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# Ultrasound Image Enhancement with the Variance of Diffusion Models

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**Presenter**: Yuxin Zhang

23 – Sept. – 2024

MIS: Image Enhancement 1 (A3L-01)

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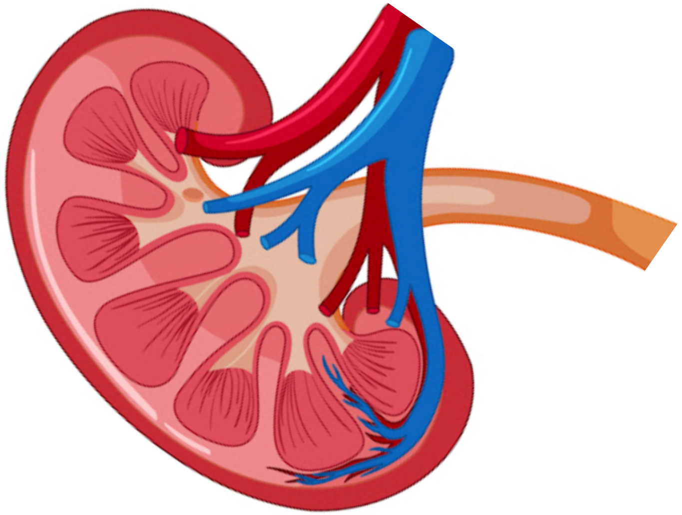
CENTRALE NANTES

# ROAD MAP

1. Introduction — Ultrasound Imaging, Modeling, and SOTA
2. Method — Linear Adaptive Beamforming, Diffusion Variance Imaging
3. Results — Quantitative & Qualitative Comparison
4. Conclusion — Take-home Message

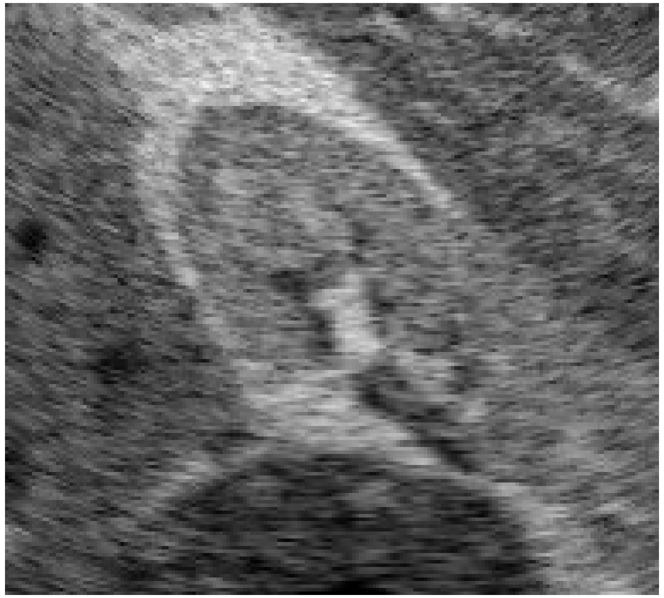
# Ultrasound Image Enhancement



Echogenicity map

(average property of the tissue)

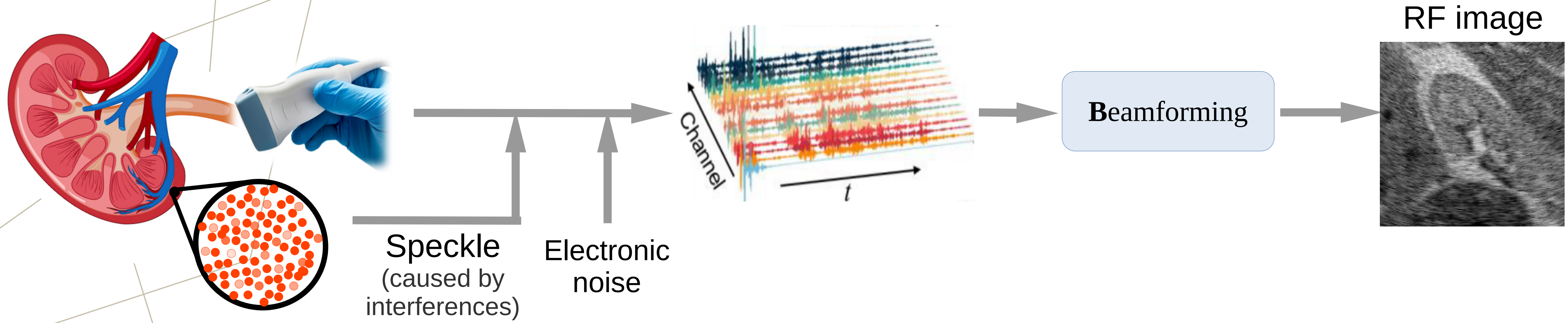
Observation



Ultrasound Image Enhancement benefits organ and tumor Classification and Segmentation.

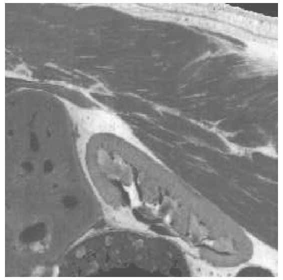
https://field-ii.dk/?examples/kidney_example/kidney_example.html
https://fr.vecteezy.com/art-vectoriel/7637674-organe-interne-humain-avec-rein

# Approximation of the Ultrasound Imaging Process

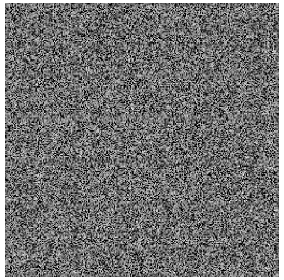



$\mathbf{p} \odot \mathbf{m}$ → PSF $\mathbf{BH}$ → $\oplus$ → $\mathbf{f}$

$\mathbf{n}$



Echogenicity map



Random field $\sim \mathcal{N}(\mathbf{0}, \boldsymbol{I})$

$$\mathbf{f} = \mathbf{BH}\left(\mathbf{m} \odot \mathbf{p}\right) + \mathbf{n}$$

# State-of-the-Art

$$\underbrace{\mathbf{f}}_{\text{RF image}} = \overbrace{\underbrace{\mathbf{BH}}_{\text{PSF}}}^{\text{Convolution}} \left( \overbrace{\underbrace{\mathbf{m}}_{\sim \mathcal{N}(\mathbf{0},\mathbf{I})}}^{\text{Speckle}} \odot \mathbf{p} \right) + \overbrace{\underbrace{\mathbf{n}}_{\sim \mathcal{N}(\mathbf{0},\gamma\mathbf{I})}}^{\text{Noise}}$$

**Deconvolution & Despeckling & Denoising**

*Remove the effect of* $\boldsymbol{BH}, \boldsymbol{n}$ *Estimate* $\boldsymbol{m} \odot \boldsymbol{p}$

[S. Goudarzi, TUFFC 2022, E. Ozkan, TUFFC 2018,
A. Besson Trans. Comput. Imag. 2019] Inverse Problem Solving

[Y. Zhang, DGM4MICCAI, 2023, S. Goudarzi, Utrasonics 2022,
D. Perdios, TMI 2022, J. Zhang, Med. Image Anal. 2021] ML

**Deconvolution & Despeckling & Denoising**

*Remove* $\boldsymbol{m}$ $(\textit{ignore}\ \boldsymbol{BH}, \boldsymbol{n})$ *Estimate* $\boldsymbol{p}$

[G. Ramos-Llordén, TIP 2015] Anisotropic Diffusion
[P. Coupe, TIP 2009] NonLocal Means
[S. Balocco, Ultrasound Med. Biol. 2010] Bilateral Filter
[S. Esakkirajan, Ultrasound Med. Biol 2013] Wavelet
[D. Mishra, ICPR 2018, C.-C. Shen, Sensors 2020] ML

## State-of-the-Art

Convolution — Speckle — Noise

$$\underbrace{\mathbf{f}}_{\text{RF image}} = \underbrace{\mathbf{BH}}_{\text{PSF}} \left( \underbrace{\mathbf{m}}_{\sim\mathcal{N}(\mathbf{0},\mathbf{I})} \odot \mathbf{p} \right) + \underbrace{\mathbf{n}}_{\sim\mathcal{N}(\mathbf{0},\gamma\mathbf{I})}$$

**Deconvolution & Despeckling & Denoising**

*Remove the effect of* $\boldsymbol{A}, \boldsymbol{n}$ *Estimate* $\boldsymbol{m} \odot \boldsymbol{p}$

A. Besson Trans. Comput. Imag. 2019] Inverse Problem Solving

[Y. Zhang, DGM4MICCAI, 2023, S. Goudarzi, Utrasonics 2022, D. Perdios, TMI 2022, J. Zhang, Med. Image Anal. 2021] ML

**Deconvolution & Despeckling & Denoising**

*Remove* $\boldsymbol{m}$ $(\textit{ignore } \boldsymbol{A}, \boldsymbol{n})$ *Estimate* $\boldsymbol{p}$

[P. Coupe, TIP 2009] NonLocal Means
[S. Balocco, Ultrasound Med. Biol. 2010] Bilateral Filter
[S. Esakkirajan, Ultrasound Med. Biol 2013] Wavelet
[D. Mishra, ICPR 2018, C.-C. Shen, Sensors 2020] ML

**We estimate p by tackling all 3 degradation effects**

**Deconvolution & Despeckling & Denoising**

*Remove the effect of* $\boldsymbol{BH}, \boldsymbol{m}, \boldsymbol{n}$ *Estimate* $\boldsymbol{p}$

[James Ng, TUFFC 2007] Wavelet
**[Y. Zhang, EUSIPCO 2024] ML**

# Overview of the Proposed Method

$$\underbrace{\mathbf{f}}_{\substack{\text{RF image} \\ (EBMV)}} = \overbrace{\mathbf{B}_{\text{EBMV}}\mathbf{H}}^{\text{Convolution}} \left( \overbrace{\underbrace{\mathbf{m}}_{\sim \mathcal{N}(\mathbf{0},\mathbf{I})}}^{\text{Speckle}} \odot \mathbf{p} \right) + \overbrace{\underbrace{\mathbf{n}}_{\sim \mathcal{N}(\mathbf{0},\gamma\mathbf{I})}}^{\text{Noise}}$$

**Deconvolution** — STEP 1 — Adaptive Beamforming

**Denoising** — STEP 2 — Obtain several estimations of $\mathbf{m} \odot \mathbf{p}$ via a Diffusion Denoiser

**Despeckling** — STEP 3 — Estimate $\mathbf{p}$ by leveraging the stochasticity of the generative sampling

# Overview of the Proposed Method

$$\underbrace{\mathbf{f}}_{\text{RF image }(EBMV)} = \underbrace{\mathbf{B}_{\text{EBMV}}\mathbf{H}}_{\text{Convolution}} \Big( \underbrace{\mathbf{m}}_{\text{Speckle} \sim \mathcal{N}(\mathbf{0},\mathbf{I})} \odot \mathbf{p} \Big) + \underbrace{\mathbf{n}}_{\text{Noise} \sim \mathcal{N}(\mathbf{0},\gamma\mathbf{I})}$$

**Deconvolution** STEP 1 Adaptive Beamforming

**Denoising** STEP 2 Obtain several estimations of $\mathbf{m} \odot \mathbf{p}$ via a Diffusion Denoiser

**Despeckling** STEP 3 Estimate $\mathbf{p}$ by leveraging the stochasticity of the generative sampling

# Overview of the Proposed Method

Convolution Speckle Noise

$$\underbrace{\mathbf{f}}_{\substack{\text{RF image} \\ (\textit{EBMV})}} = \mathbf{B}_{\text{EBMV}}\mathbf{H}\left(\underbrace{\mathbf{m}}_{\sim\mathcal{N}(\mathbf{0},\mathbf{I})} \odot \mathbf{p}\right) + \underbrace{\mathbf{n}}_{\sim\mathcal{N}(\mathbf{0},\gamma\mathbf{I})}$$

Deconvolution

STEP 1 Adaptive Beamforming

$$\mathbf{B}_{\text{DAS}}\mathbf{H} \approx \mathbf{I} \quad ✗$$

$$\mathbf{B}_{\text{EBMV}}\mathbf{H} \approx \mathbf{I} \quad ✓$$

$$\underbrace{\mathbf{f}}_{\substack{\text{RF image} \\ (\textit{EBMV})}} = \underbrace{\mathbf{m}}_{\sim\mathcal{N}(\mathbf{0},\mathbf{I})} \odot \mathbf{p} + \underbrace{\mathbf{n}}_{\sim\mathcal{N}(\mathbf{0},\gamma\mathbf{I})}$$

# Overview of the Proposed Method

$$\underbrace{\mathbf{f}}_{\substack{\text{RF image} \\ (EBMV)}} = \underbrace{\mathbf{m}}_{\sim\mathcal{N}(\mathbf{0},\mathbf{I})} \odot \mathbf{p} + \underbrace{\mathbf{n}}_{\sim\mathcal{N}(\mathbf{0},\gamma\mathbf{I})}$$

**Deconvolution** — STEP 1 — Adaptive Beamforming

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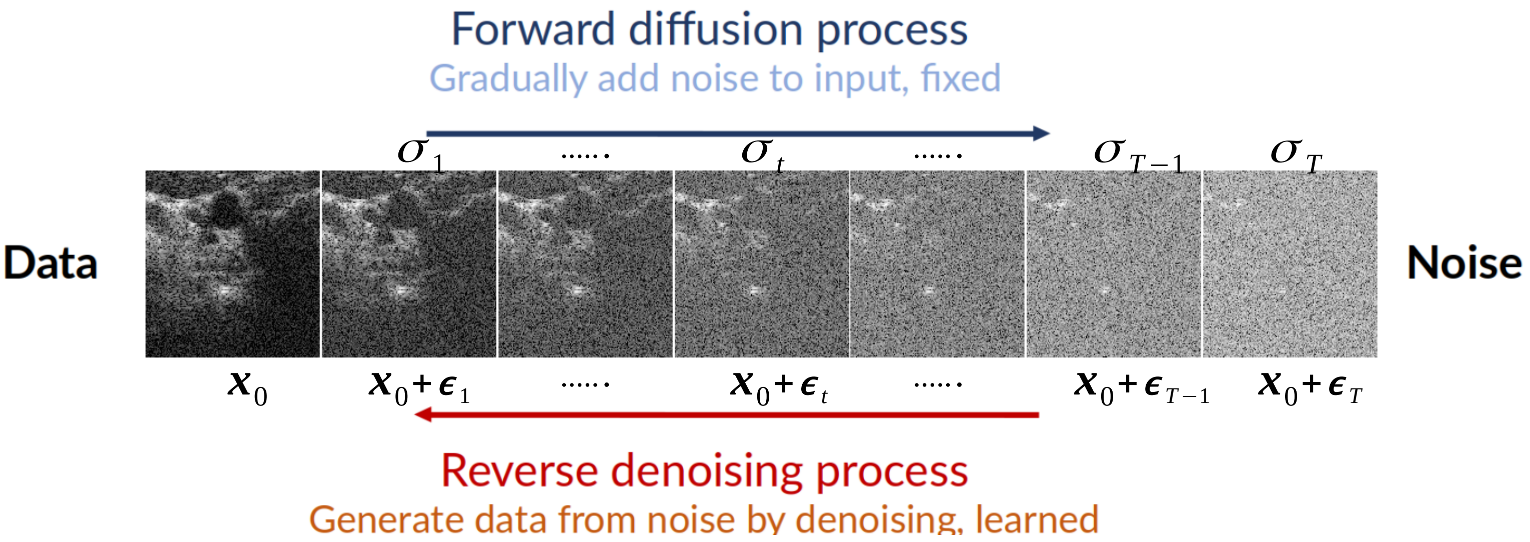
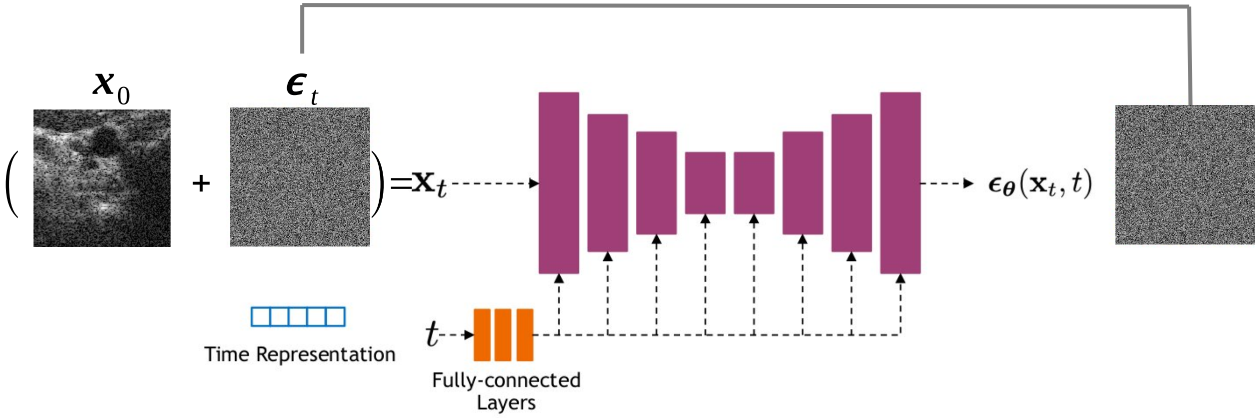
**Despeckling** — STEP 3 — Estimate $\mathbf{p}$ by leveraging the stochasticity of the generative sampling

# Denoising Diffusion Generative Models



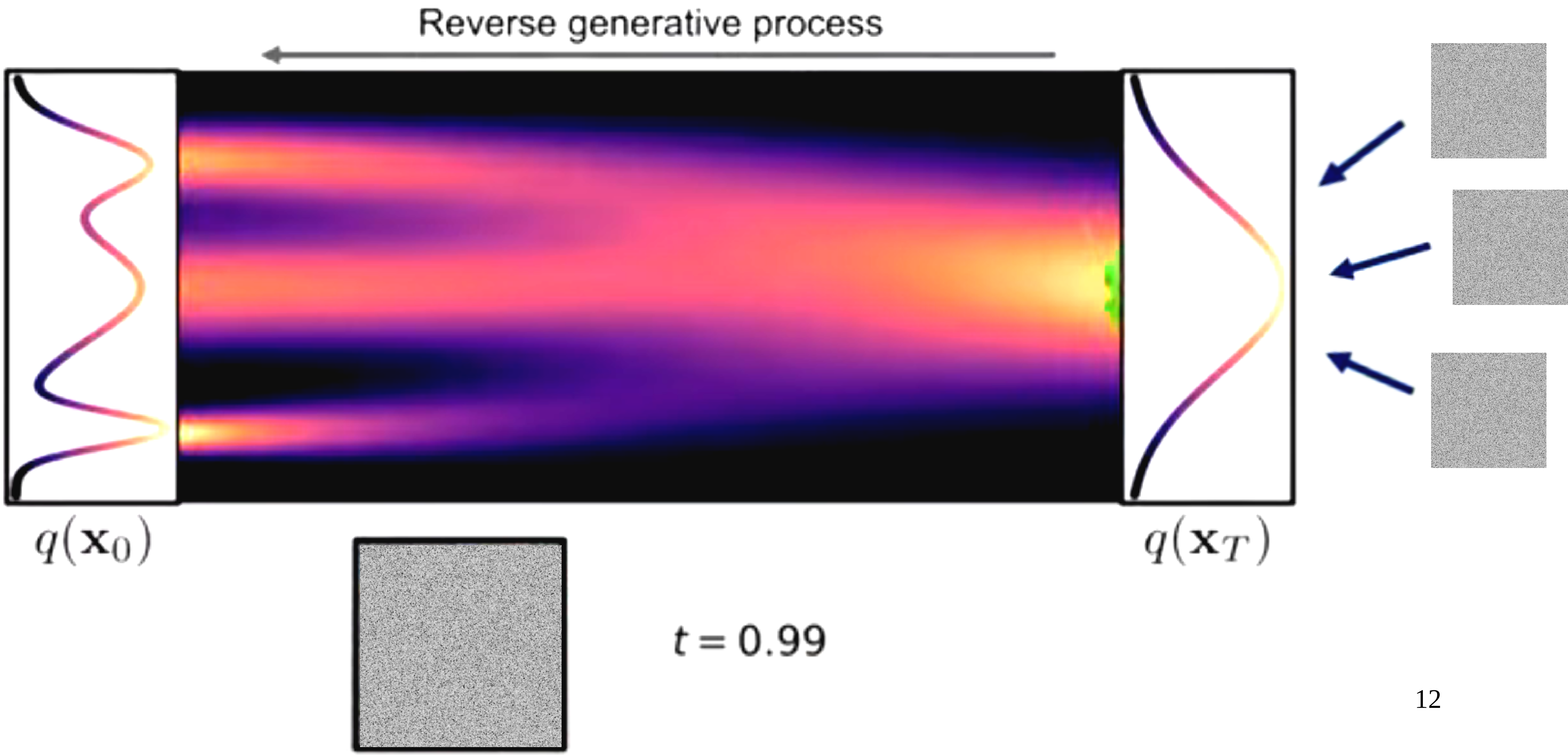




$$simpleLoss = \mathbb{E}_{\mathbf{x}_0\sim p_{\text{data}}}\mathbb{E}_{\boldsymbol{\epsilon}_t\sim\mathcal{N}(\mathbf{0},\sigma_t \boldsymbol{I})}\|\epsilon_\theta(x_t,t)-\epsilon_t\|_2^2$$

P. Dhariwal and A. Nichol, Diffusion models beat GANs on image synthesis, NeurIPS, 2021
A. Q. Nichol and P. Dhariwal, Improved Denoising Diffusion Probabilistic Models, ICML, 2021

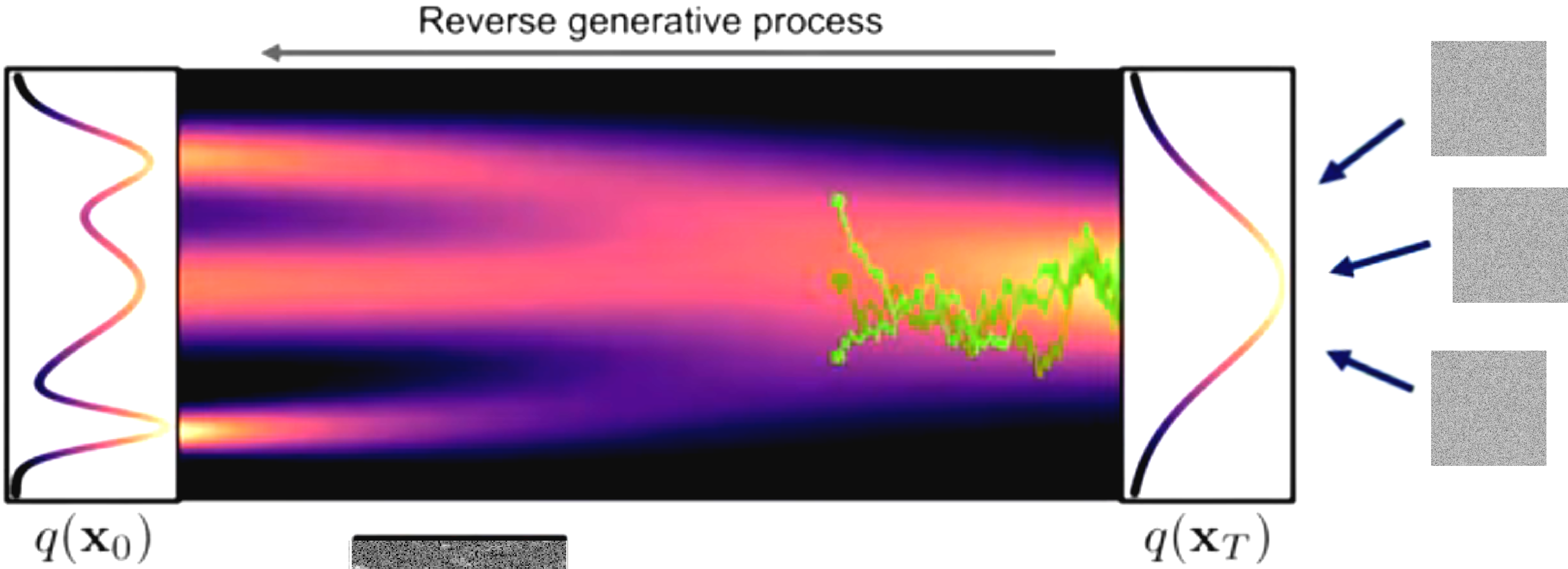
# Diffusion Generative Process

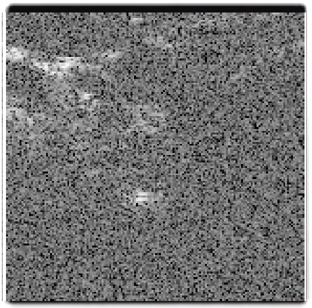
Unconditional



# Diffusion Generative Process

Unconditional

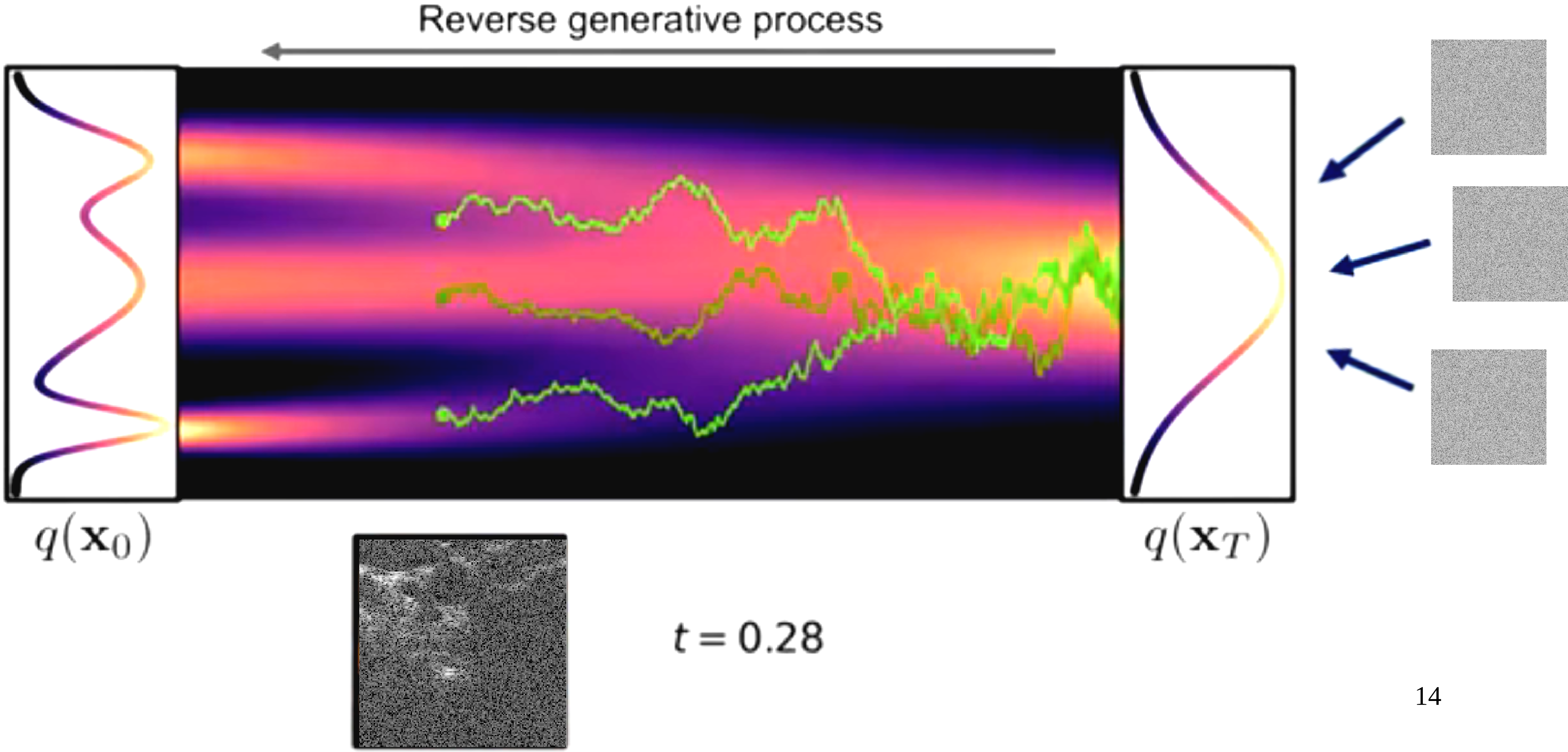


$t = 0.70$

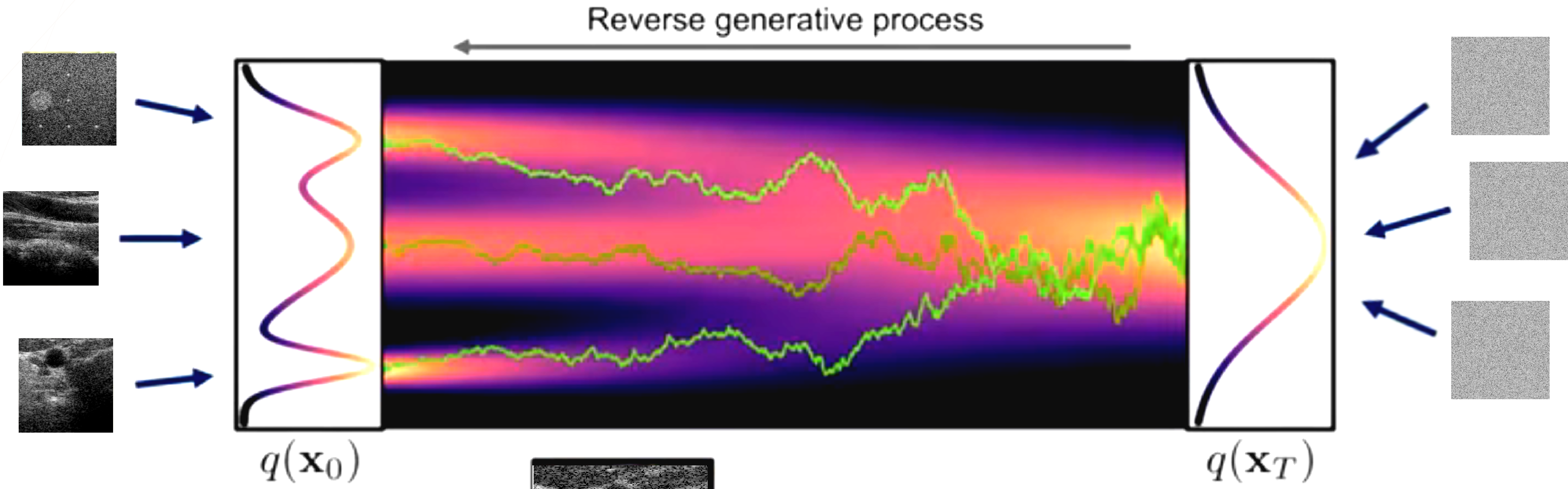
# Diffusion Generative Process

Unconditional



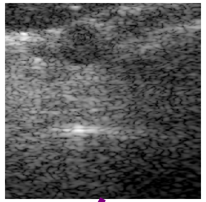
# Diffusion Generative Process

Unconditional




# Diffusion Reconstruction of Ultrasound Images

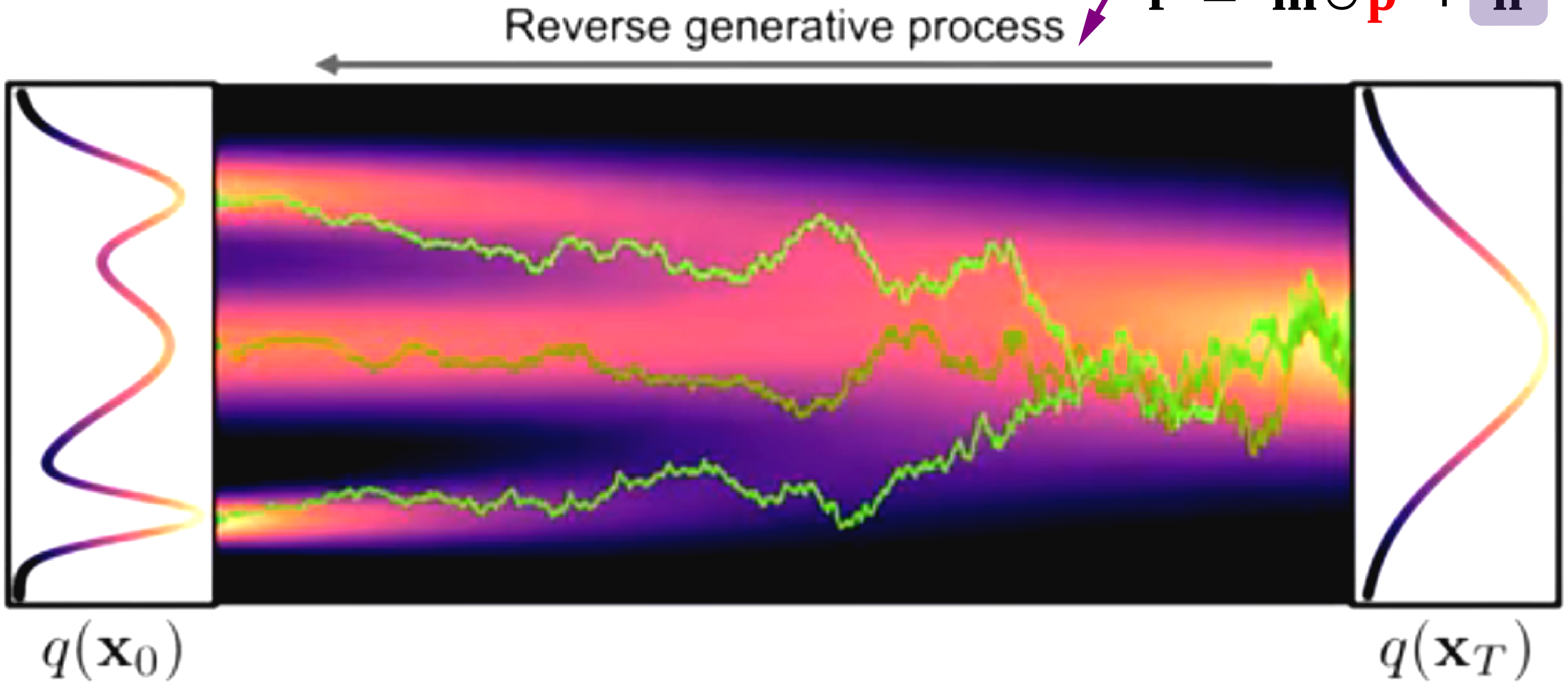
**Conditional**



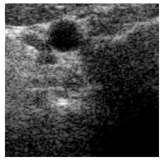
$\mathbf{f}$ (RF image)

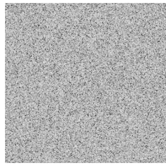
std is a parameter

$$\mathbf{f} = \mathbf{m} \odot \mathbf{p} + \mathbf{n}$$




$$\widehat{(\mathbf{m} \odot \mathbf{p})}$$





Y. Zhang et al., Ultrasound image reconstruction with denoising diffusion restoration models. MICCAI, 2023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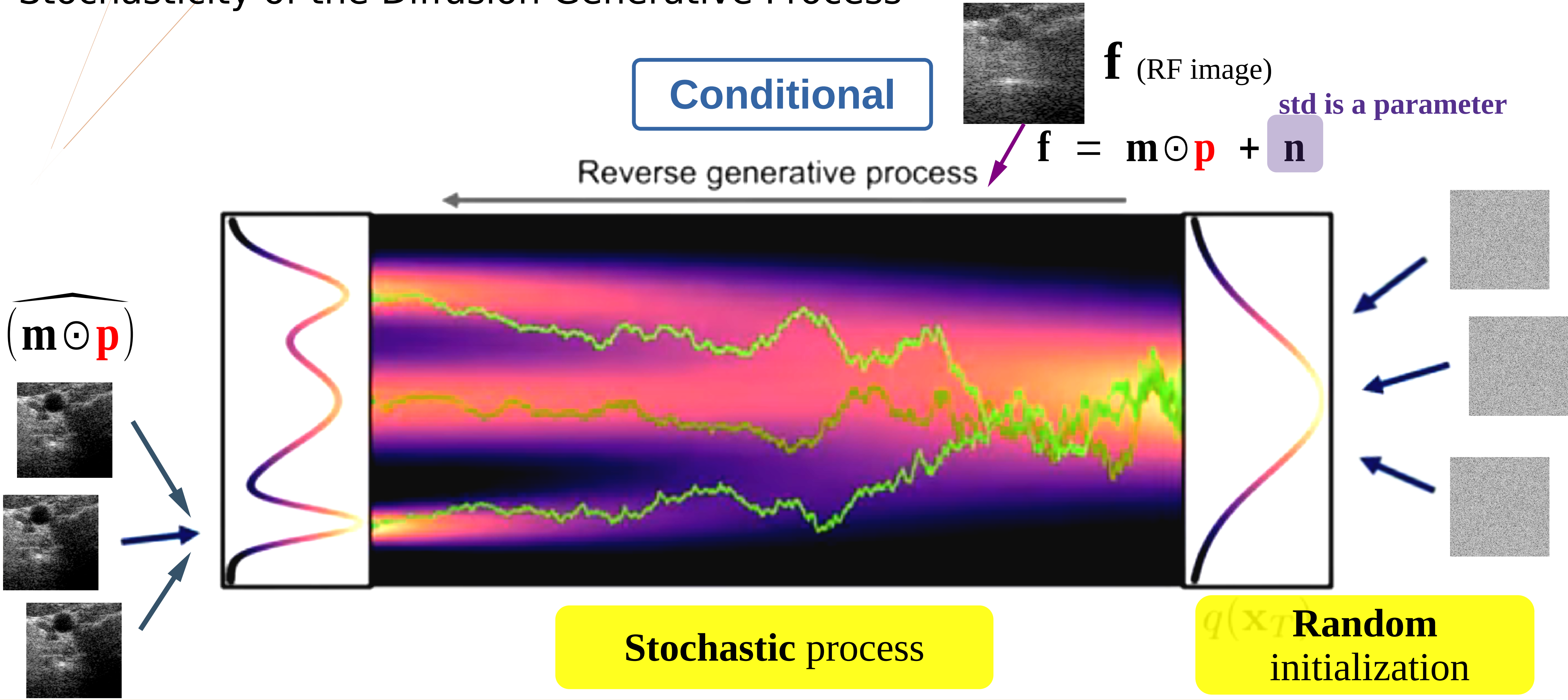
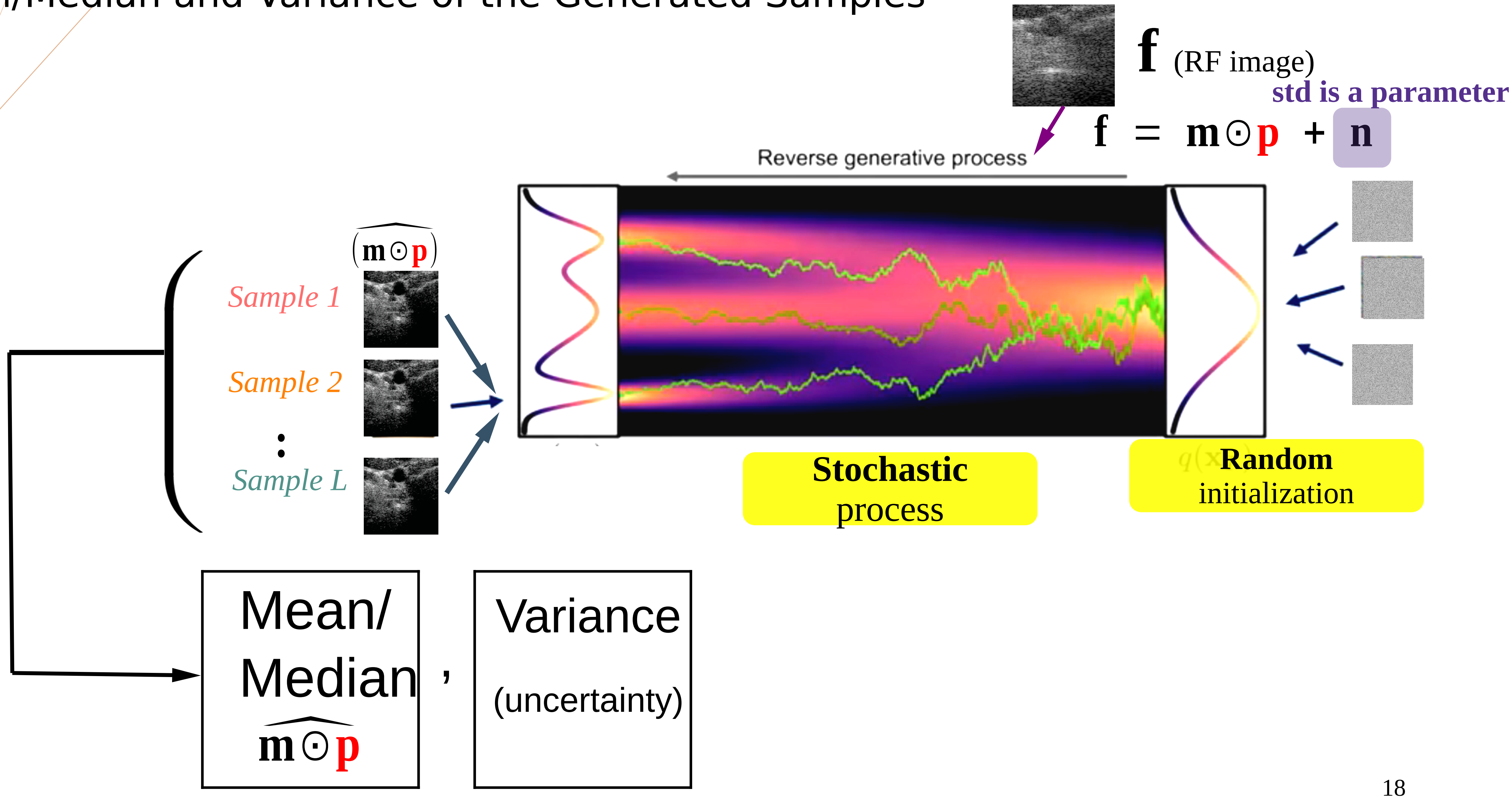
# Stochasticity of the Diffusion Generative Process




We can generate unlimited number of **different** $\widehat{(\mathbf{m} \odot \mathbf{p})}$ from a **single observation**

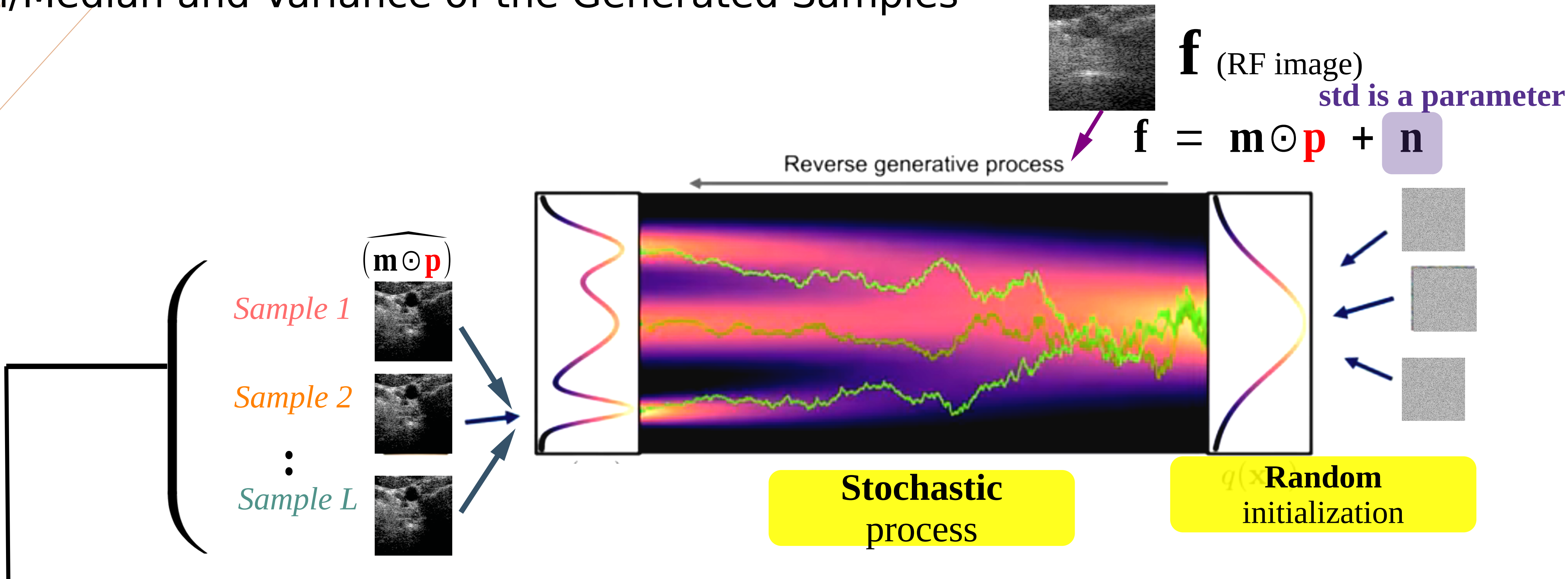
# Mean/Median and Variance of the Generated Samples






Chung, H. et al., Score-based diffusion models for accelerated MRI. Medical image analysis, 2022

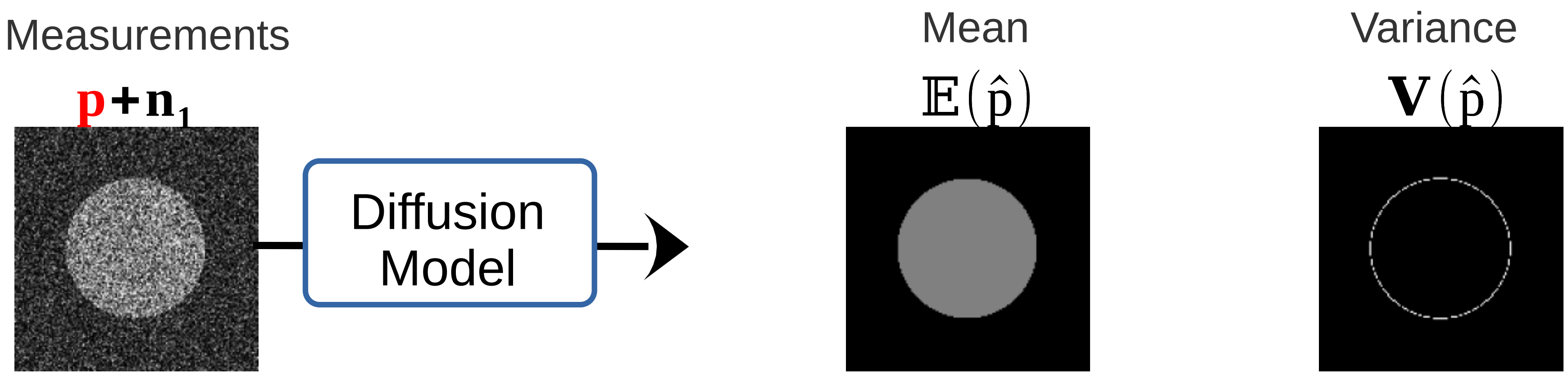
# Mean/Median and Variance of the Generated Samples




**Diffusion Variance is proportional to the level of the multiplicative noise (p)**

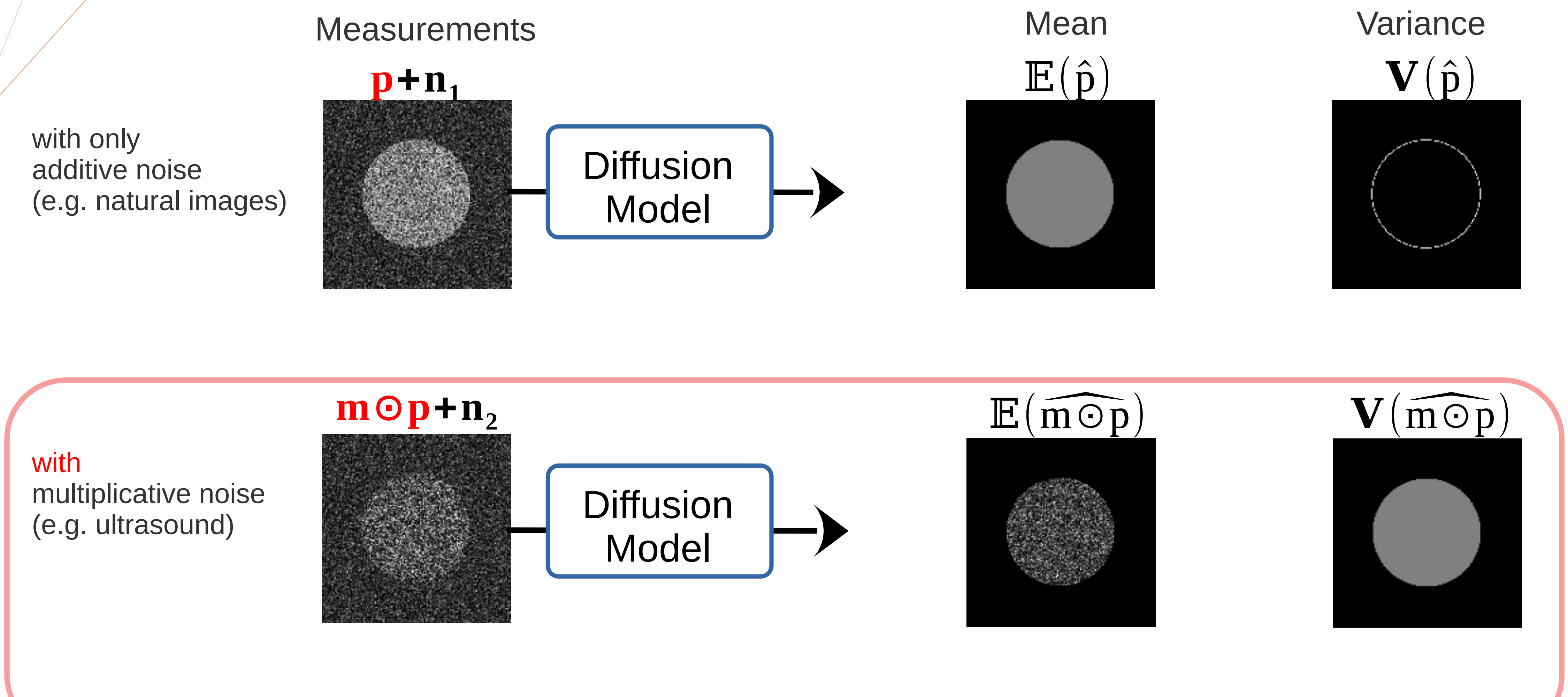
# Diffusion Variance Behavior

with only
additive noise
(e.g. natural images)




Kawar, B. et al., SNIPS: Solving noisy inverse problems stochastically. NeurIPS, 2021

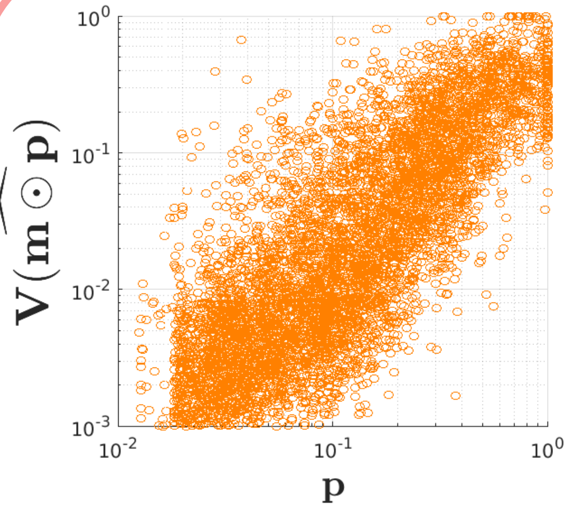
# Diffusion Variance Behavior



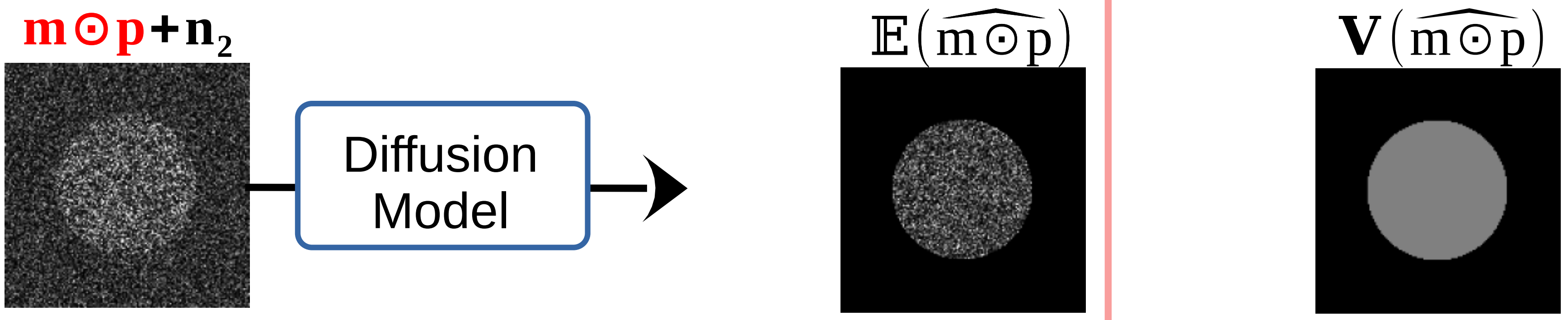

**Variance of diffusion samples inform the level of the multiplicative noise**

# Diffusion Variance Behavior

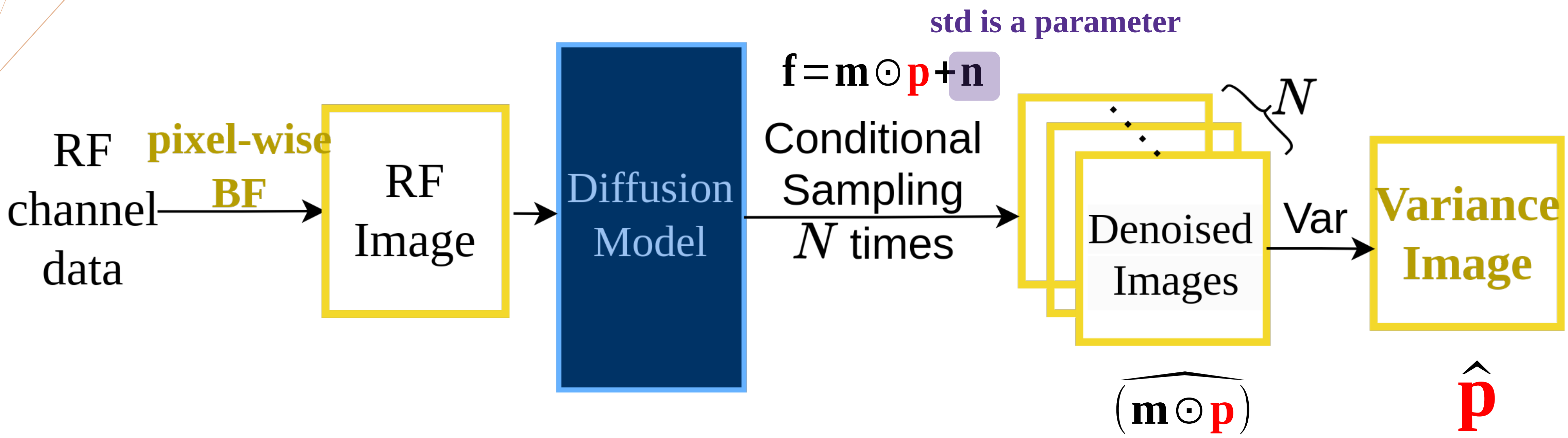
**Variance of diffusion samples inform the level of the multiplicative noise**




with
multiplicative noise
(e.g. ultrasound)



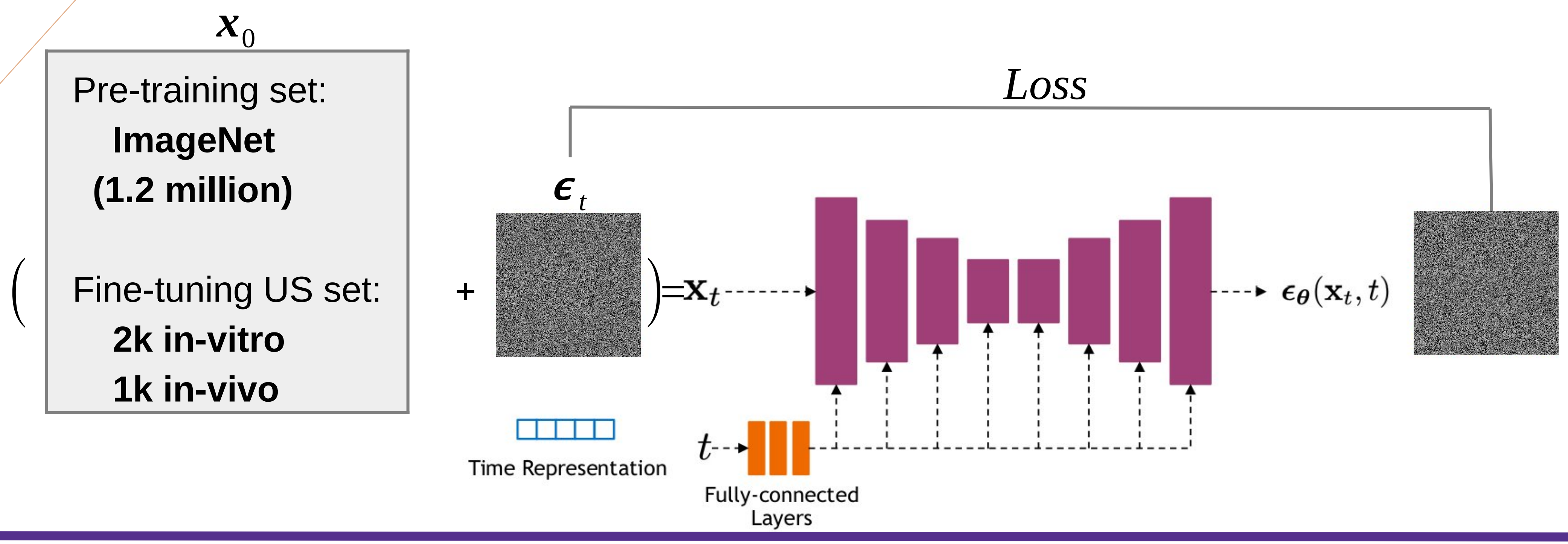
# Workflow



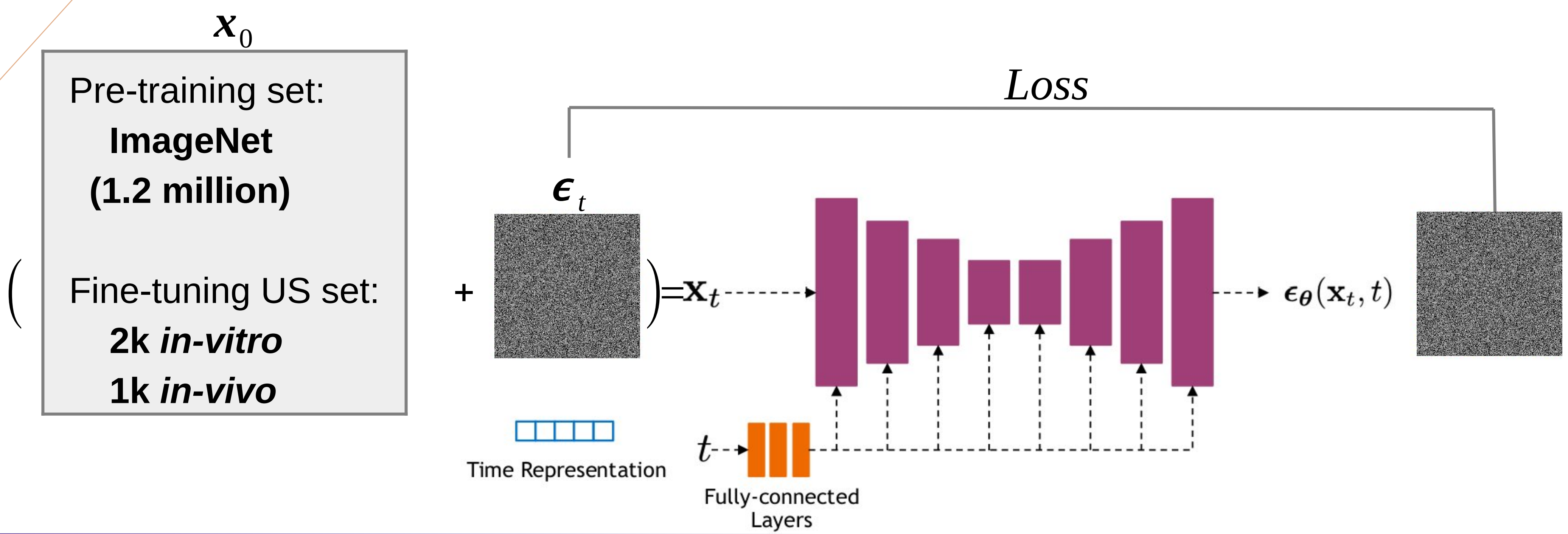

**10** samples

**50** iterative steps for each sampling

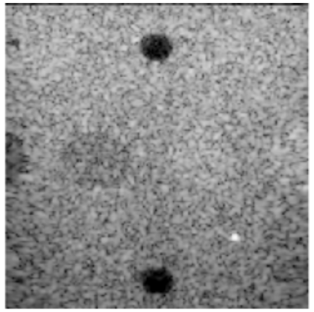
# Experimental Setup



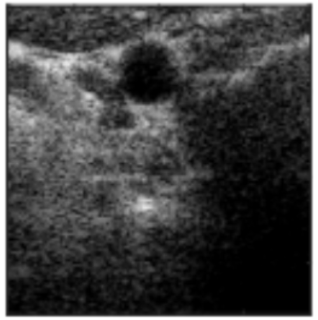
# Experimental Setup




Validation dataset: (**PICMUS**)



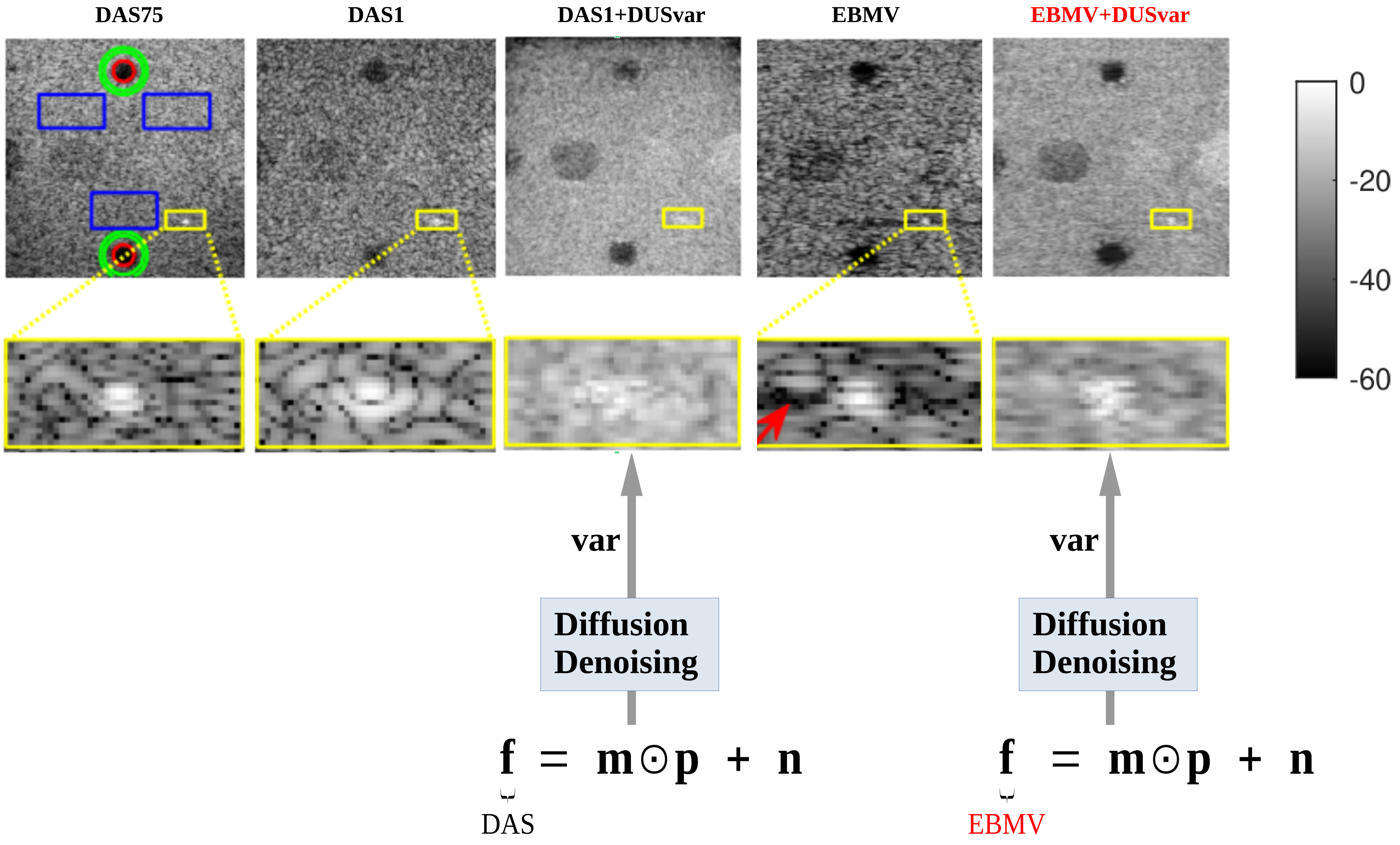
*in-vitro*



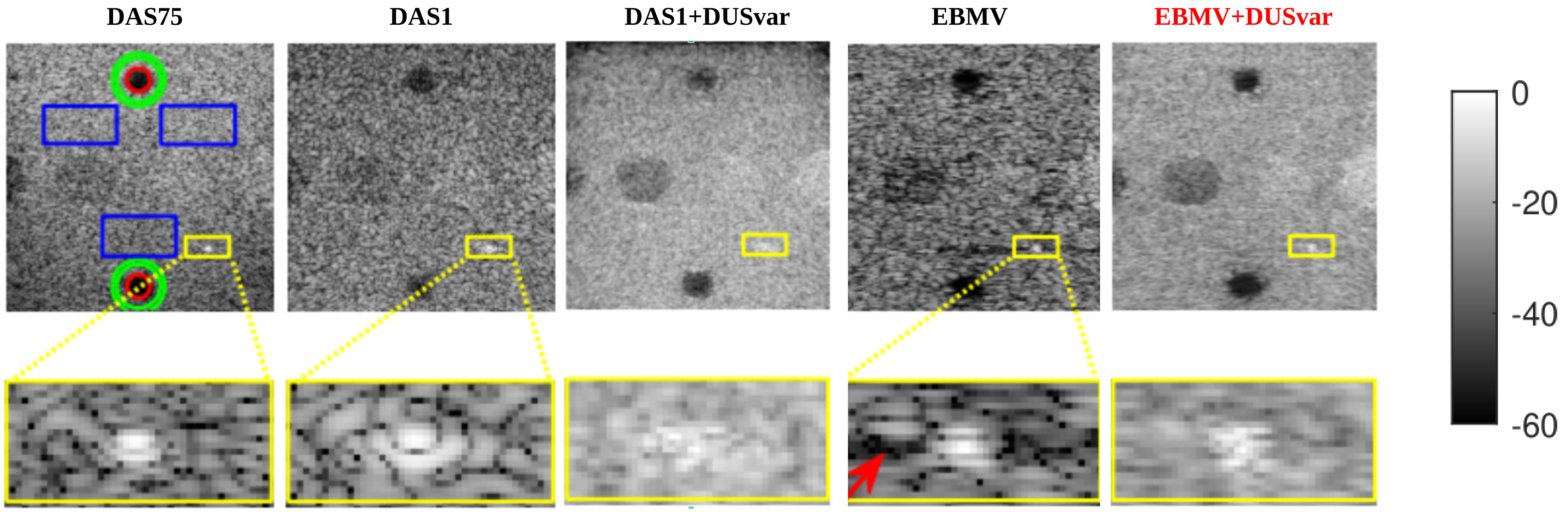
*in-vivo*

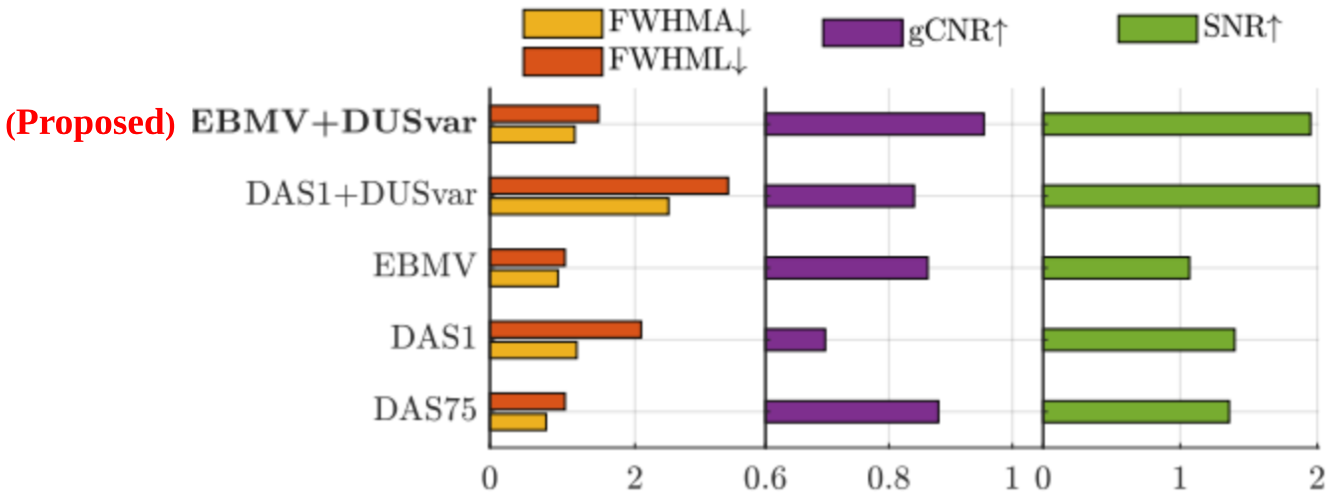
**1 PW reconstruction**

# On an Experimental Dataset

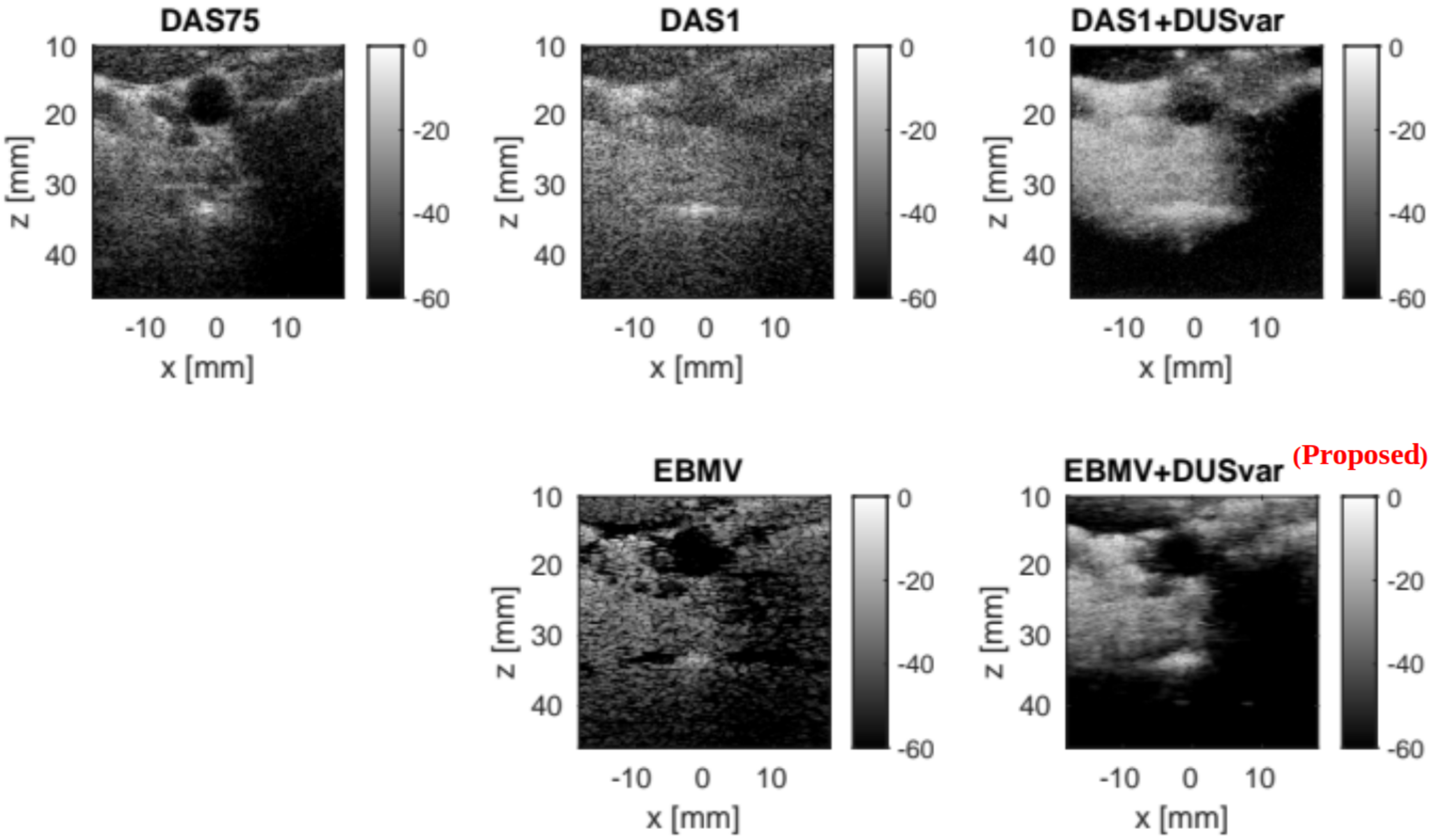


# On an Experimental Dataset

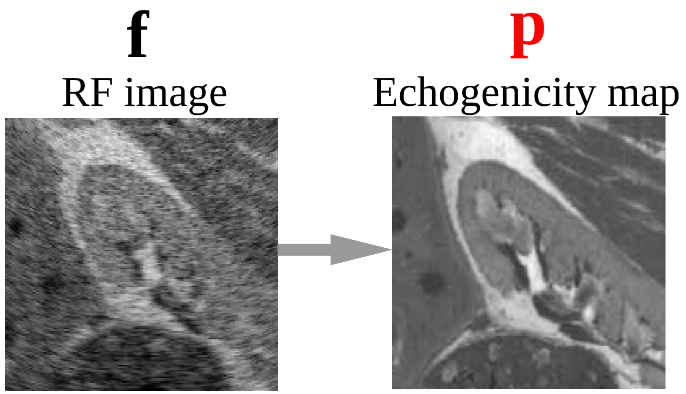


# On an *In-Vivo* Dataset



# Take-Home Message




Problem: Ultrasound Image Enhancement

Contribution:

1) Introducing an adaptive beamforming-based diffusion variance imaging, which achieves deconvolution & denoising & despeckling.

2) Showing the complementary effects of combining pixel-wise beamforming with denoising diffusion variance imaging, particularly for resolution improvement and background recovery.

# THANK YOU!

yuxin.zhang@ls2n.fr

**GitHub**

# State-of-the-Art

**Previous Work**

$$\underbrace{\mathbf{f}}_{\substack{\text{RF image}\\(DAS)}} = \underbrace{\mathbf{A}}_{\text{PSF}}\left(\underbrace{\mathbf{m}}_{\sim\mathcal{N}(\mathbf{0},\mathbf{I})} \odot \mathbf{p}\right) + \underbrace{\mathbf{n}}_{\sim\mathcal{N}(\mathbf{0},\gamma\mathbf{I})}$$

**STEP 1** Estimate $\mathbf{m}\odot\mathbf{p}$ via a Diffusion **Inverse Problem** Solver

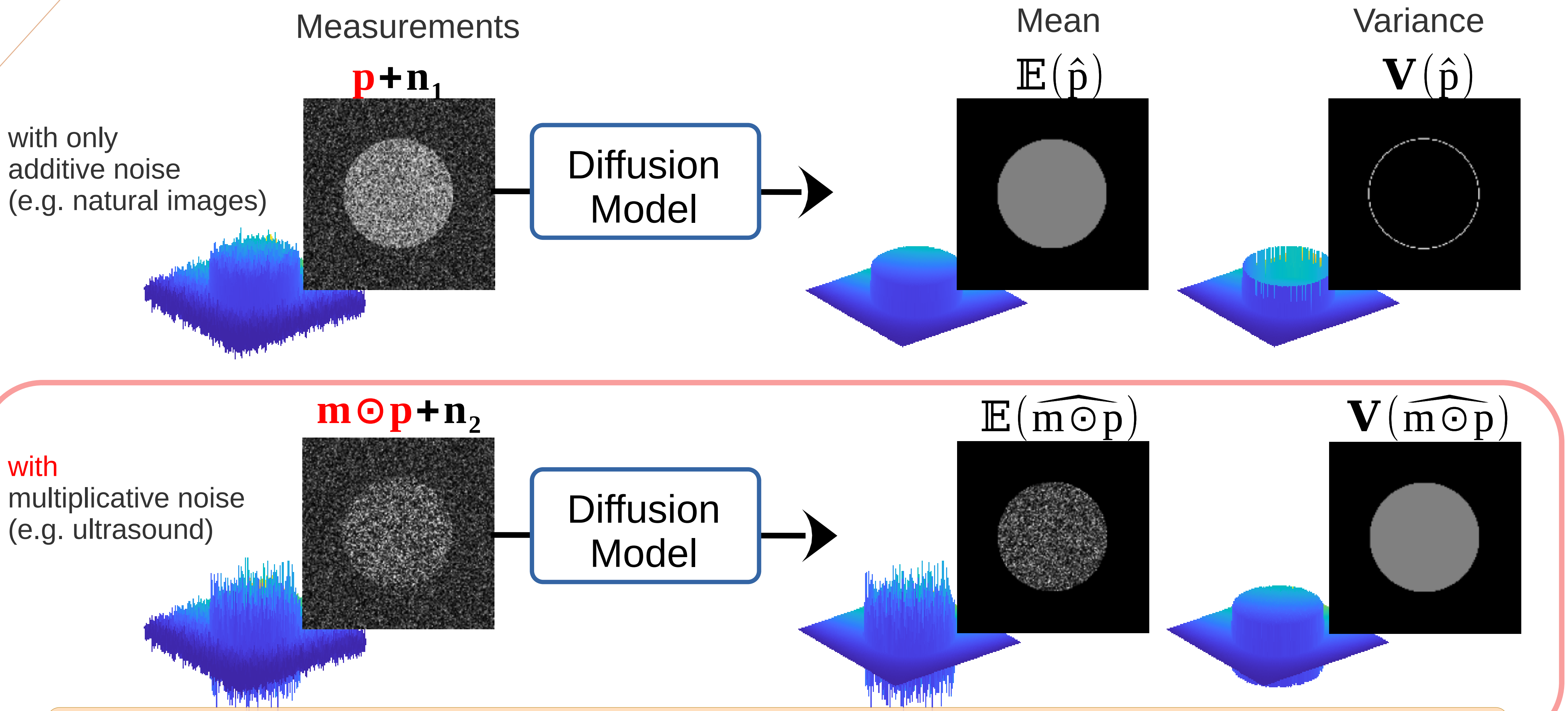
SLOW !!!
Due to the complexity of **A**

**STEP 2** Estimate $\mathbf{p}$ by leveraging the stochasticity of the generative sampling



Y. Zhang et al., Ultrasound Imaging based on the Variance of a Diffusion Restoration Model. EUSIPCO, 2024

# Diffusion Variance Behavior




**Variance of diffusion samples inform the level of the multiplicative noise**