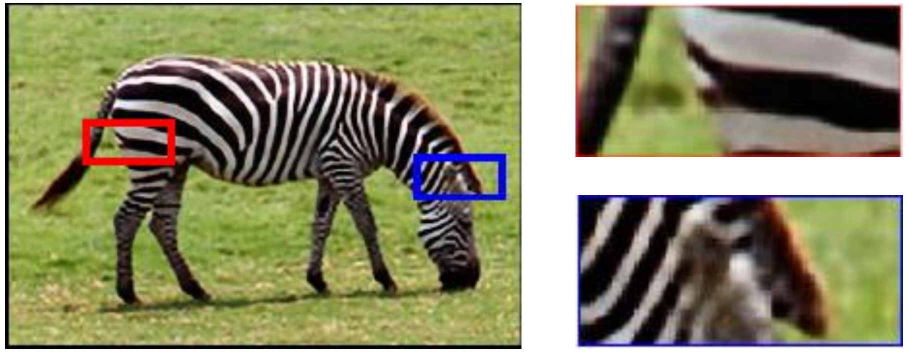
Ground Truth



SRResNet **[Trained]**



Bicubic **[Not Trained]**



Deep Image Prior **[Not Trained]**

OVERVIEW

1. Mathematically: What is Prior?
2. Intuitively: What is a Prior?
3. Implicit and Explicit Prior
4. Deep Image Prior
5. Results
6. Conclusion

PARAMETERIZATION

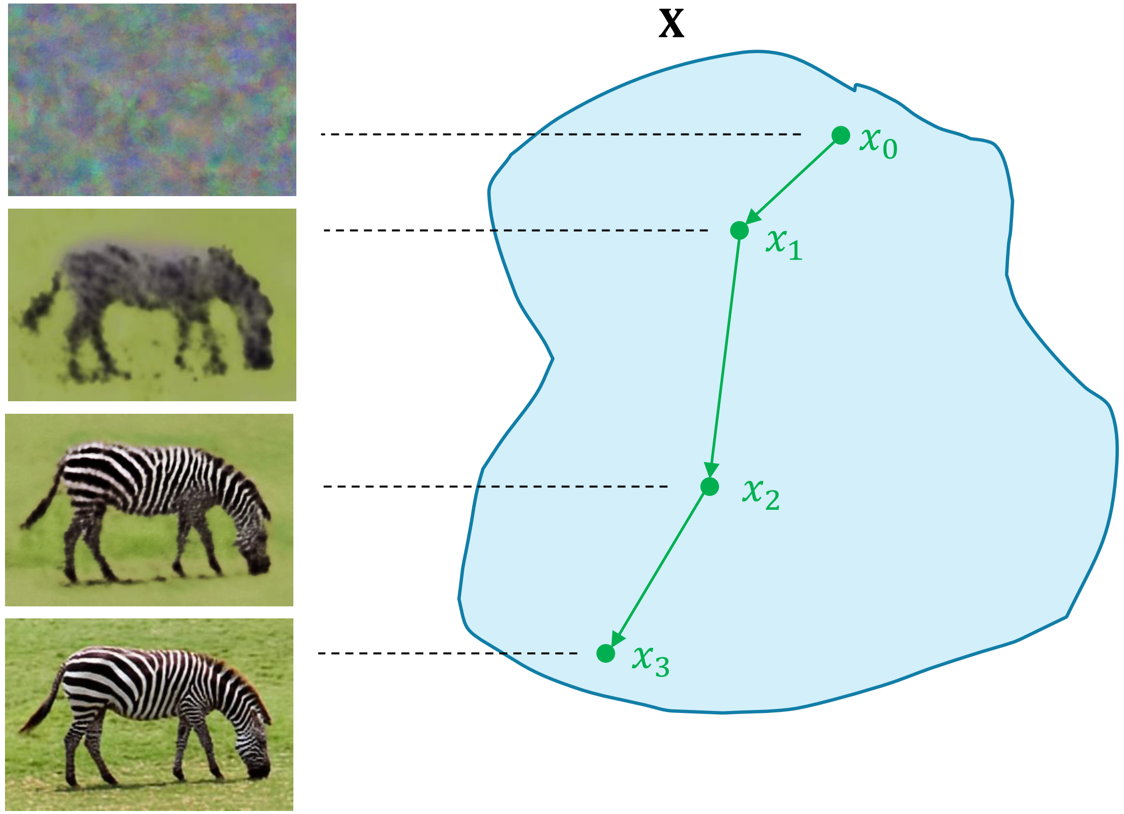
x – *Clean Image*

$\hat{x}$ – *Degraged Image*

x^* – *Restored Image*

In Image Space: $argmin_x E(x, \hat{x}) + R(x)$

REGULAR IMAGE SPACE



$$argmin_x E(x, \hat{x}) + R(x)$$

(Visualization by Pratik Katte, 2019)

PARAMETERIZATION

x $-$ *Clean Image*

$\hat{x}$ $-$ *Degraged Image*

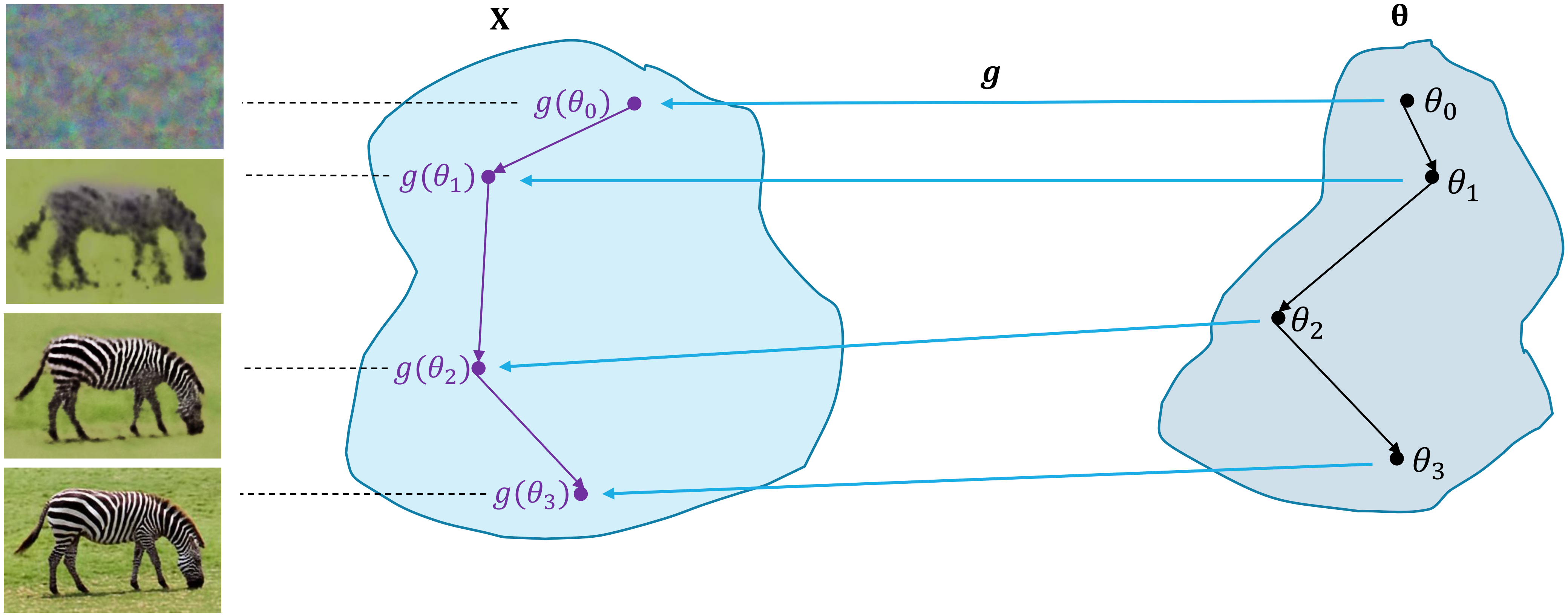
x^* $-$ *Restored Image*

In Image Space: $argmin_x E(x, \hat{x}) + R(x)$

$$g(\theta) = x$$

In Some Parameter Space: $argmin_\theta \underbrace{E(g(\theta), \hat{x})}_{\text{Task-Dependent Term}} + \underbrace{R(g(\theta))}_{\text{Prior}}$

PARAMETER SPACE



$$argmin_\theta E(g(\theta), \hat{x}) + R(g(\theta))$$

(Visualization by Pratik Katte, 2019)

WHY PARAMETERIZATION?

- Here the mapping function g acts as a tunable hyperparameter
- $g(\theta)$ acts as a prior $\rightarrow$ helps choose the best parameter $\rightarrow$ maps to the best output image
- Instead of optimizing both the components, we just optimize the data term now
  - *Easy to optimize*
  - *Contains implicit prior while also being Task-Dependent*

In Theory: If g is surjective ($\mathbf{g}\colon \boldsymbol{\theta} \rightarrow \mathbf{x}$) The solutions from the two equations are: $g(\theta) = x$

In Practice: This is not the case as it would be a local optimization, so the results may differ

OVERVIEW

1. Mathematically: What is Prior?
2. Intuitively: What is a Prior?
3. Implicit and Explicit Prior
4. Deep Image Prior
5. Results
6. Conclusion

NEURAL NETWORK PARAMETERIZATION

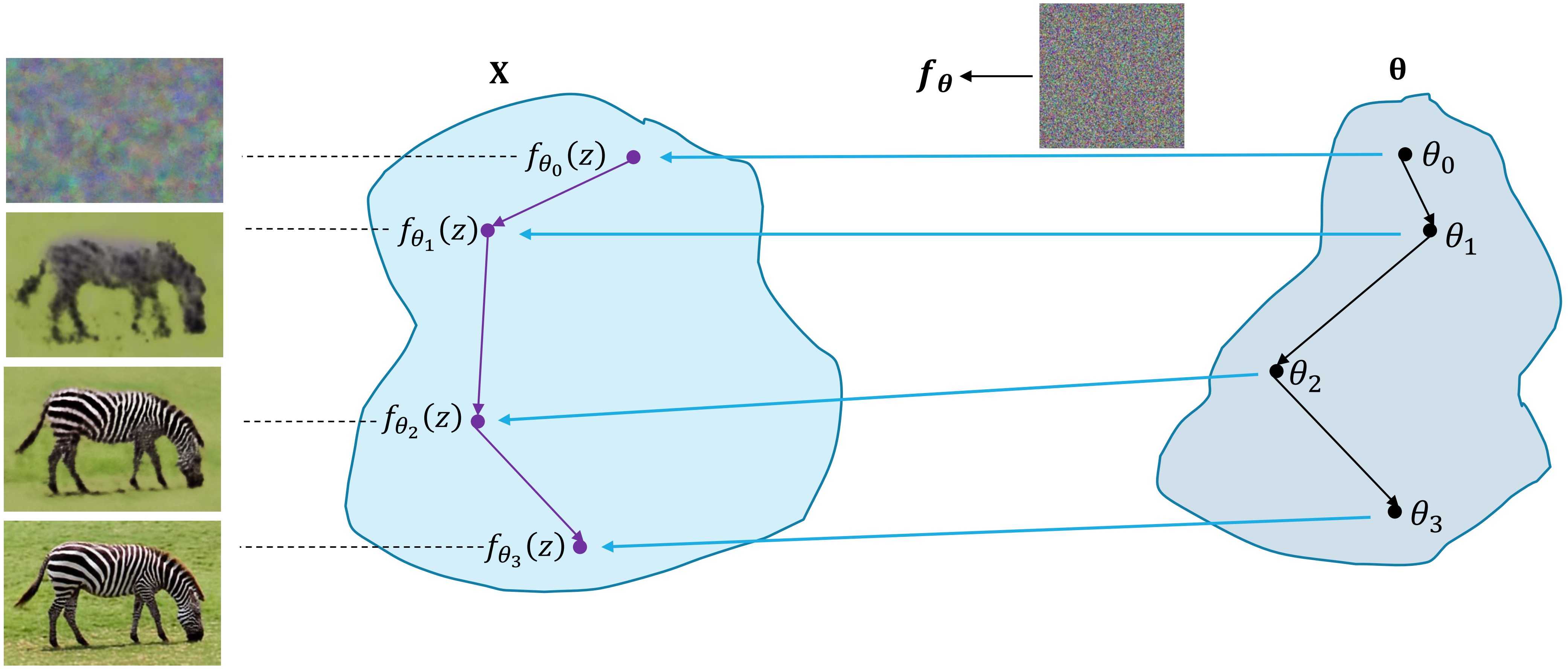
In Some Parameter Space: $argmin_{\theta} E(g(\theta), \hat{x}) + R(g(\theta))$

$$x = g(\theta) \equiv f_{\theta}(z)$$

$\boldsymbol{f_{\theta}}$ $\rightarrow$ Chosen Deep Learning Network with weights θ

$\boldsymbol{z}$ $\rightarrow$ Fixed Input Image

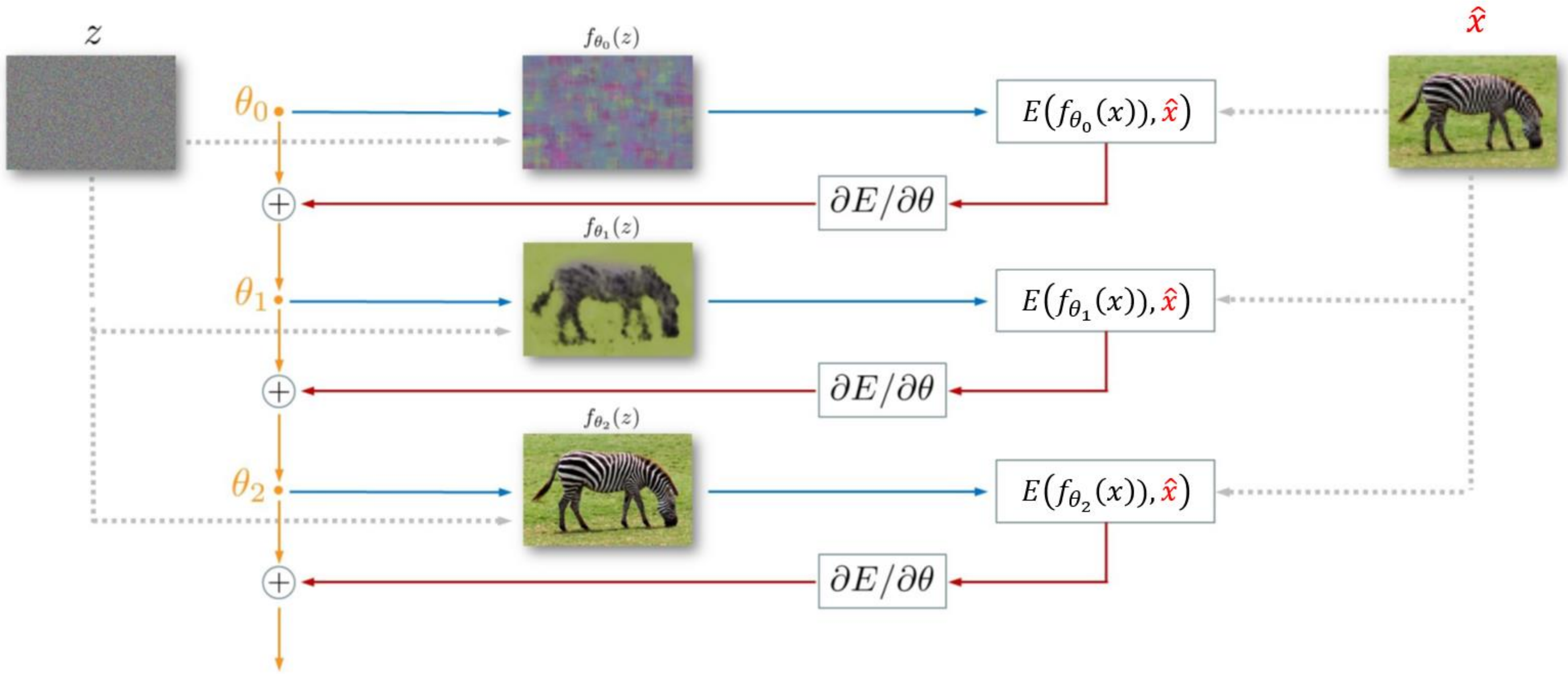
NEURAL NETWORK PARAMETER SPACE



$$argmin_\theta E(f_\theta(\mathrm{z}), \hat{x}) + R(f_\theta(\mathrm{z}))$$

(Visualization by Pratik Katte, 2019)

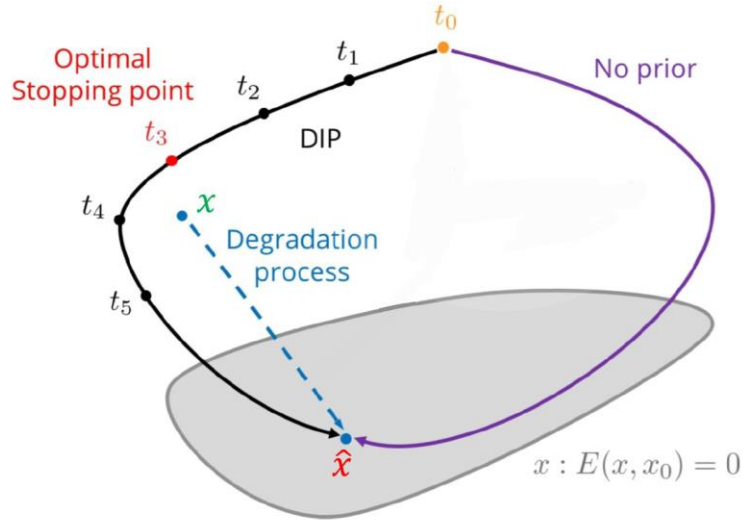
METHODOLOGY



Parameter optimization process using Deep Image Prior

OPTIMIZATION WITH PRIORS

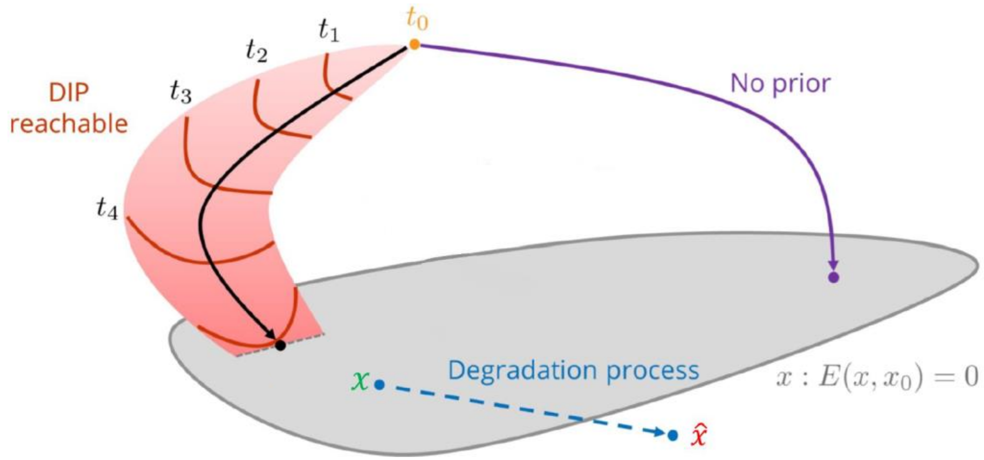
Denoising a noisy image



With Prior: Good image at t_3, but after further optimization returns corrupted image

No Prior: Corrupted image is the restored image

Super-Resolution

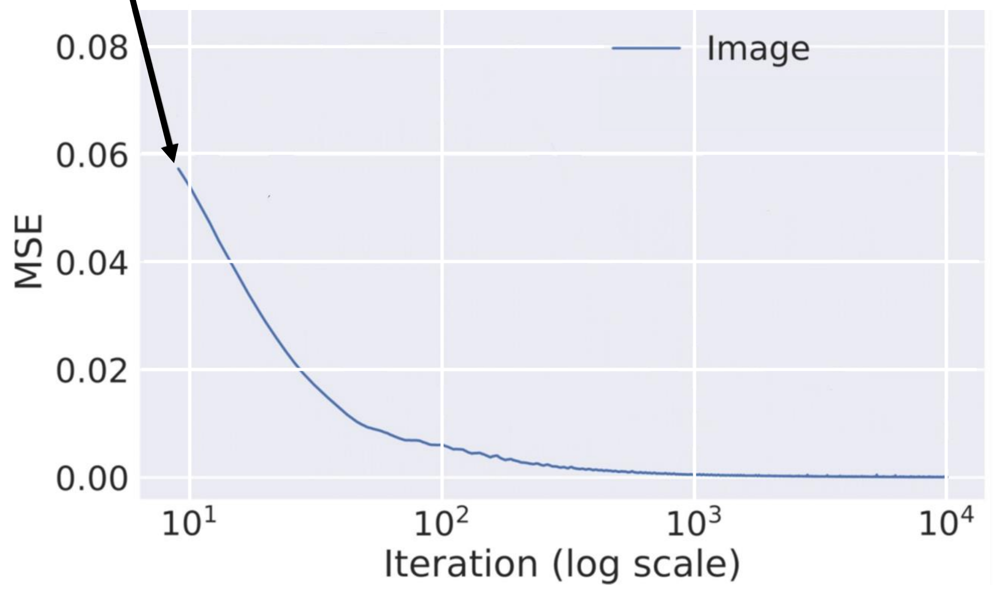


With Prior: When fully optimized, the restored image would be close to the actual image x

No Prior: Restored image is far from actual image

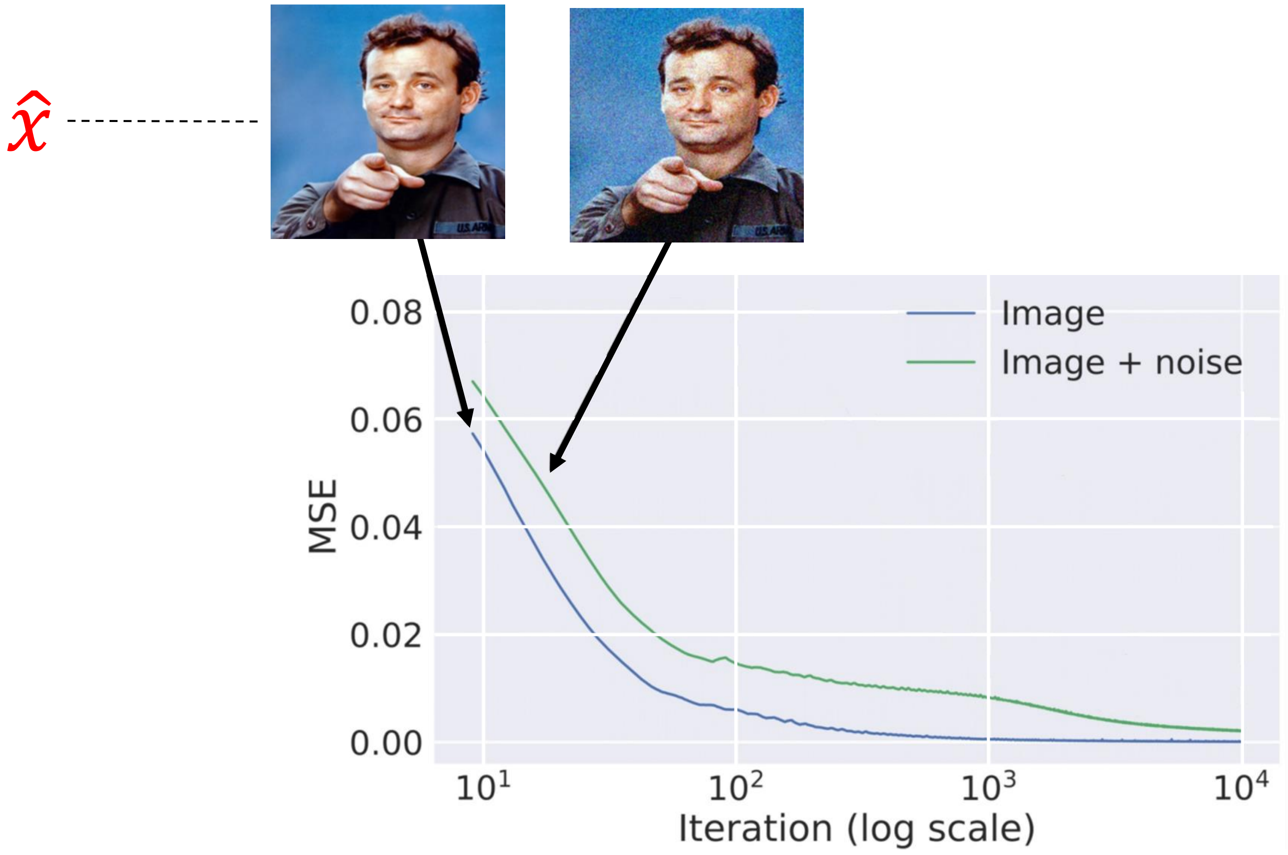
LEARNING CURVES

$\hat{x}$



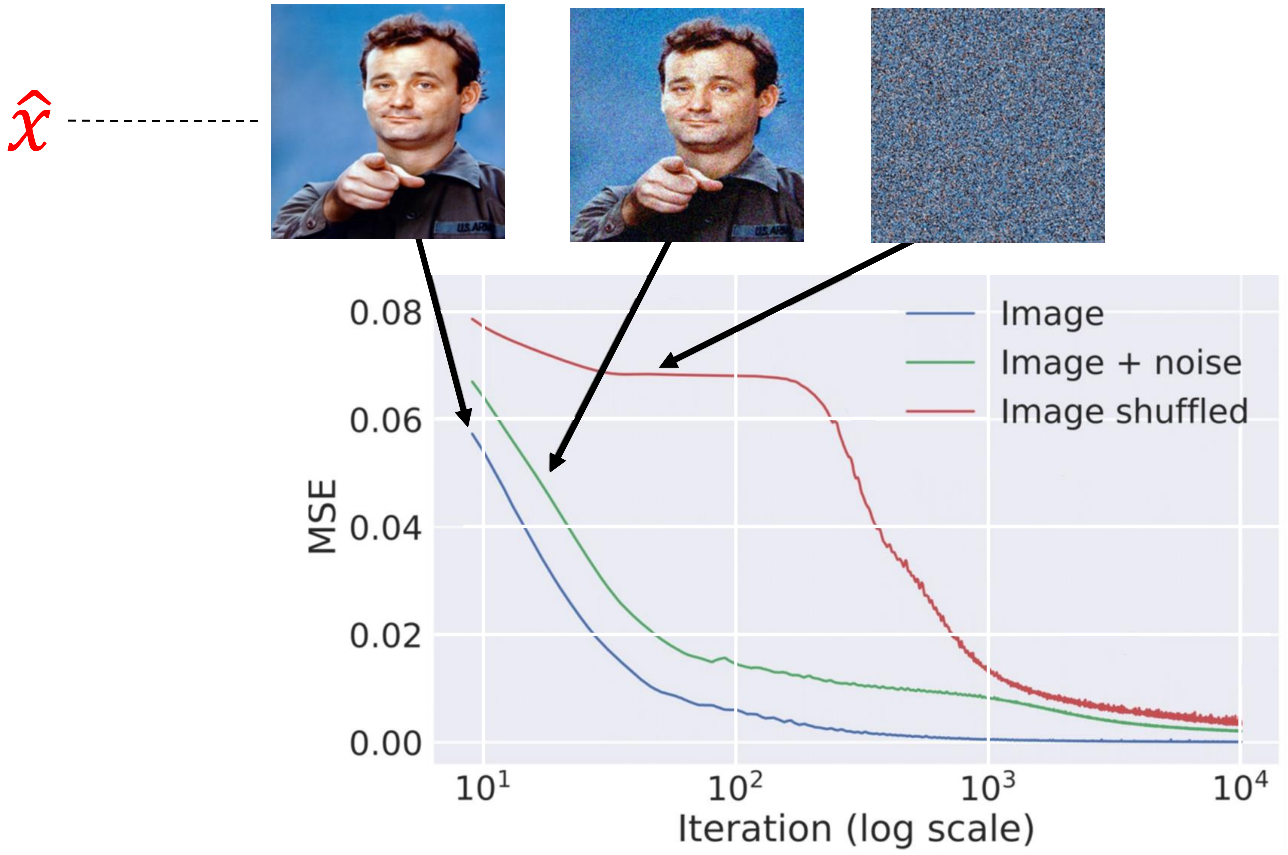
$$E(x, \hat{x}) = ||x - \hat{x}||^2$$

LEARNING CURVES



$$E(x, \hat{x}) = ||x - \hat{x}||^2$$

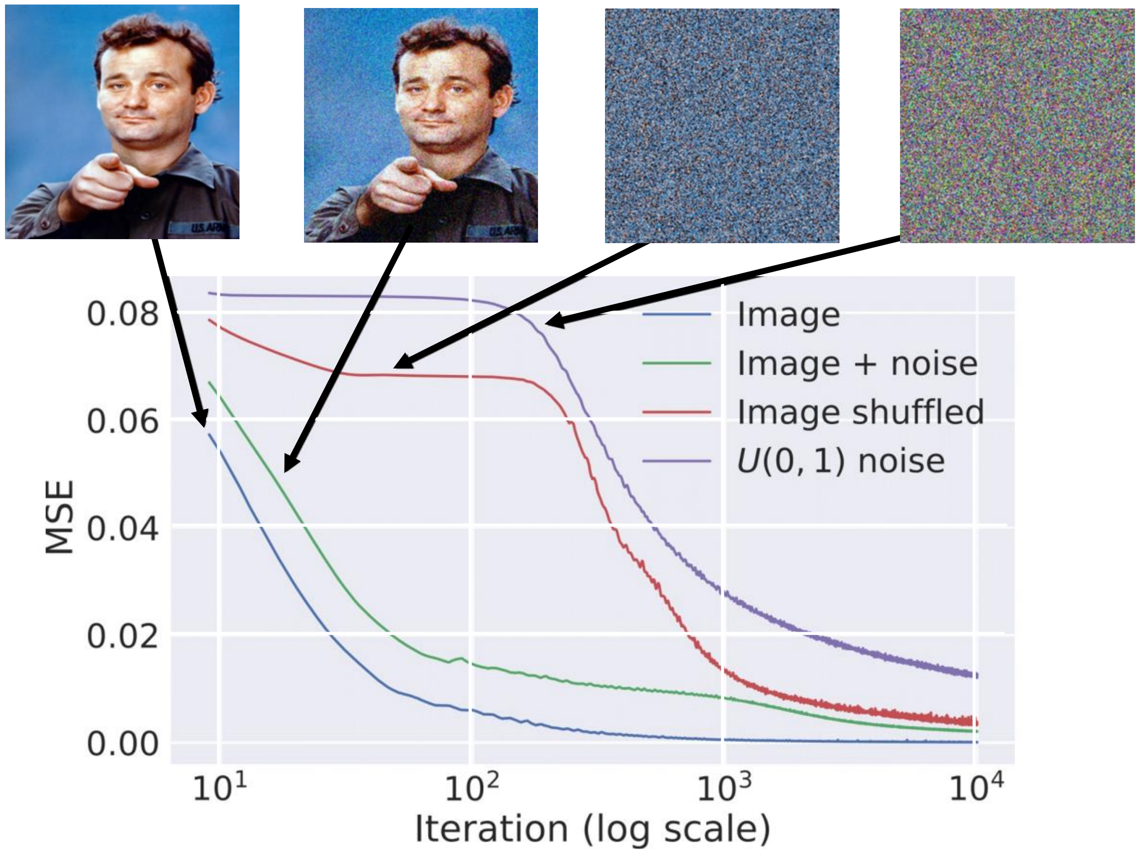
LEARNING CURVES



$$E(x, \hat{x}) = ||x - \hat{x}||^2$$

LEARNING CURVES

$\hat{x}$



$$E(x, \hat{x}) = ||x - \hat{x}||^2$$

OVERVIEW

1. Mathematically: What is Prior?
2. Intuitively: What is a Prior?
3. Implicit and Explicit Prior
4. Deep Image Prior
5. Results
6. Conclusion

DENOISING

Corrupted Image

Generated Image

DENOISING

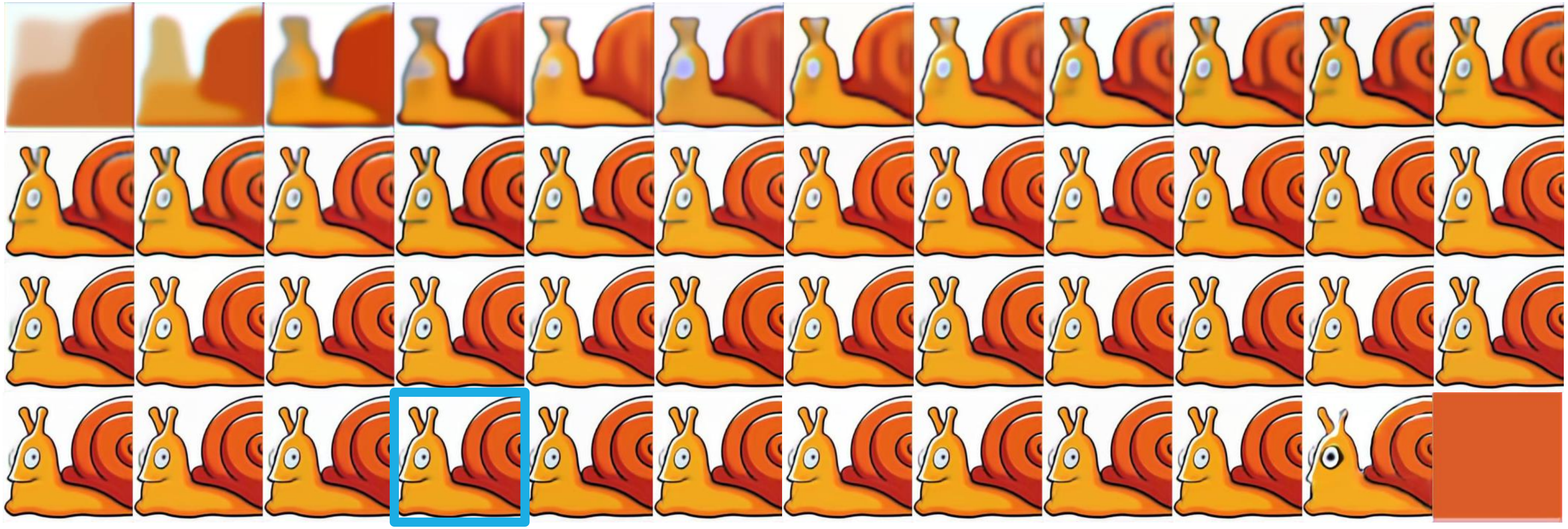
Iteration
0

Iteration
300

Iteration
900

Iteration
1900

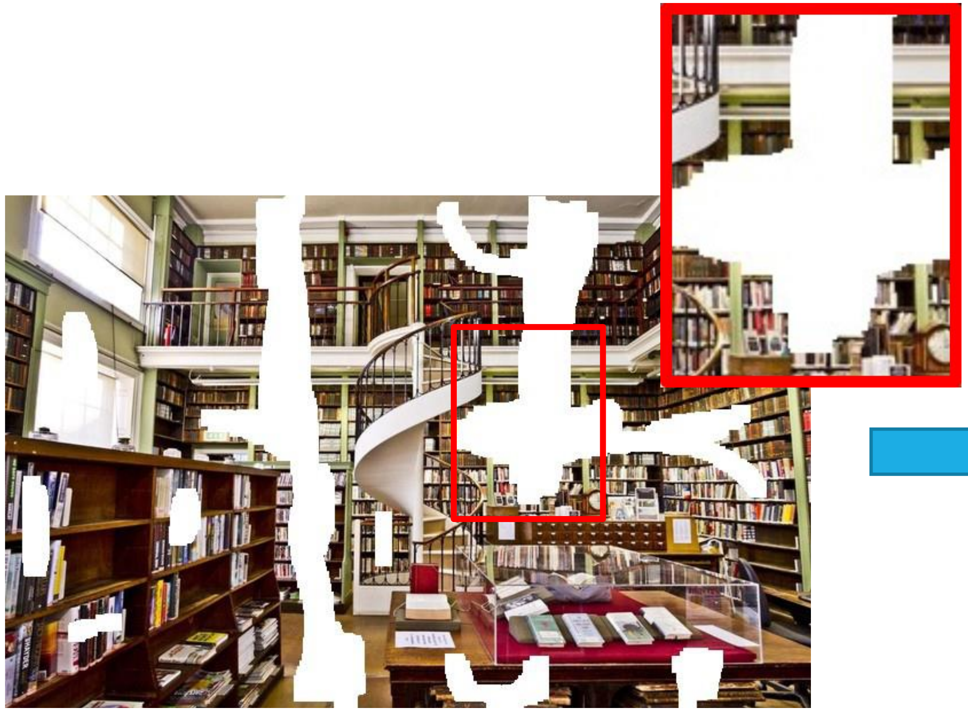
DENOISING



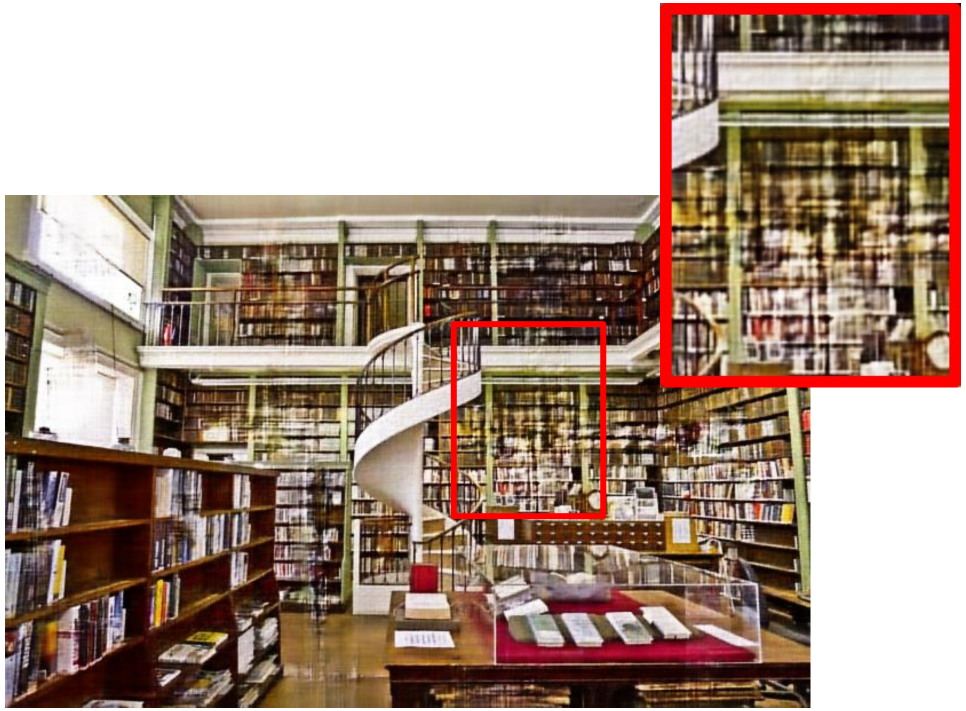
Problems of Overfitting

https://www.reddit.com/r/MachineLearning/comments/7gls3j/r_deep_image_prior_deep_superresolution/dqkcocp/?utm_source=share&utm_medium=web2x&context=3

INPAINTING



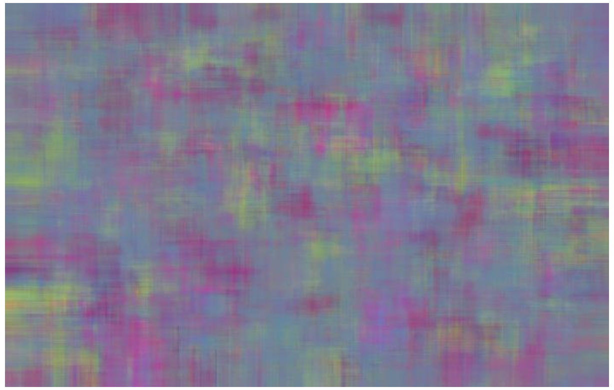
Corrupted Image



Generated Image

INPAINTING

Iteration 0

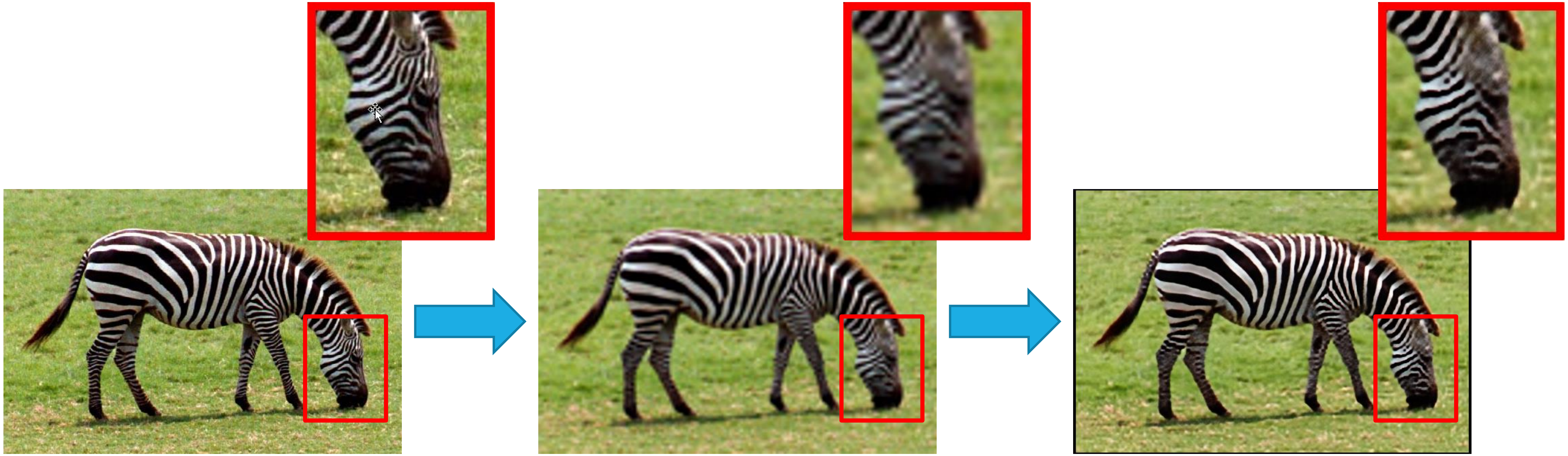


Iteration 300

Iteration 1450

Iteration 2000

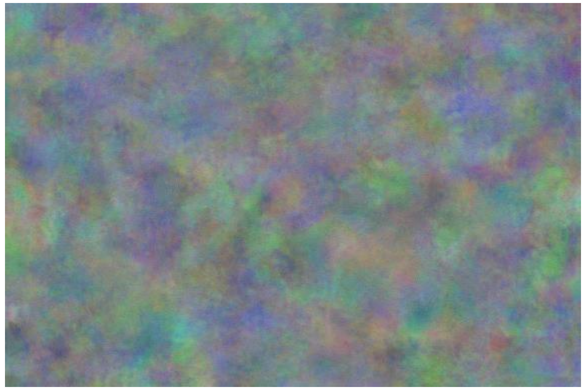
SUPER RESOLUTION



Original Image | Downsampled Image | Generated Image

SUPER RESOLUTION

Iteration
0



Iteration
150

Iteration
700

Iteration
1600

OVERVIEW

1. Mathematically: What is Prior?
2. Intuitively: What is a Prior?
3. Implicit and Explicit Prior
4. Deep Image Prior
5. Results
6. Conclusion

CONCLUSION

- The paper suggests –
  - Huge dataset is not the only factor that helps networks learn the features
  - Even the network architecture holds capability to capture prior information

- The current model does not have direct practical applications –
  - It takes many iterations to perform any restoration task
  - Models trained with huge datasets can perform inference in just one forward pass

- The author does not claim this to be a SOTA model for image restoration
  - Instead, this paper opens new research areas in deep learning which have not been explored before

BIBLIOGRAPHY

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

- Deep Image Prior [https://dmitryulyanov.github.io/deep_image_prior]

- Pratik Katte. "Demystifying - Deep Image Prior." 2019 [https://towardsdatascience.com/demystifying-deep-image-prior-7076e777e5ba]