STAR

<u>ST</u>ochastic <u>A</u>stronomical TU<u>R</u>BO

M. Drozdova, V. Kinakh, Y. Belousov, O. Bait, D. Piras, E. Lastufka, M. Dessauges-Zavadsky, T. Holotyak, D. Schaerer, and S. Voloshynovskiy

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Problem formulation

Challenges: Accurate reconstruction and localization of astronomical sources under limited observational data.

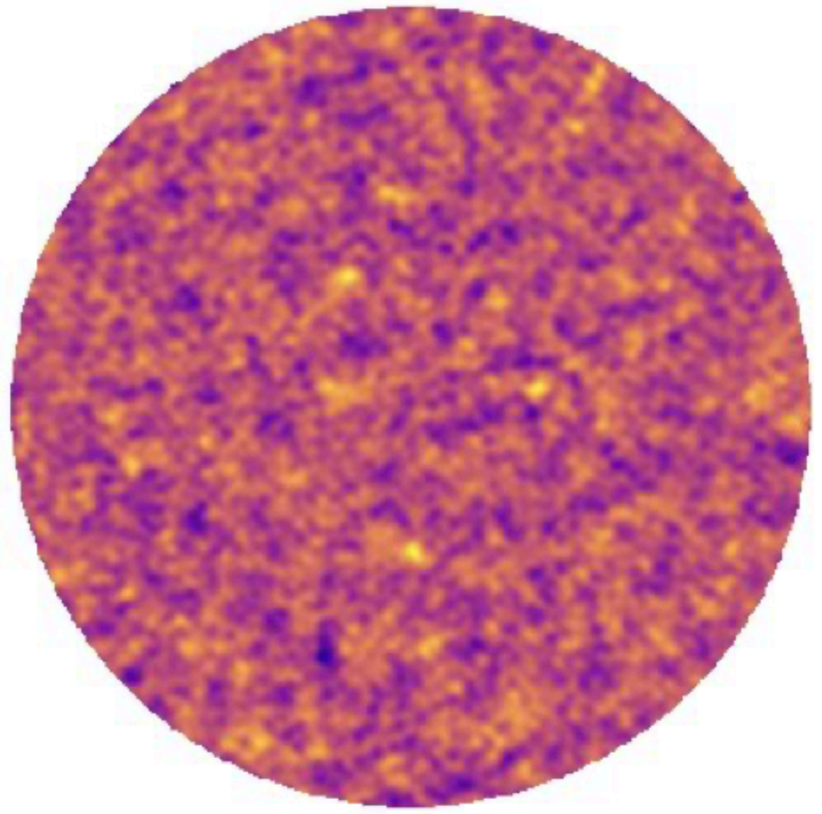
Solution: Framework separating **content** (astronomical sources) from **style** (imaging artifacts and noise) - STAR.

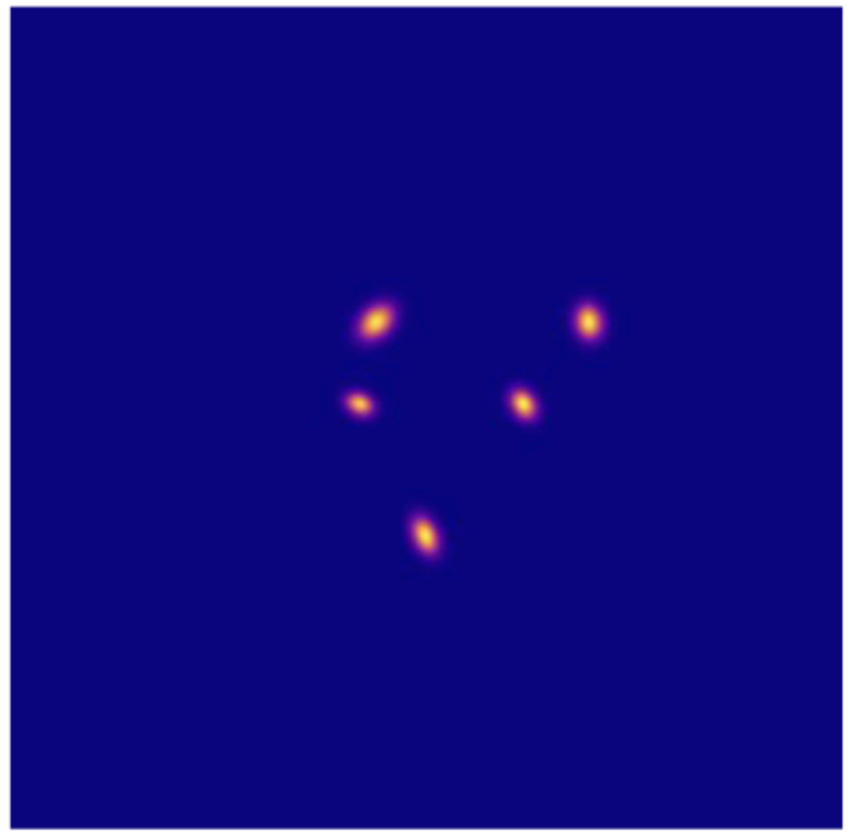
Improved sources localization while keeping the complexity low due to the changes in training procedure.

Possibility to generate synthetic data to overcome limitations in training data availability and quality.

Dataset

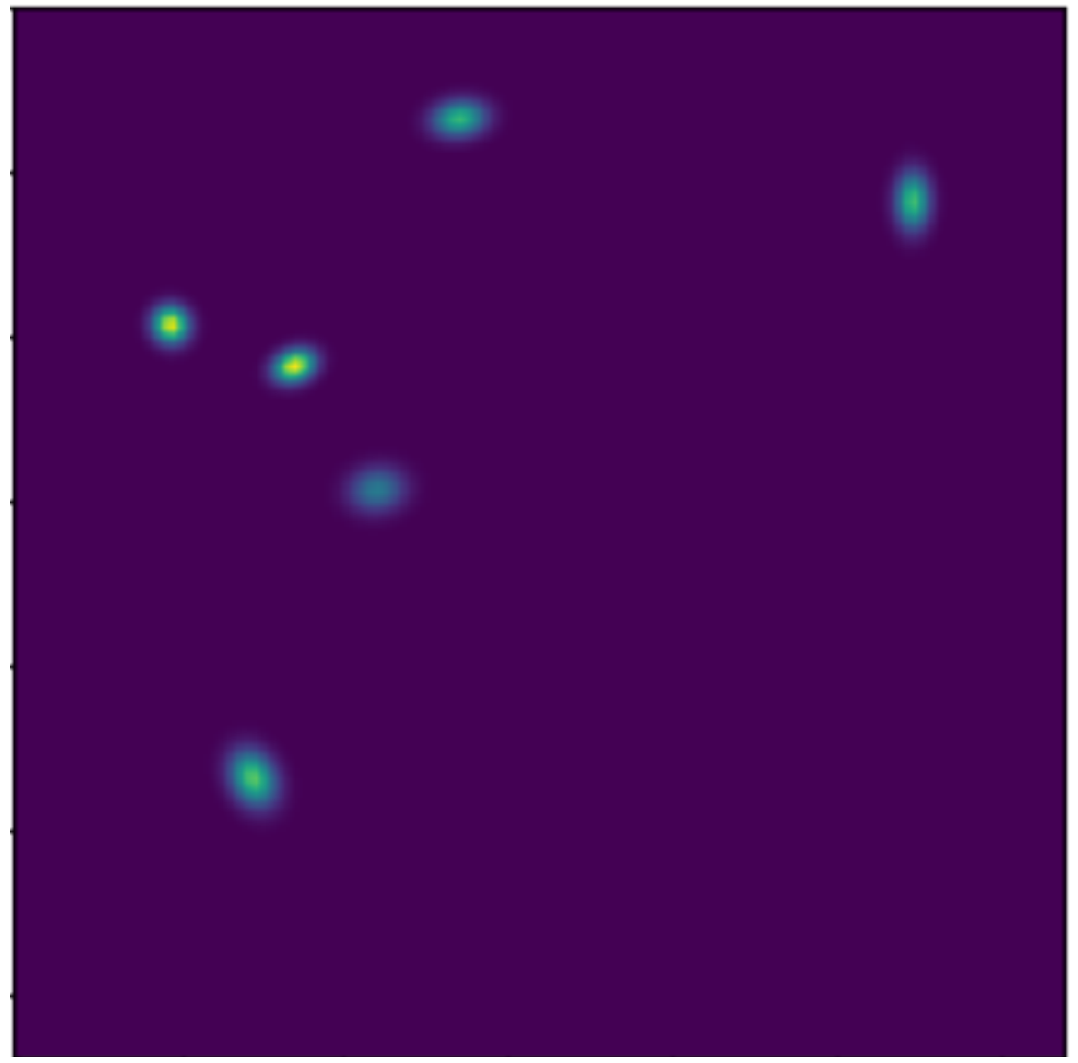
- simulated with CASA data processing software v6.2
- fixed ALMA configuration cycle 5.3
- image size 512x512 corresponding to 51.2'×51.2′ across
- 9164 simulated sky models and the corresponding dirty images (1-5 sources per image)
- 1000 dirty images without sources
- a total of 27632 sources
- the root-mean-squared of the noise is 50 μJy





Gap between observation and ground truth

Sky model

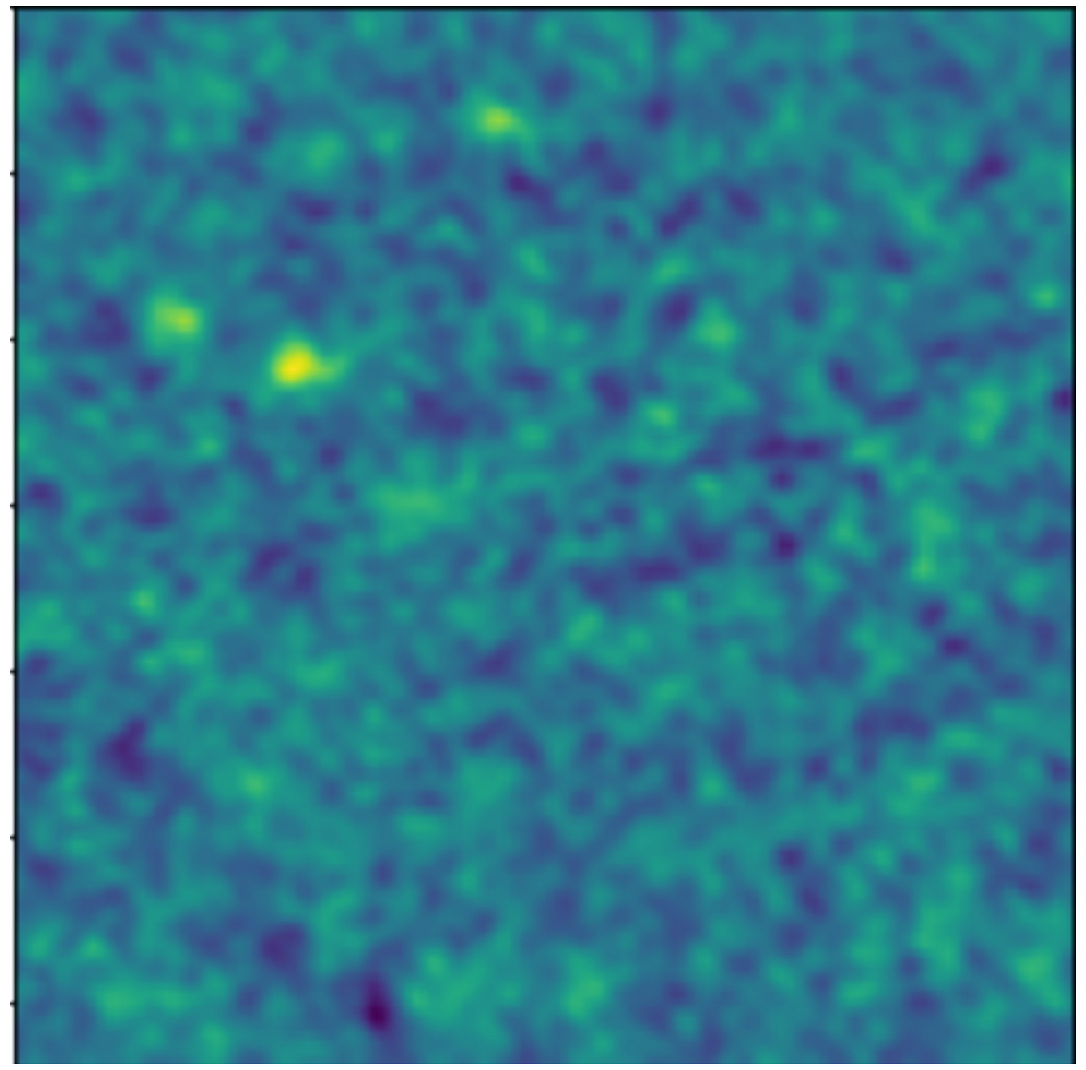


$\mathbf{c}$

$$\mathbf{c} \xrightarrow{\mathbf{x} = \phi(H\mathbf{c}) + \epsilon} \mathbf{x}$$

$$\tilde{\mathbf{c}} \xleftarrow[?]{} \mathbf{x}$$

Dirty image



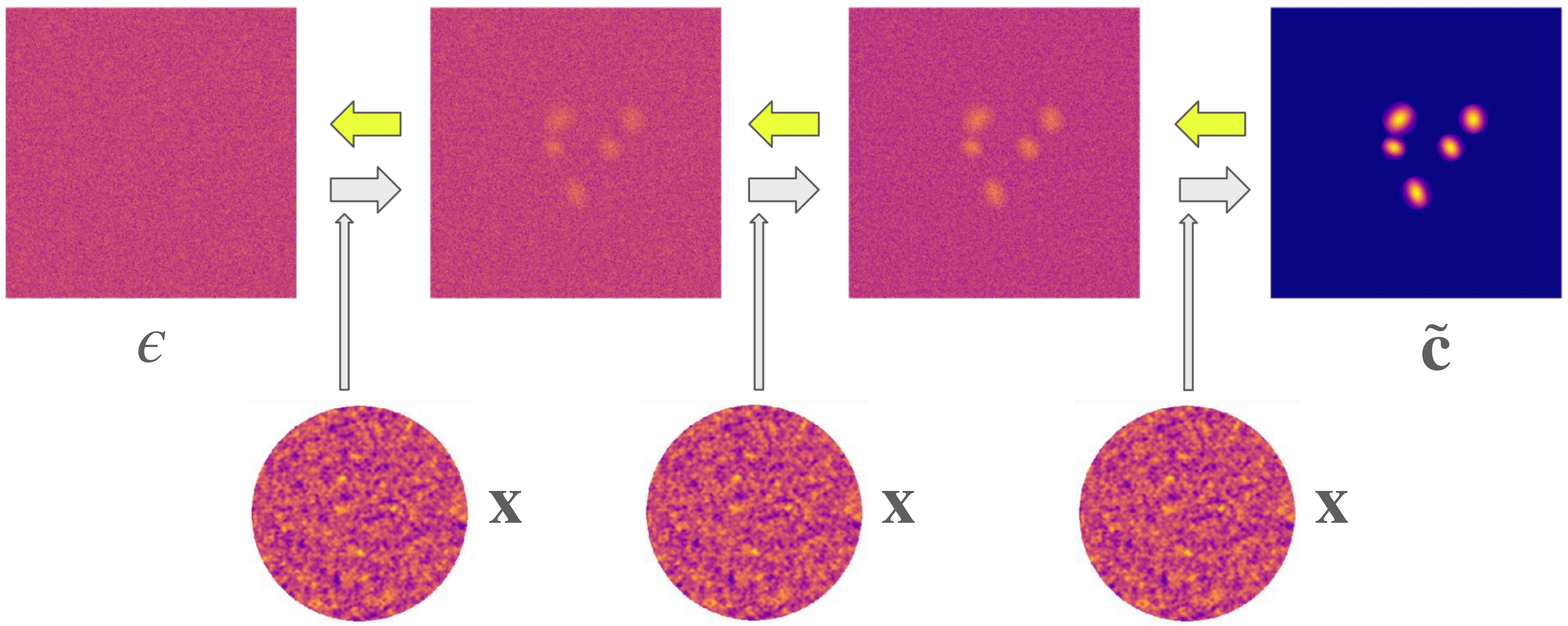
$\mathbf{x}$

$\mathbf{x} \rightarrow \tilde{\mathbf{c}}$ is an inverse ill-posed problem with many solutions => we need (a)regularizations or priors and (b)stochasticity

Denoising Diffusion Probabilistic Model approach

Previously: multi-stage conditional image generation via DDPM (Palette)

+ State-of-the-art accuracy
+ Stochasticity
- Very high complexity



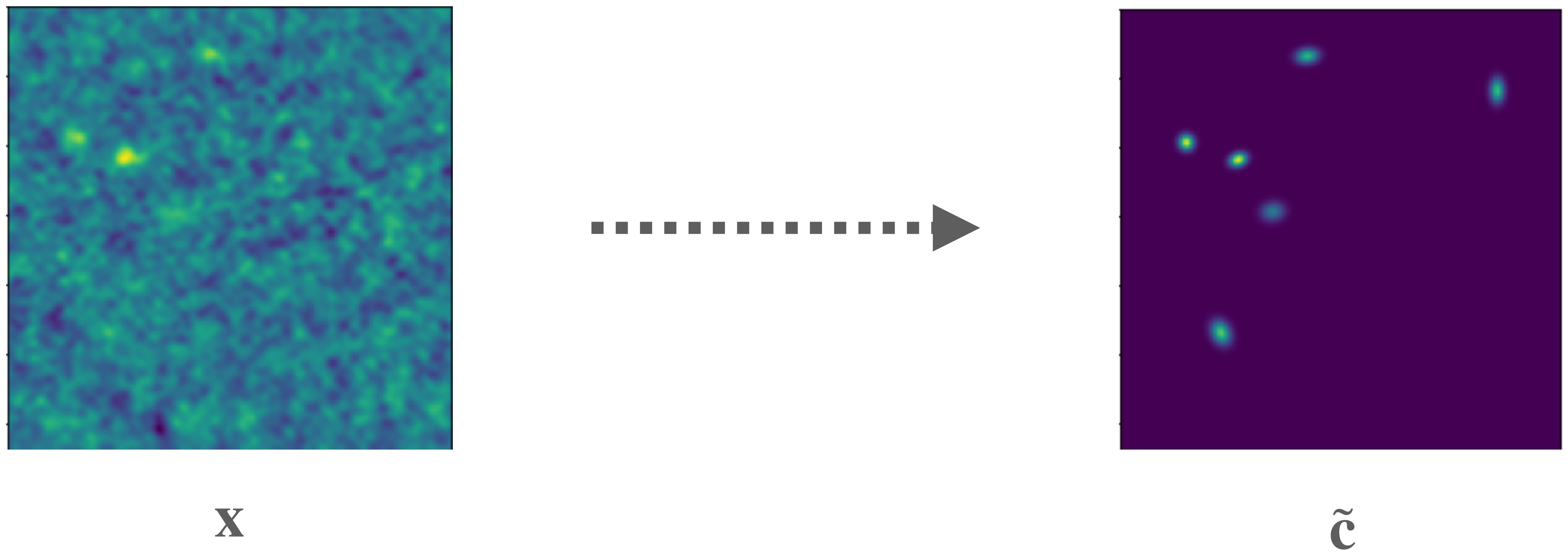
Palette: Image-to-Image Diffusion Models, C. Saharia et al. 2022 SIGGRAPH
Radio-astronomical image reconstruction with a conditional denoising diffusion model, M. Drozdova et al. 2024, Astronomy&Astrophysics

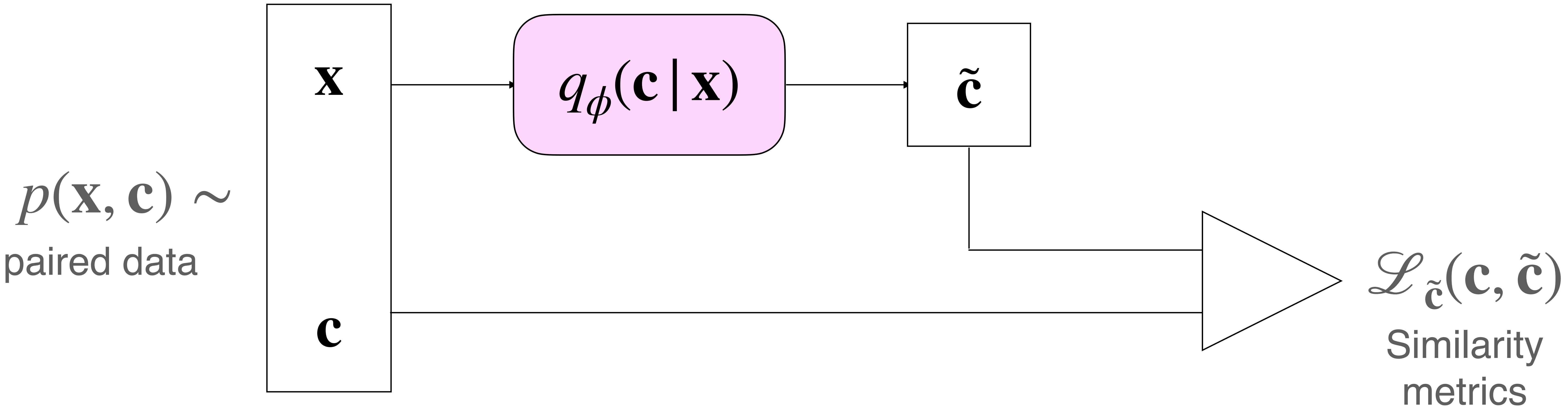
Concept of TURBO

Given: Paired dataset

Goal: Learn mapping $\mathbf{x} \rightarrow \tilde{\mathbf{c}}$

Solution: Encoder $q_\phi(\mathbf{c} \mid \mathbf{x})$ with MSE loss.





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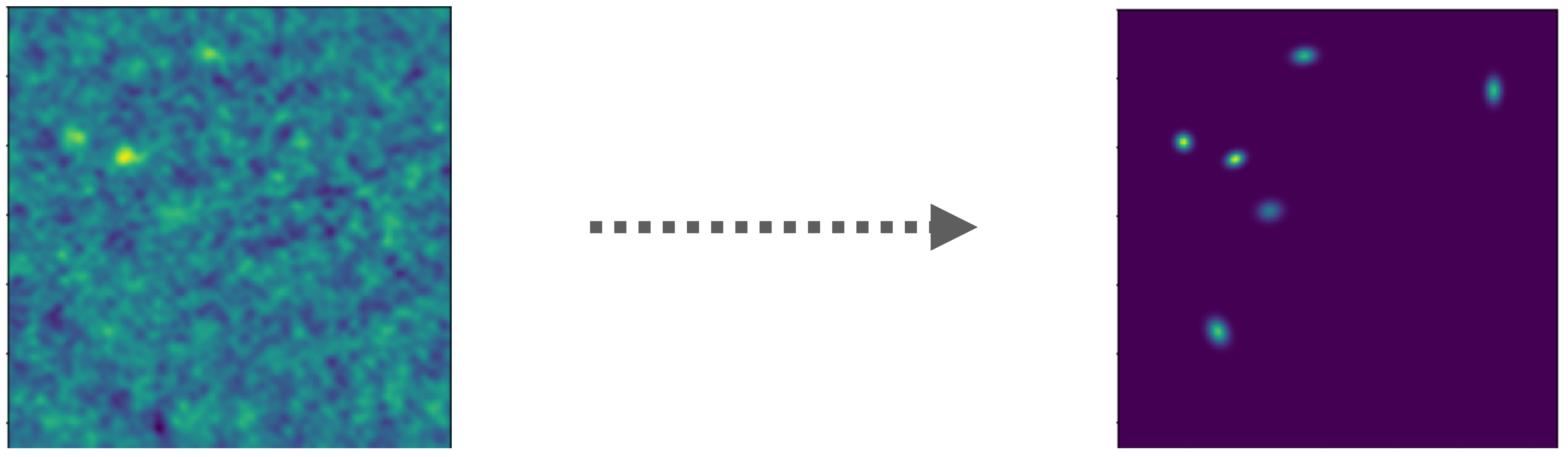
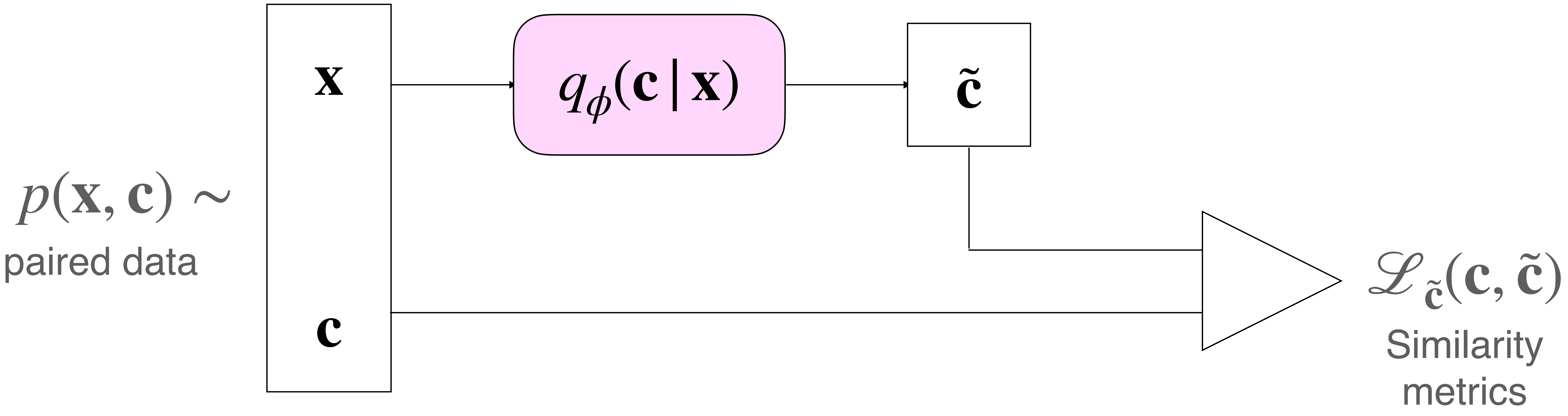


$\mathbf{x}$ $\tilde{\mathbf{c}}$

Can we do better?

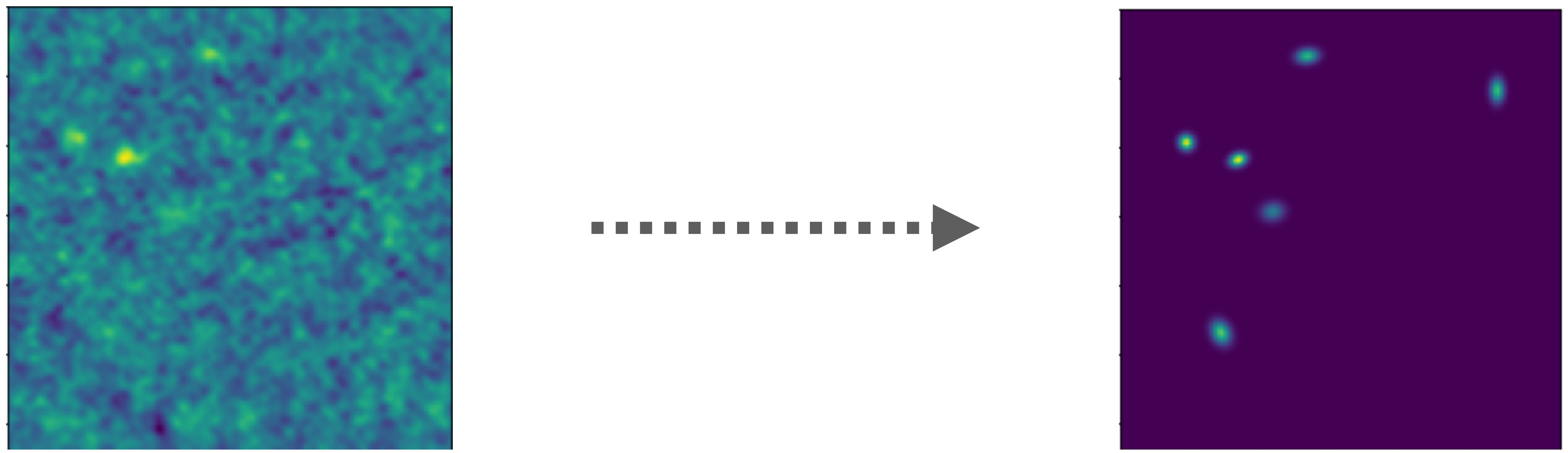


Concept of TURBO

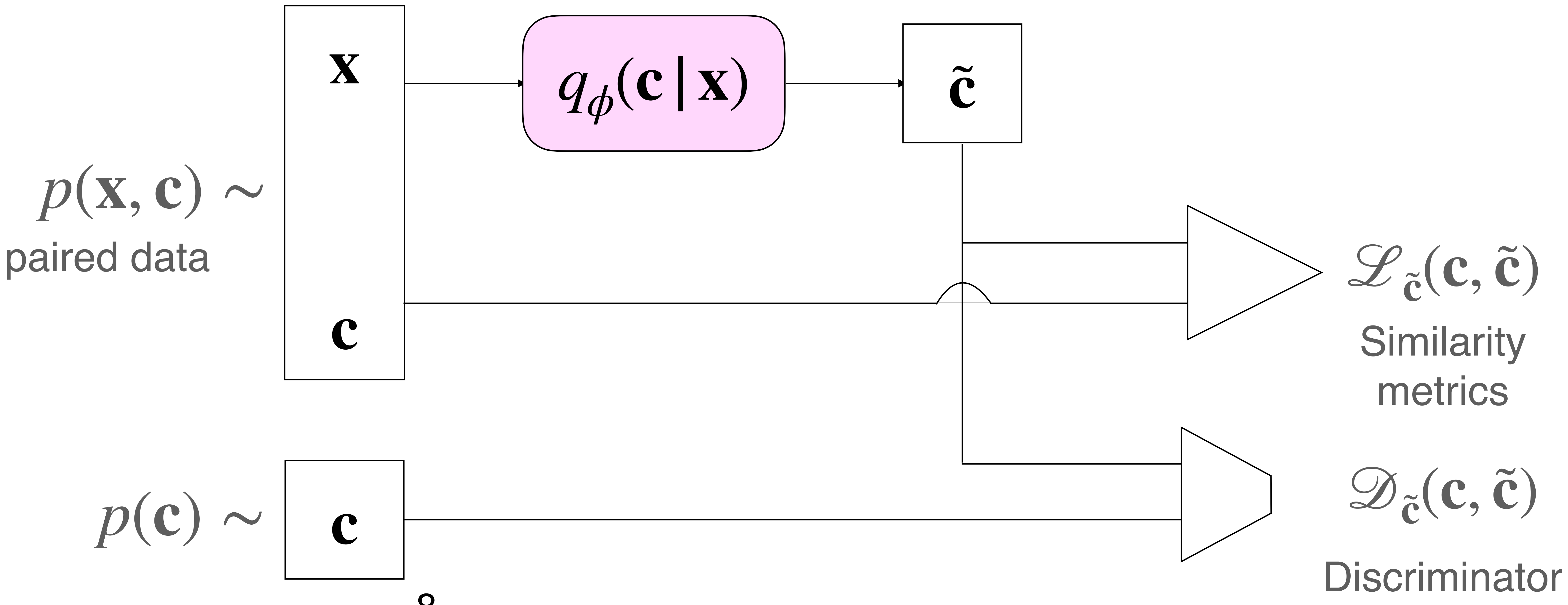
Given: Paired dataset

Goal: Learn mapping $\mathbf{x} \rightarrow \tilde{\mathbf{c}}$

Solution: Encoder $q_\phi(\mathbf{c} \,|\, \mathbf{x})$ with MSE loss and discriminator. (Pix2pix)



$\mathbf{x}$ $\tilde{\mathbf{c}}$



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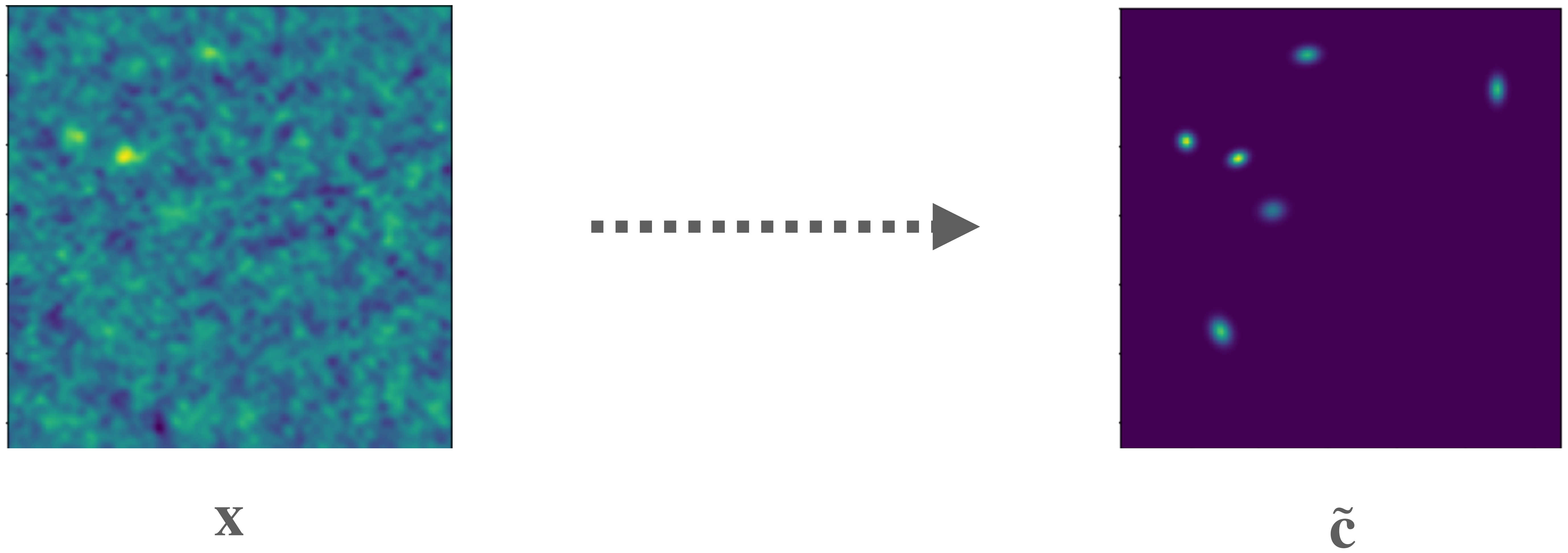
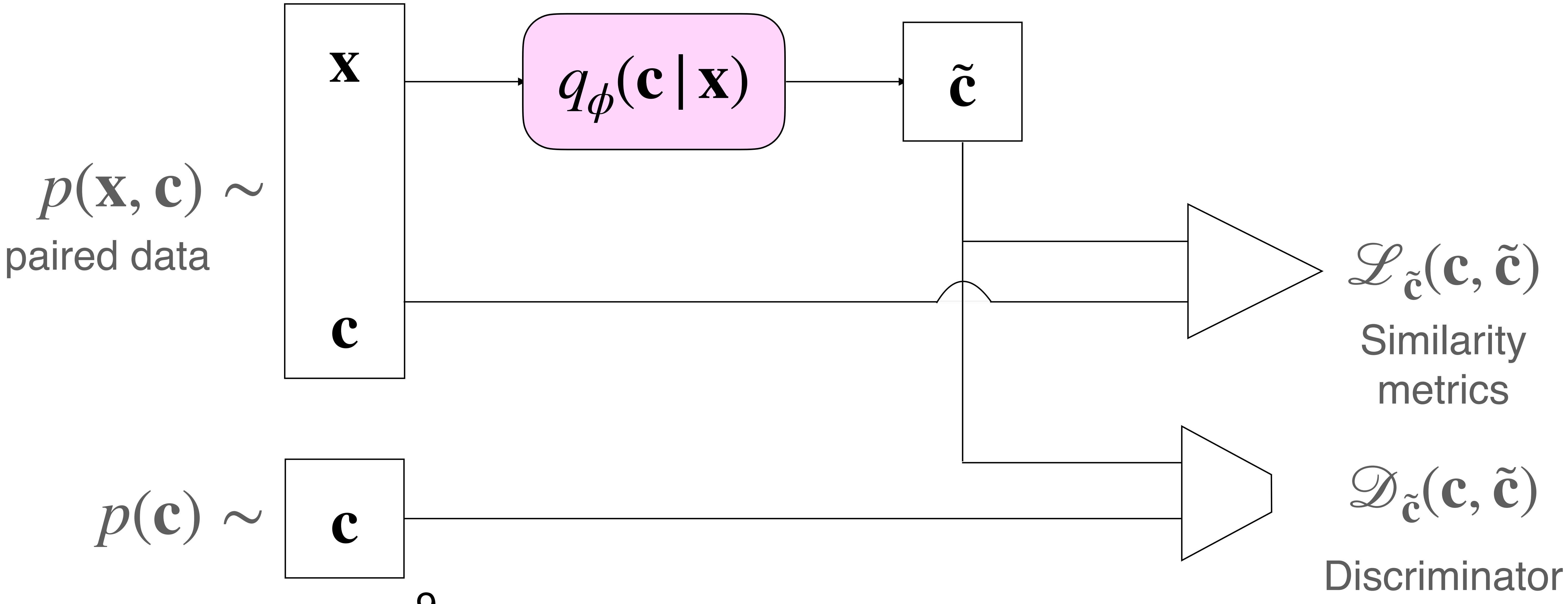


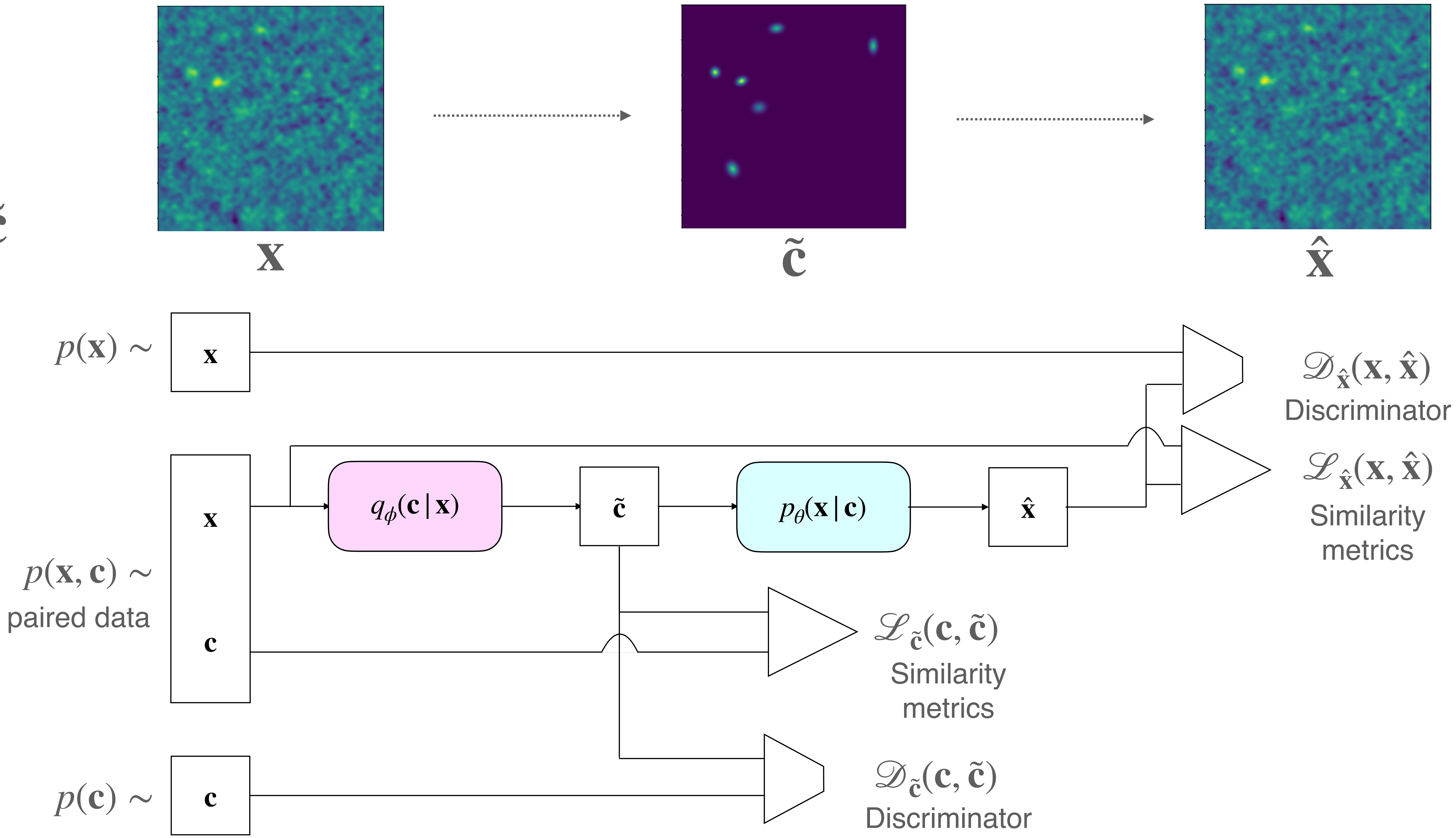


Concept of TURBO

Given: Paired dataset

Goal: Learn mapping $\mathbf{x} \rightarrow \tilde{\mathbf{c}}$

Solution: Two encoders $q_\phi(\mathbf{c}\,|\,\mathbf{x})$ and $p_\phi(\mathbf{x}\,|\,\mathbf{c})$ with MSE loss and discriminator.



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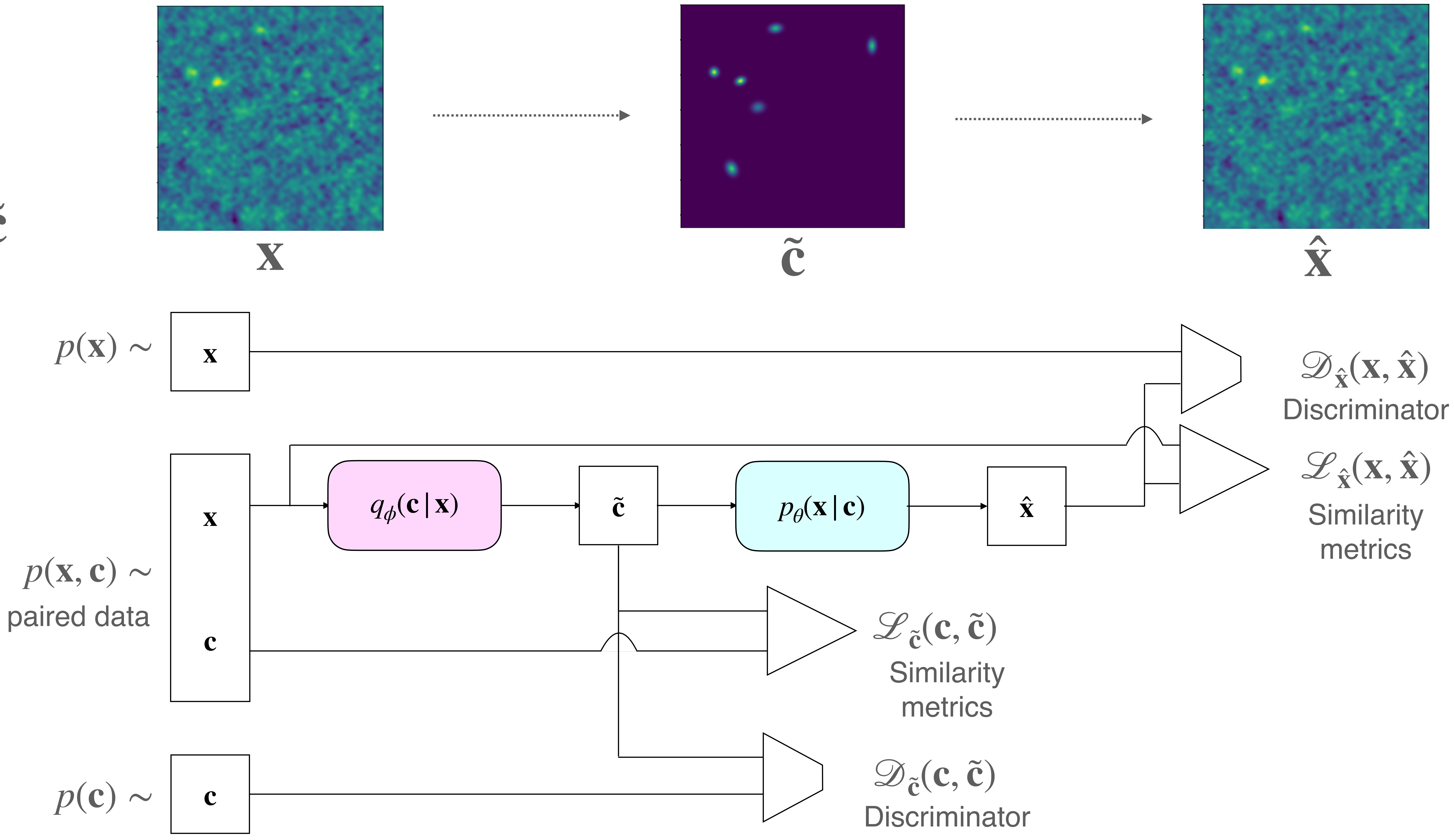
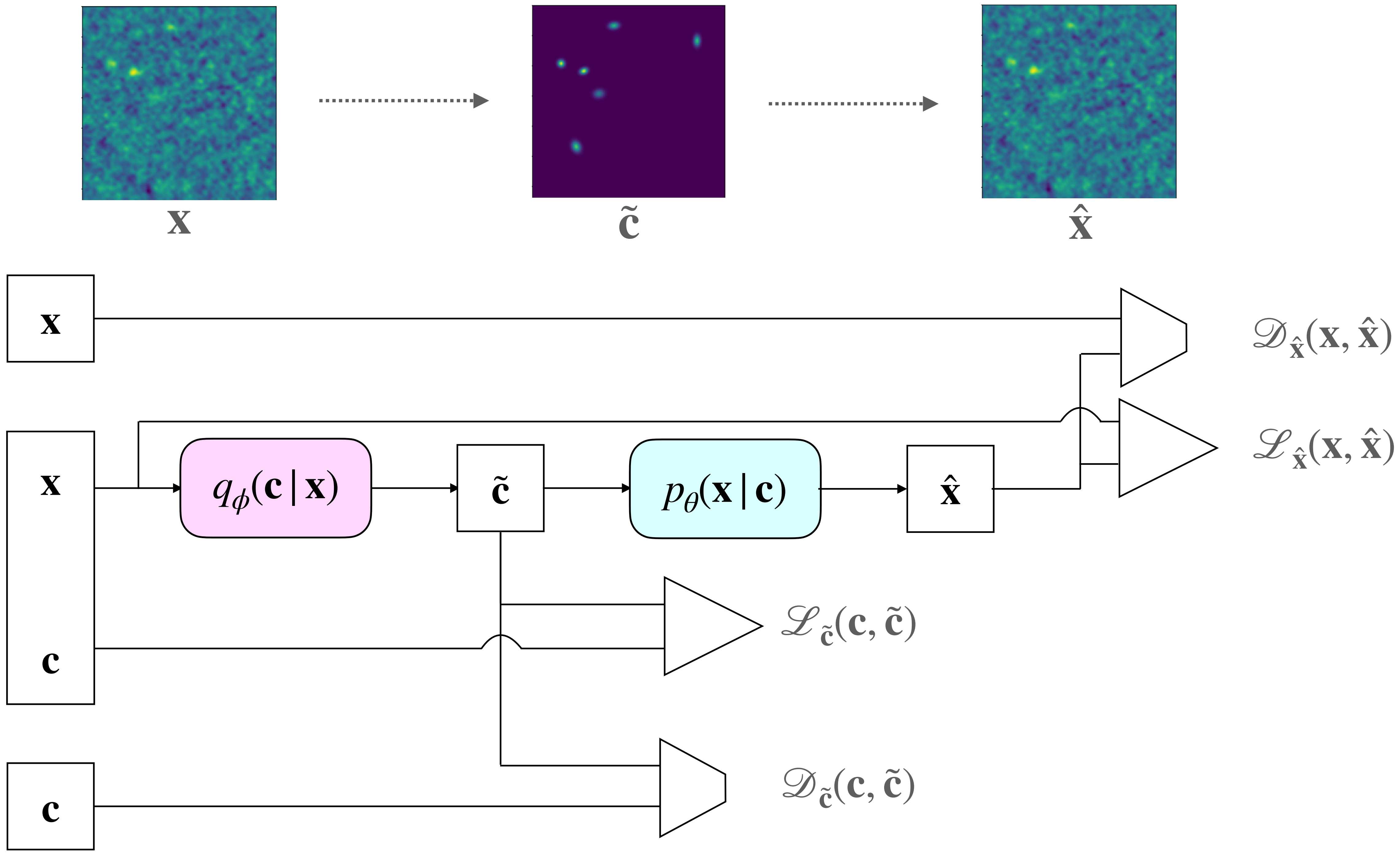
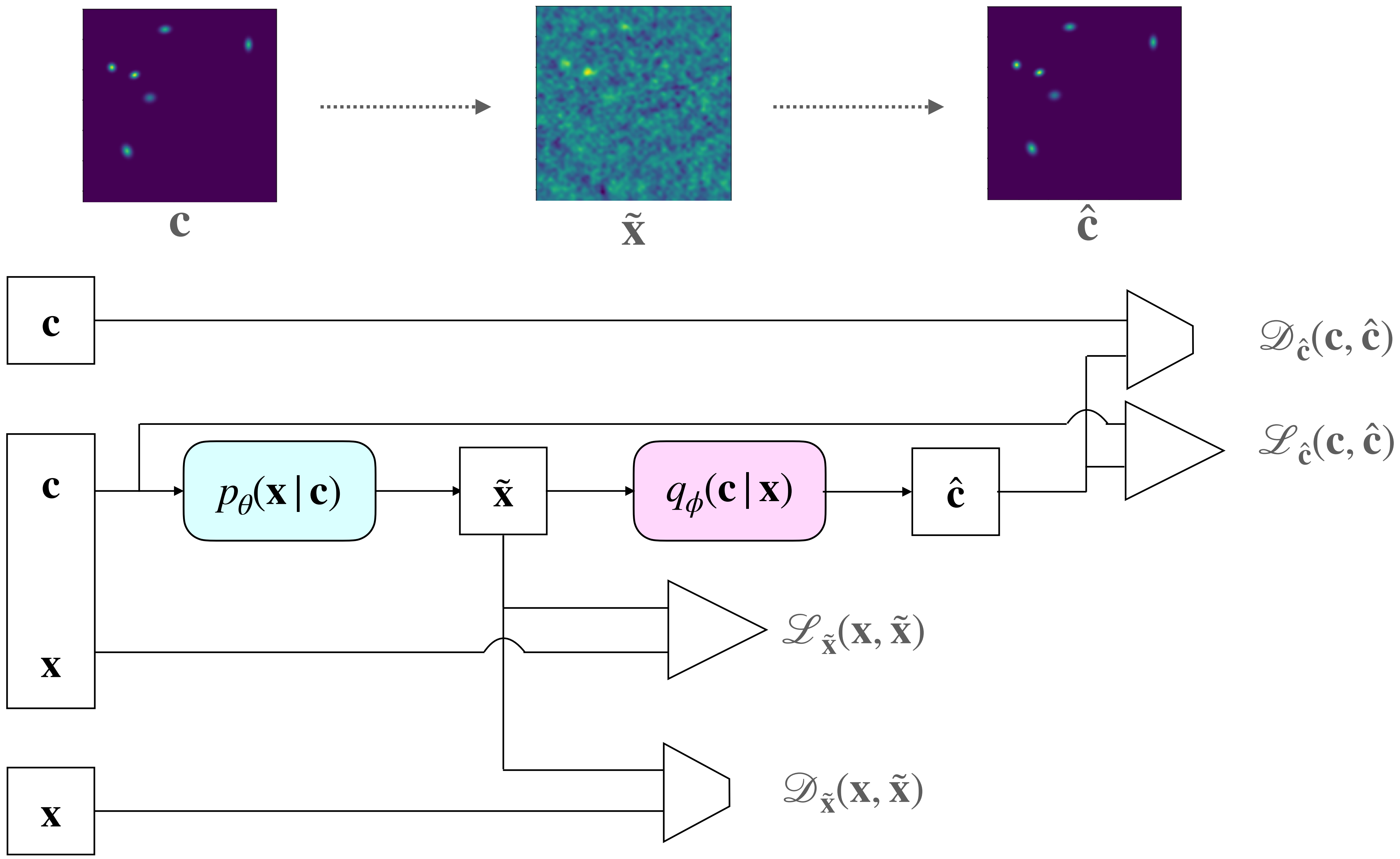


TURBO

Two branches





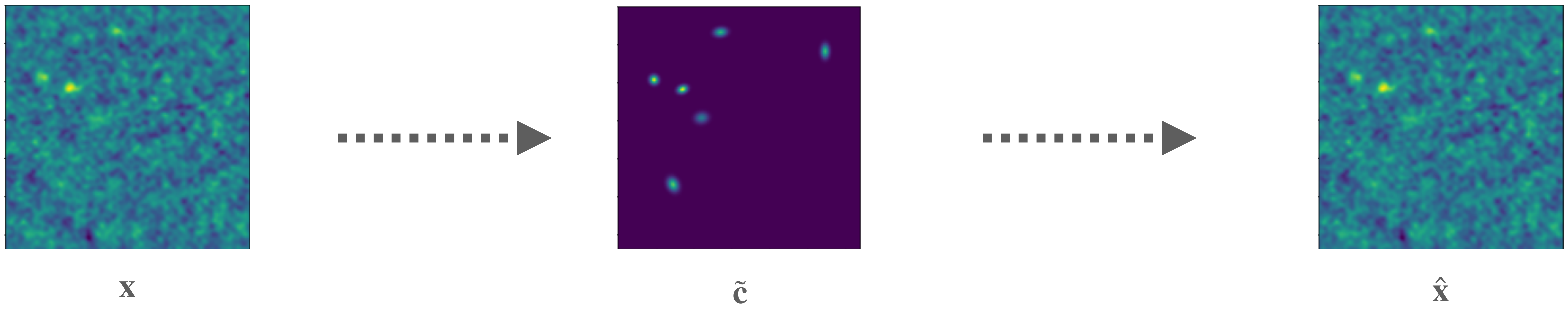
A powerful framework that generalizes pix2pix and CycleGAN.

However, it is **deterministic**.

[Turbo-Sim: a generalised generative model with a physical latent space, G.Quetant, M.D. et al., 2021 NeurIPS Workshop](#)

Stochastic TURBO

Suggestion: Disentangling content and style.



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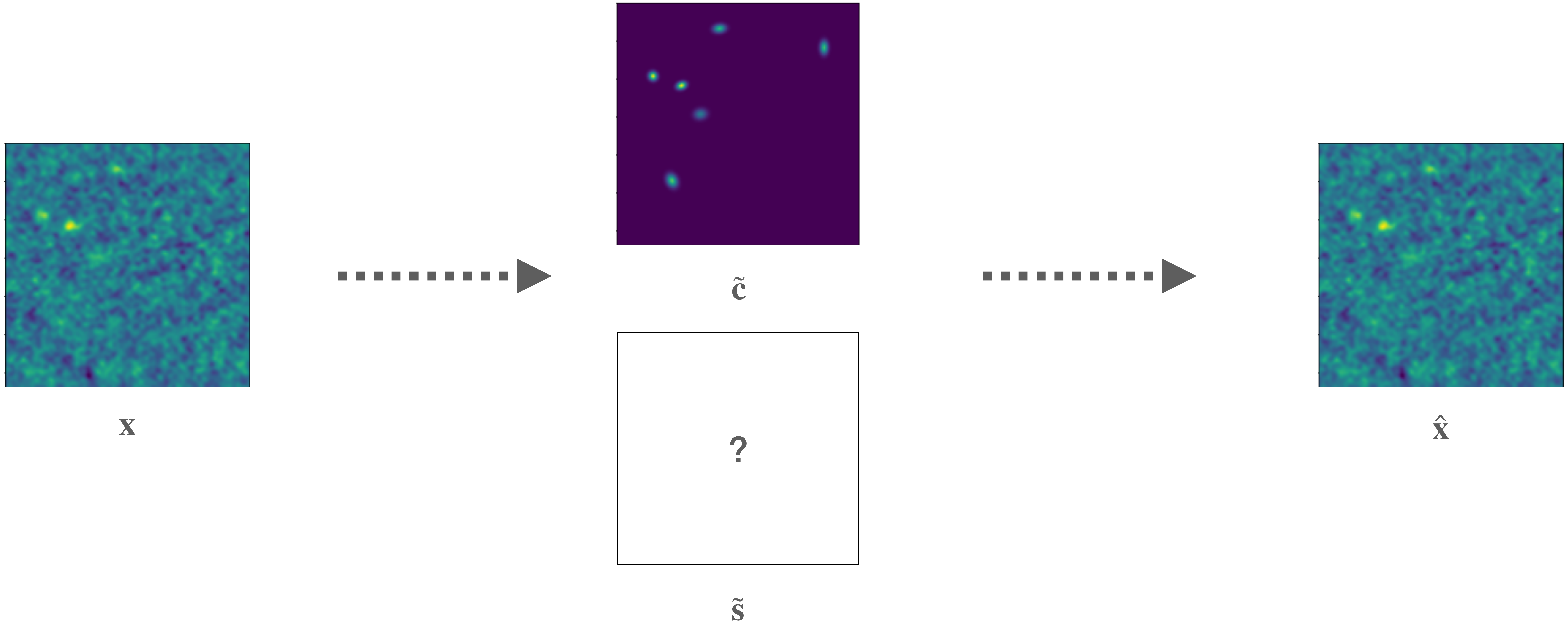
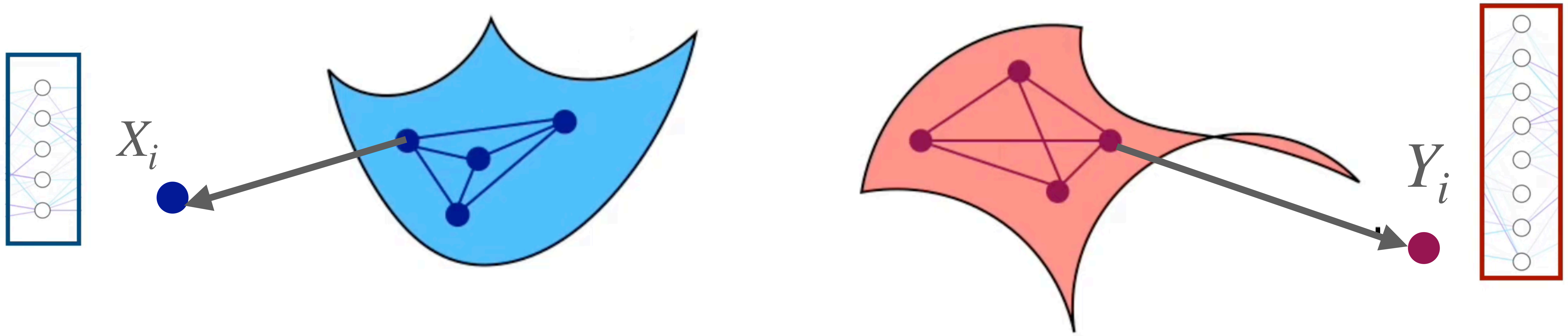


Goal: the content $\tilde{\mathbf{c}}$ and style $\tilde{\mathbf{s}}$ should be disentangled ($\tilde{\mathbf{c}} \perp\!\!\!\perp \tilde{\mathbf{s}}$)
Question: how to achieve it in practice without adversarial games?

Distance correlation: a basic concept



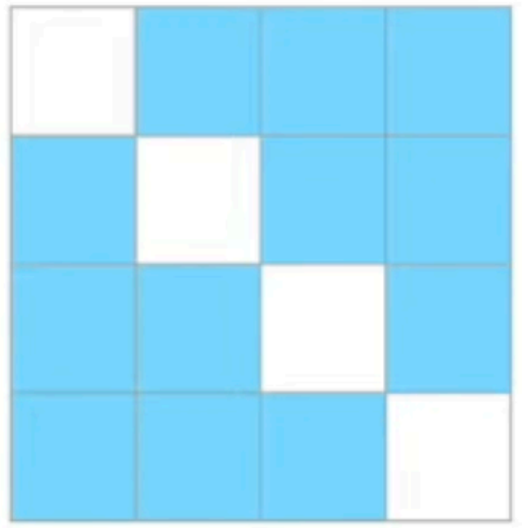
$(X_i, Y_i), 1 \leq i \leq m$

Distance matrix: $a_{k,l} = ||X_k - X_l||$

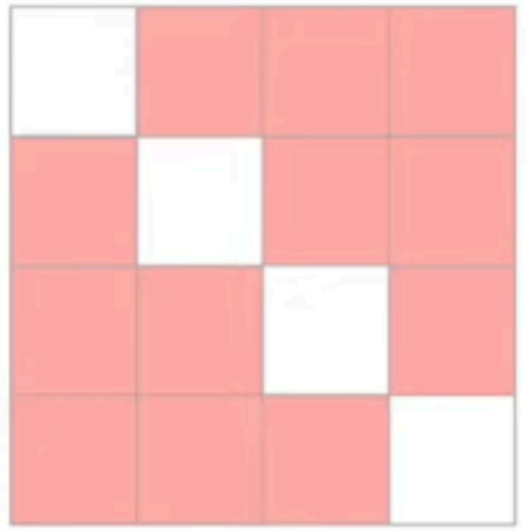
Normalization: $A_{k,l} = a_{k,l} - \bar{a}_{k,\cdot} + \bar{a}_{\cdot,\cdot}$

$b_{k,l} = ||Y_k - Y_l||$:

$B_{k,l} = b_{k,l} - \bar{b}_{k,\cdot} + \bar{b}_{\cdot,\cdot}$

$A =$ 

Distance correlation

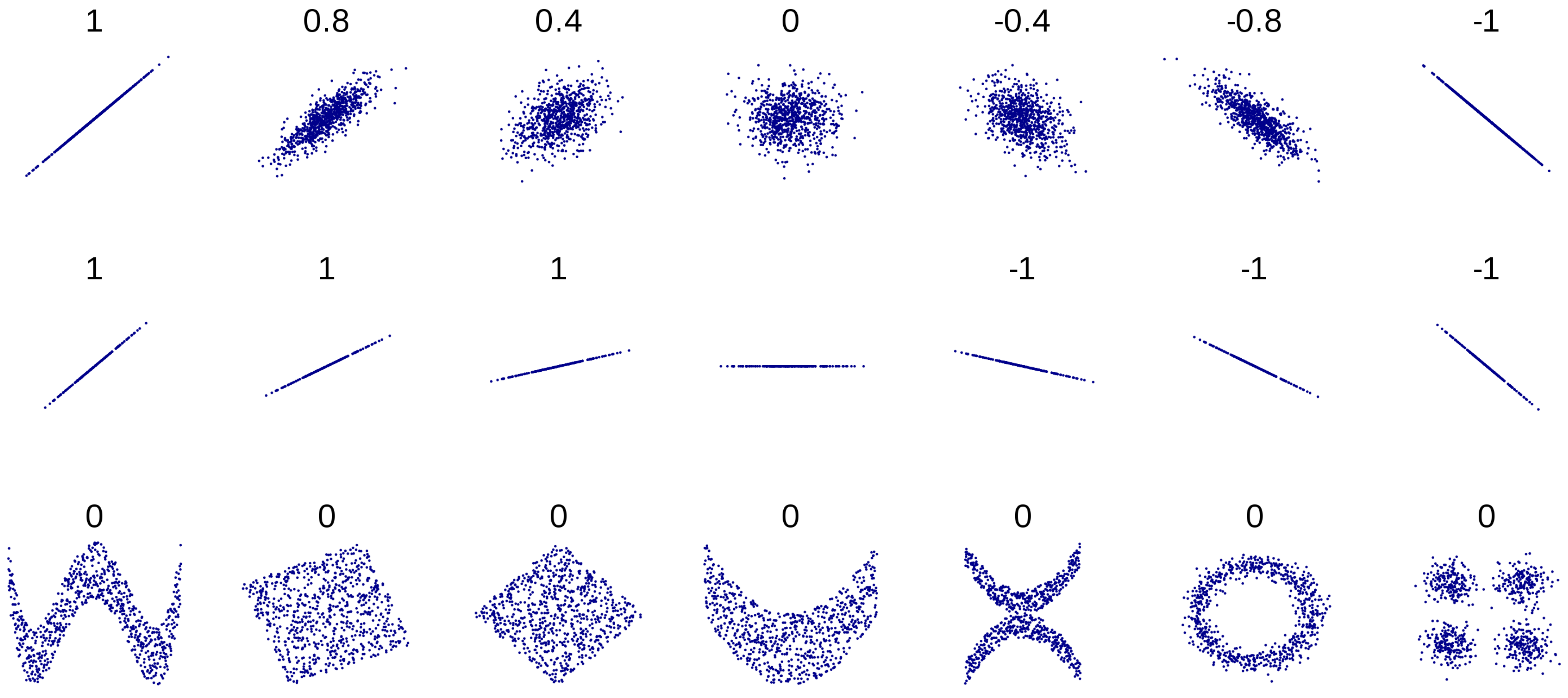
$B =$ 

$$\text{dcor}_{X,Y}(X, Y) = \frac{\sum_{k,l} A_{k,l} B_{k,l}}{\sqrt{(\sum_{k,l} A_{k,l} A_{k,l})(\sum_{k,l} B_{k,l} B_{k,l})}}$$

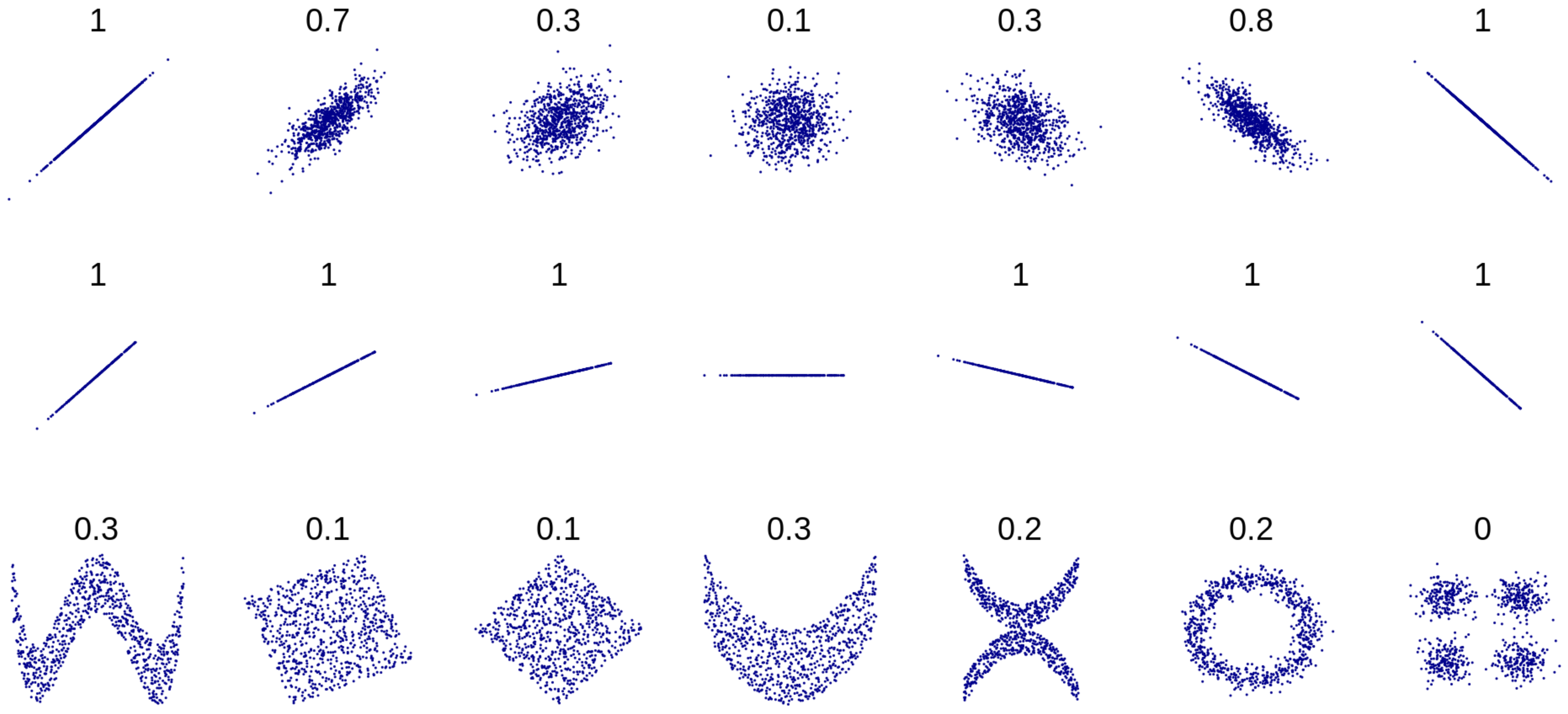
On the Versatile Uses of Partial Distance Correlation in Deep Learning, Zhen et al. 2022, Best Award Paper 2022

Distance correlation: basic properties

- Dependence measure between two vectors (linear correlation)
- Vectors can be of **different dimensions**
- Between 0 and 1



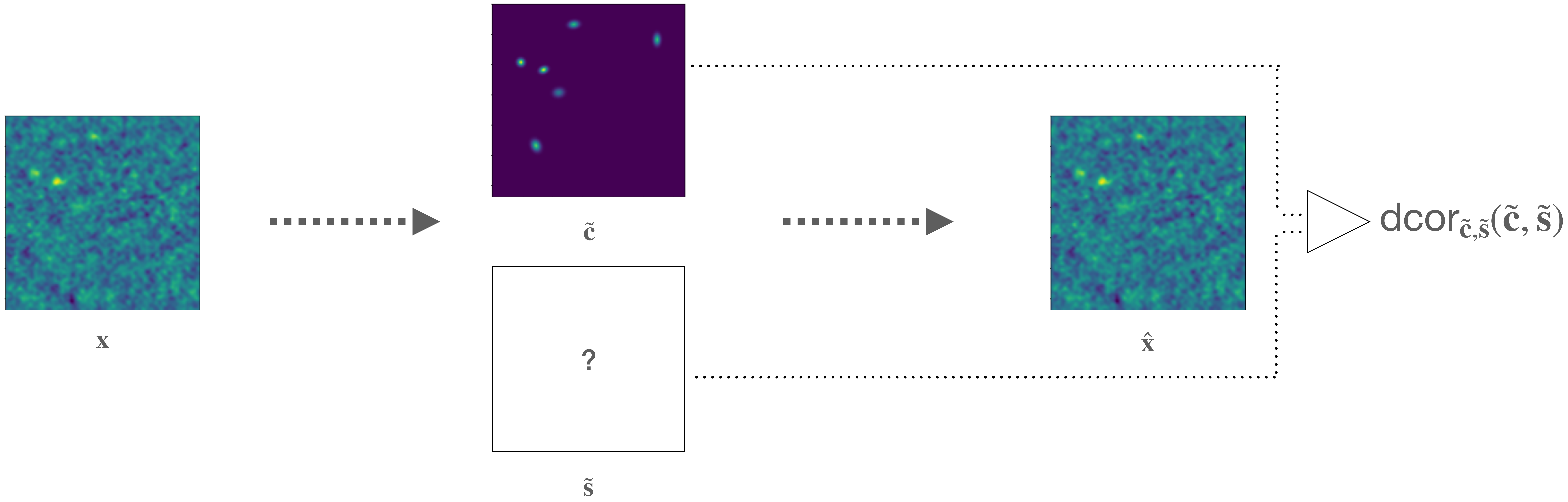
Pearson correlation



Distance correlation

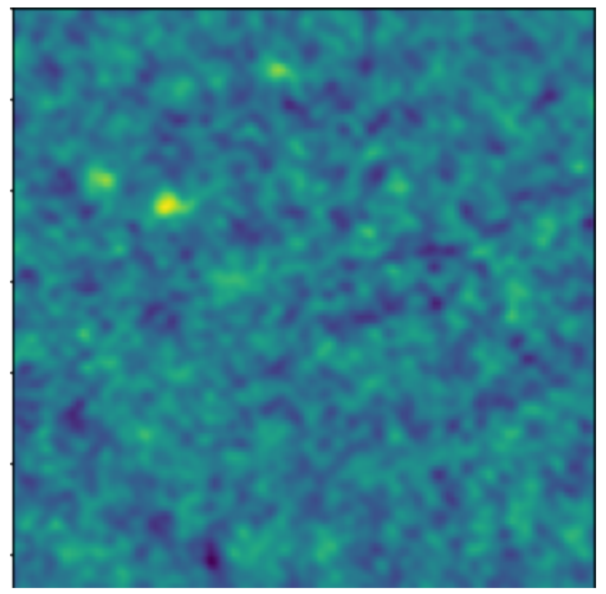
Stochastic TURBO

Suggestion: Disentangling content and style based on dCor.

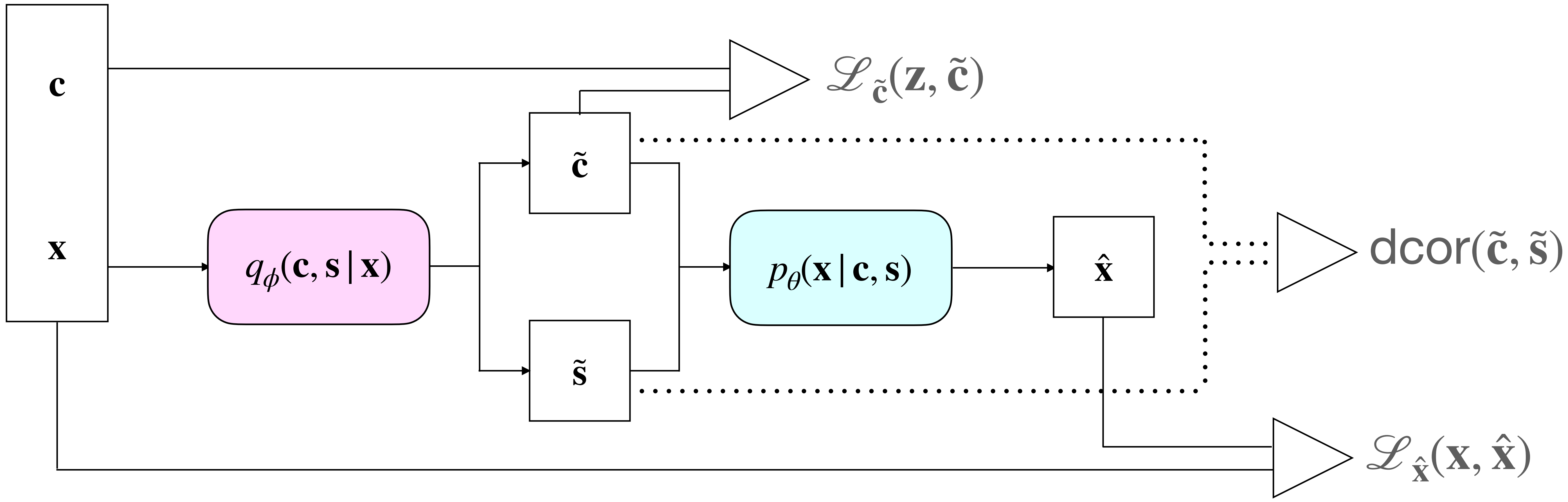


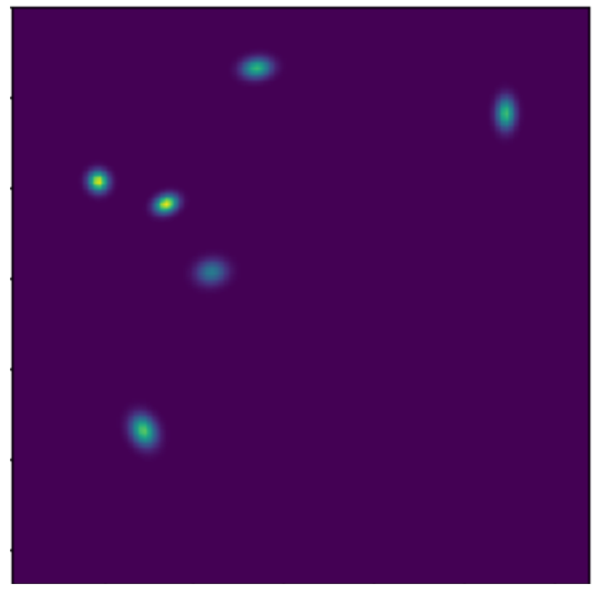
This framework overcomes limitations of deterministic Turbo and DDPM by combining their strengths.

STAR model (simplified without discriminators)

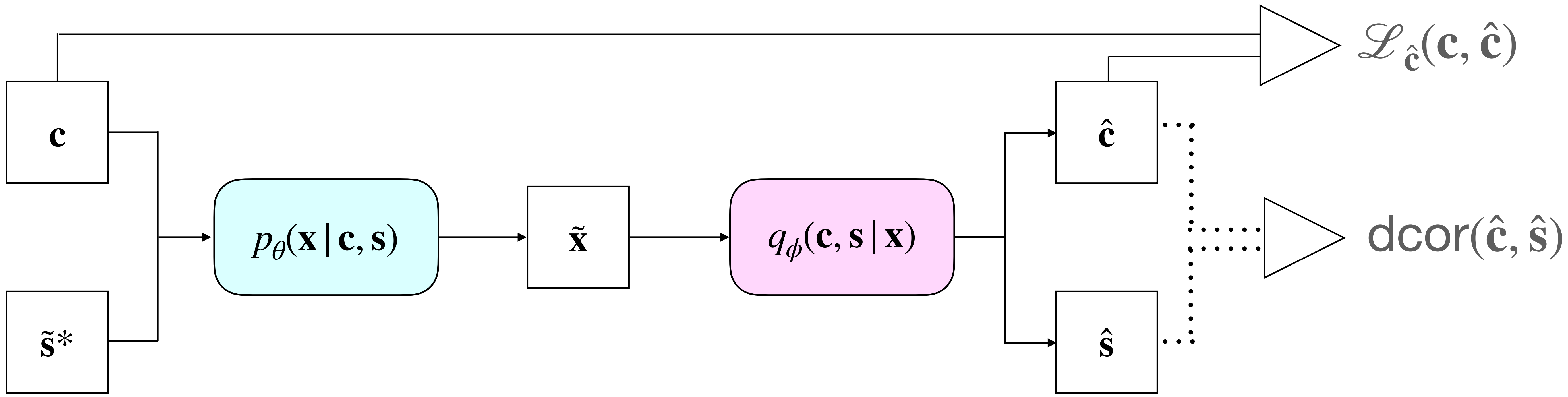


x

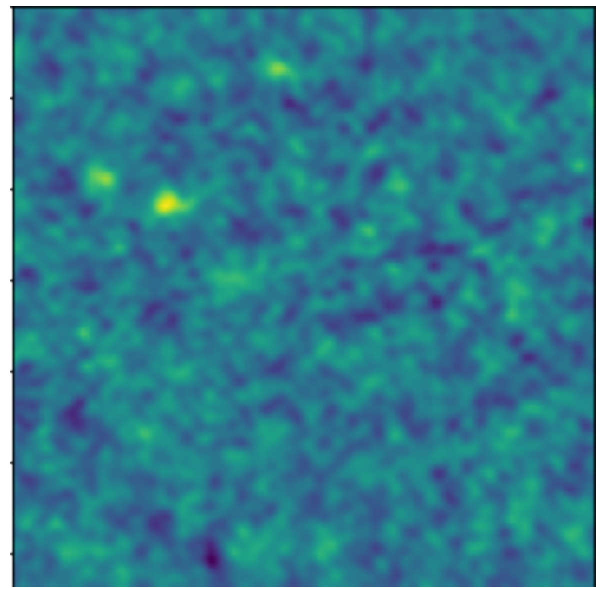




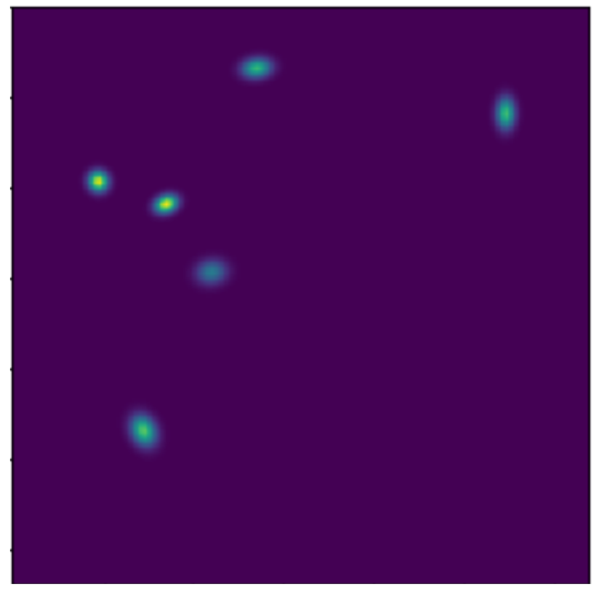
c



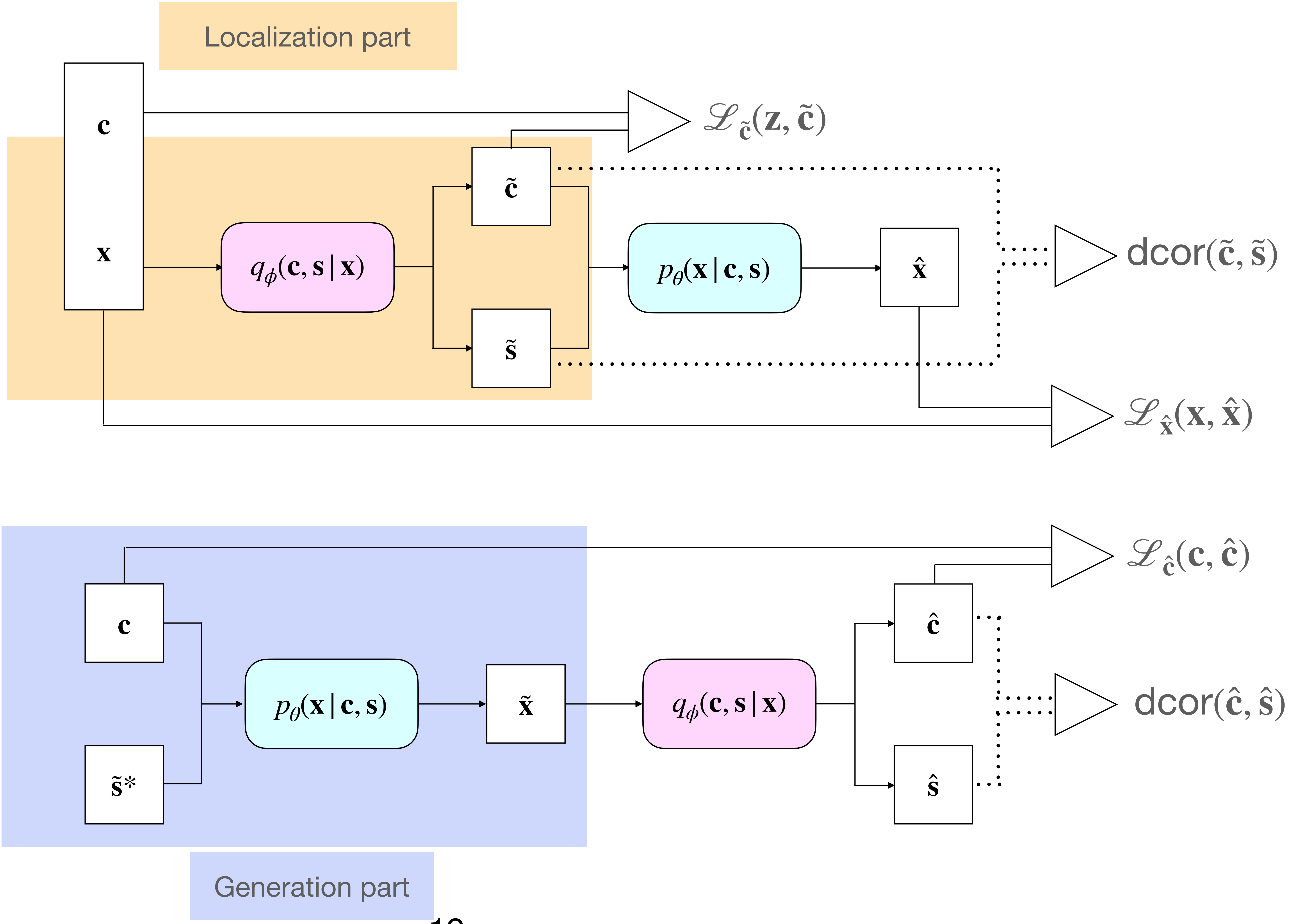
STAR model



$\mathbf{x}$



$\mathbf{c}$



Results: Source detector

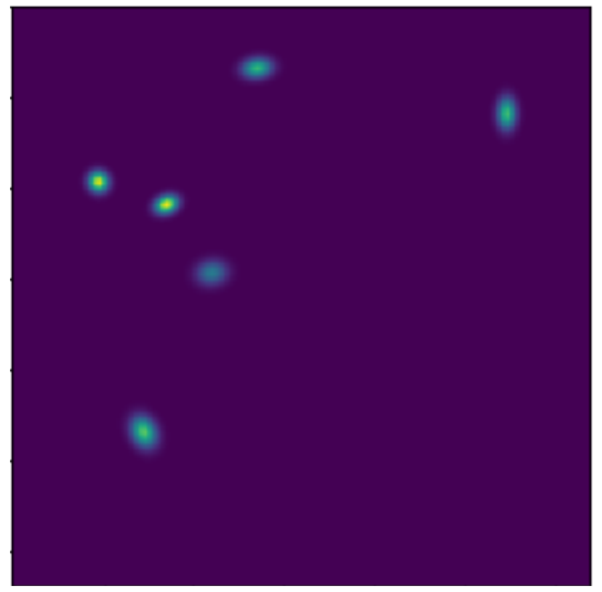
	Purity	Completeness	F1 Score	L2	Network runs
Only MSE	93.23	93.60	93.41	1.61E-05	1
DDPM	99.30	97.05	**98.16**	1.19E-05	250*20
STAR (MSE, without dcor)	91.55	93.63	92.58	1.69E-05	1
STAR (MSE, dcor)	93.98	94.09	94.03	1.56E-05	1
STAR (MSE, dcor, 2 branches)	**97.16**	**93.39**	**95.23**	**1.62E-05**	**1**

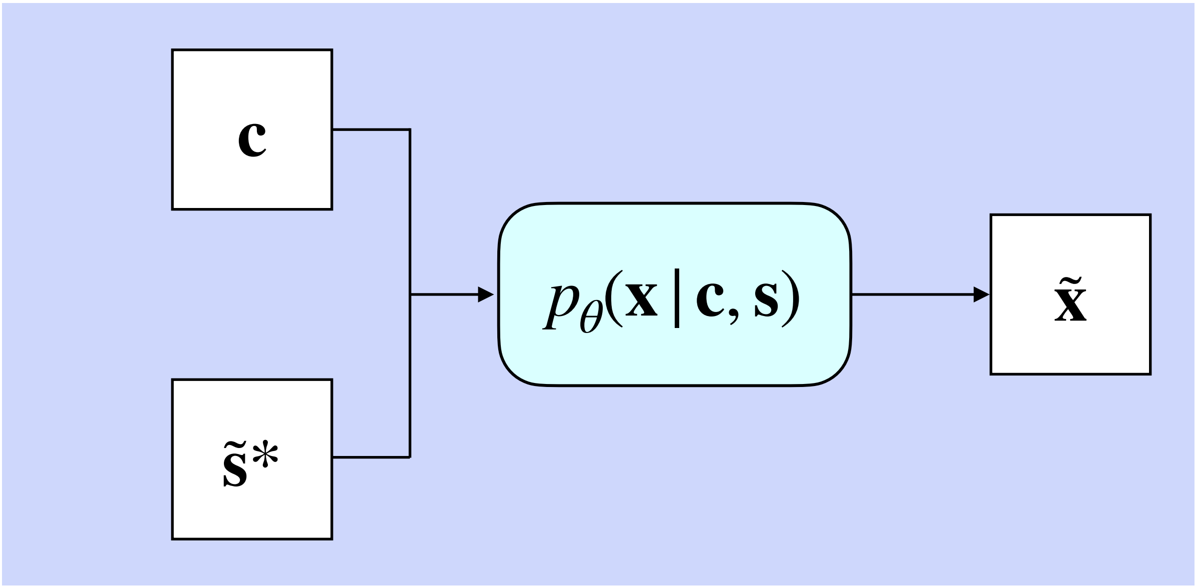
STAR:
- encoder 13.85M parameters
- decoder 10.96M parameters
- one run

DDPM:
- UNet 36M parameters
- 250 steps
- 20 runs

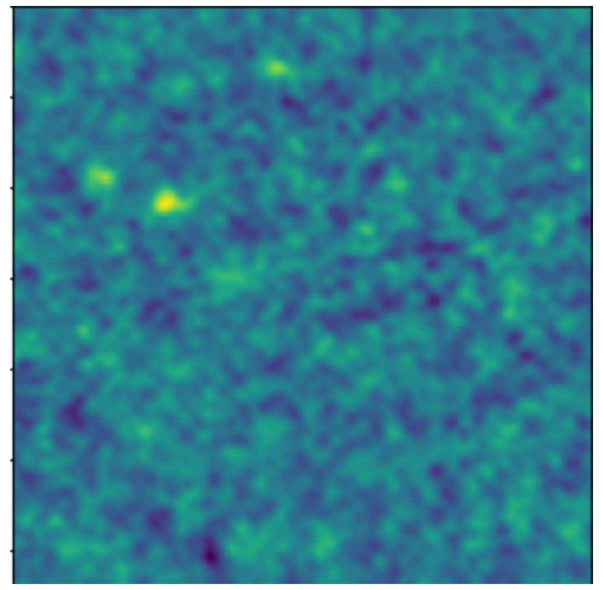
Generator

Sky model (CASA synthetic)

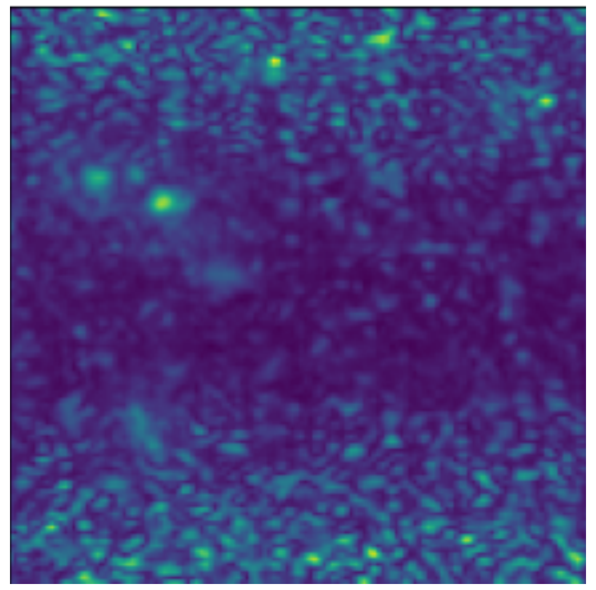




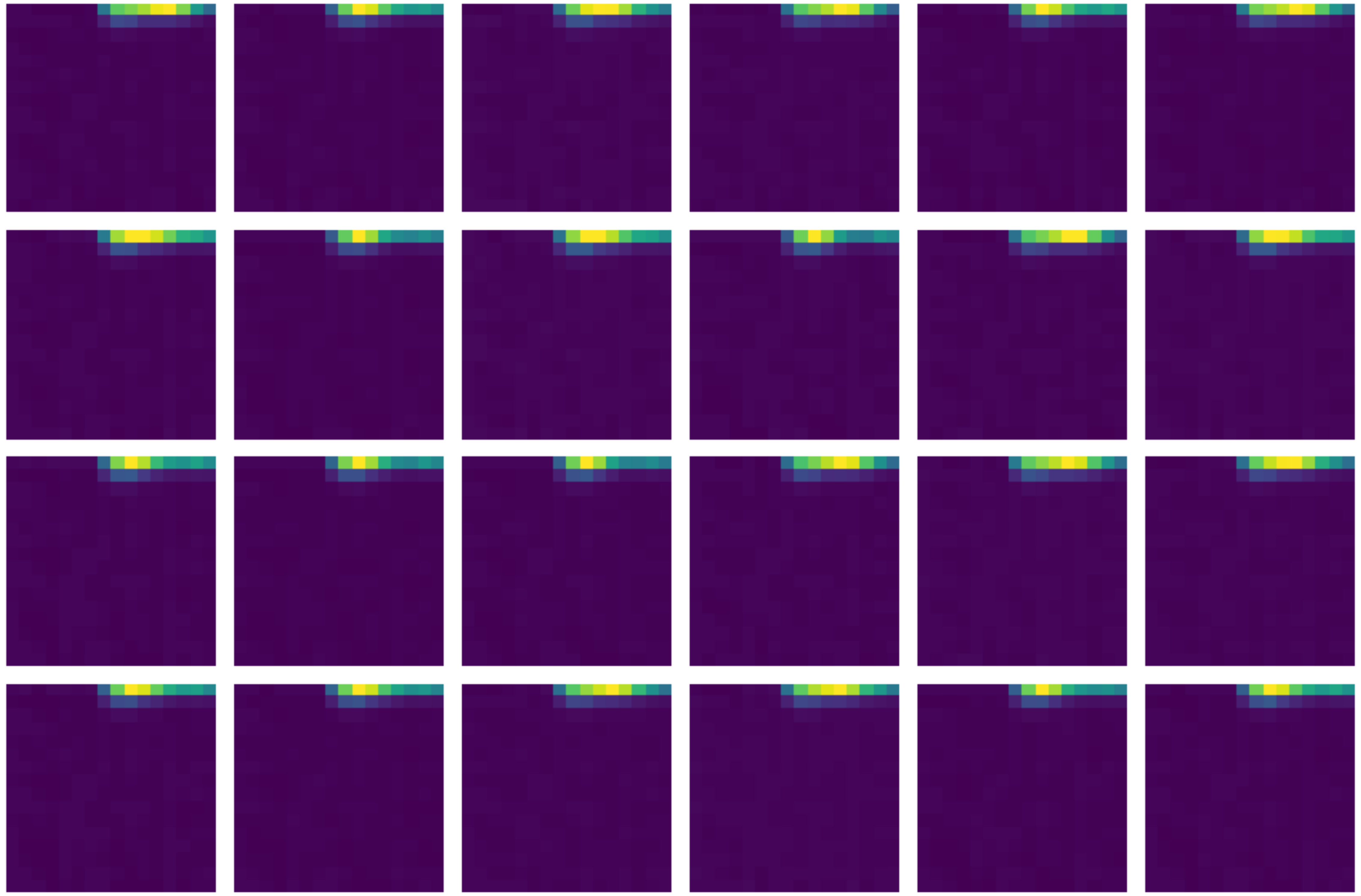
Mean of generated



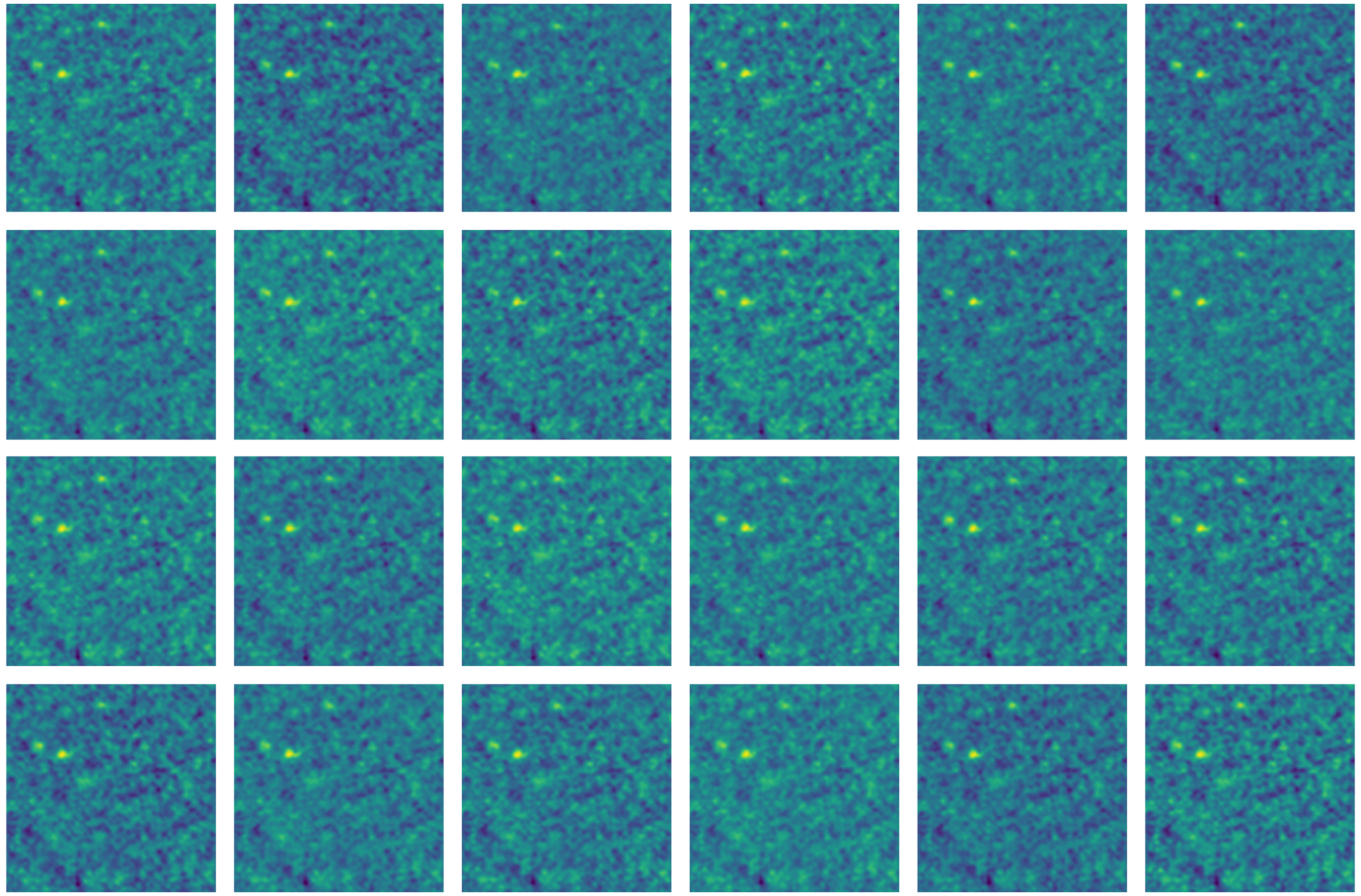
Std



Styles

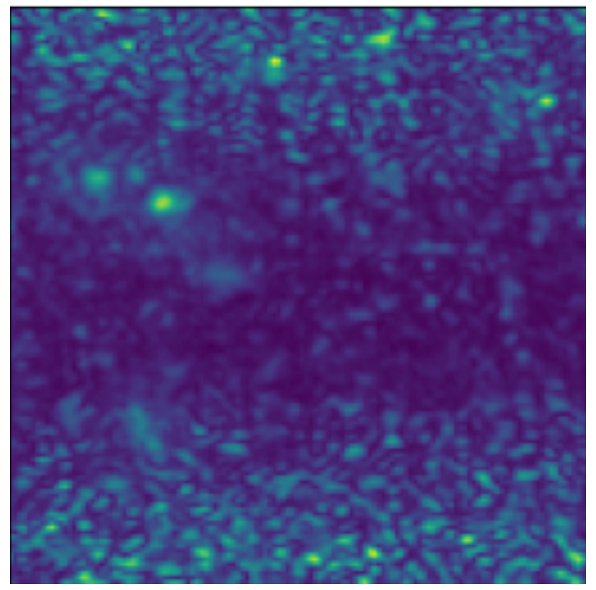


Dirty Images (generated)

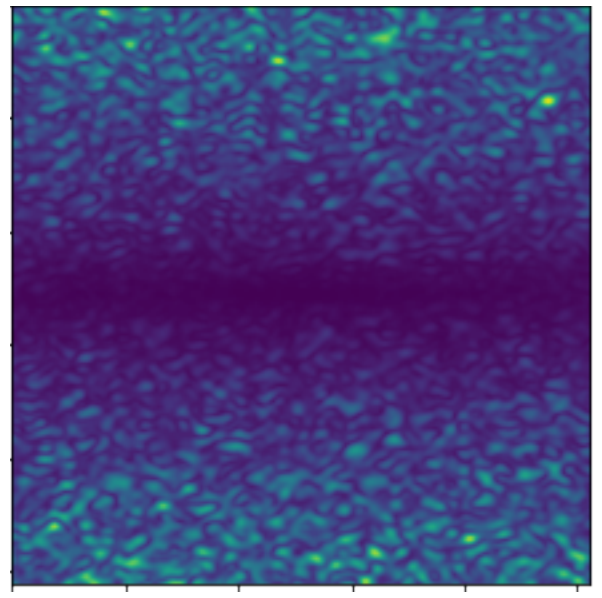


CASA generated data statistics

Std



Std (CASA generated data)



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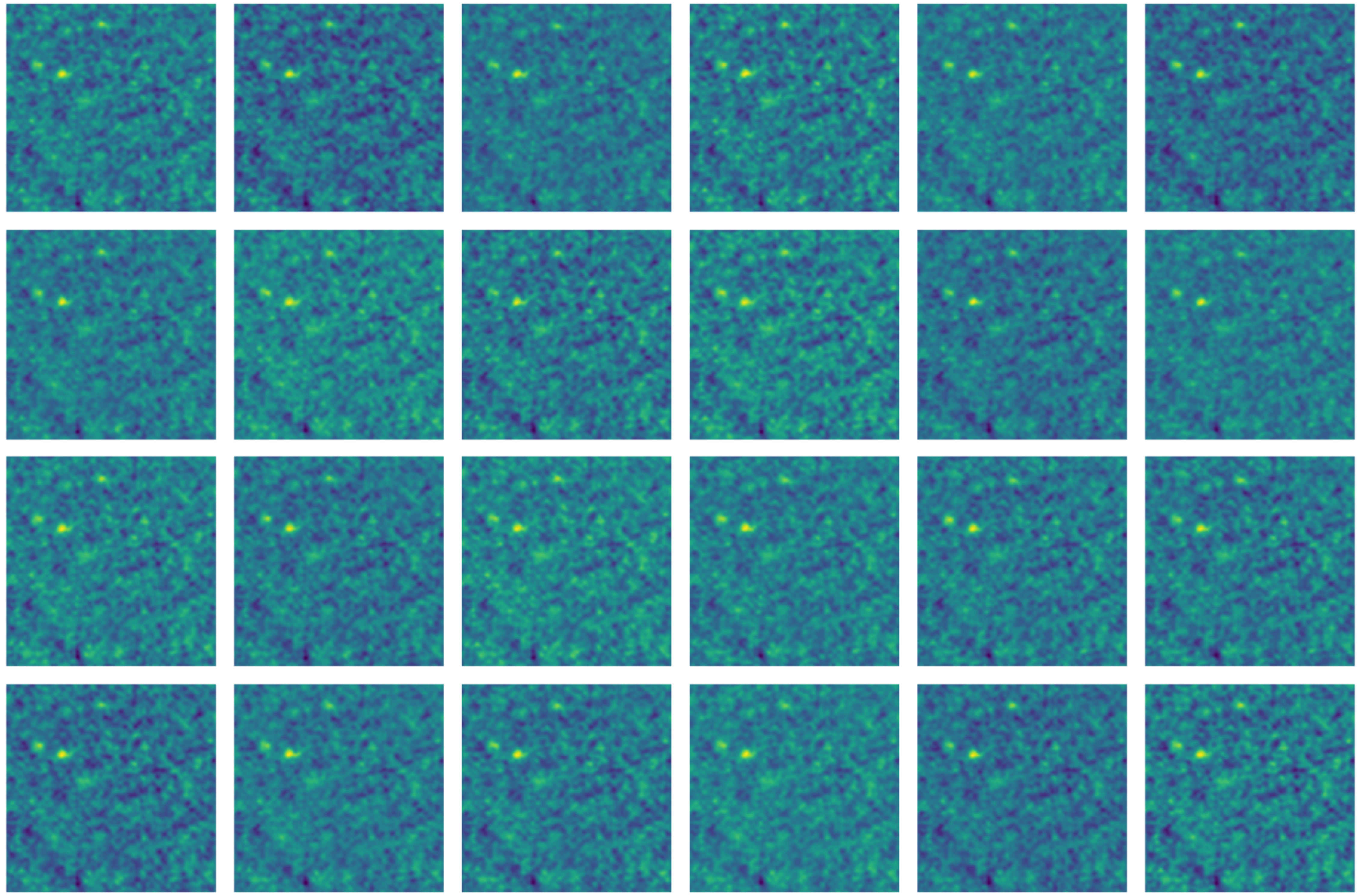

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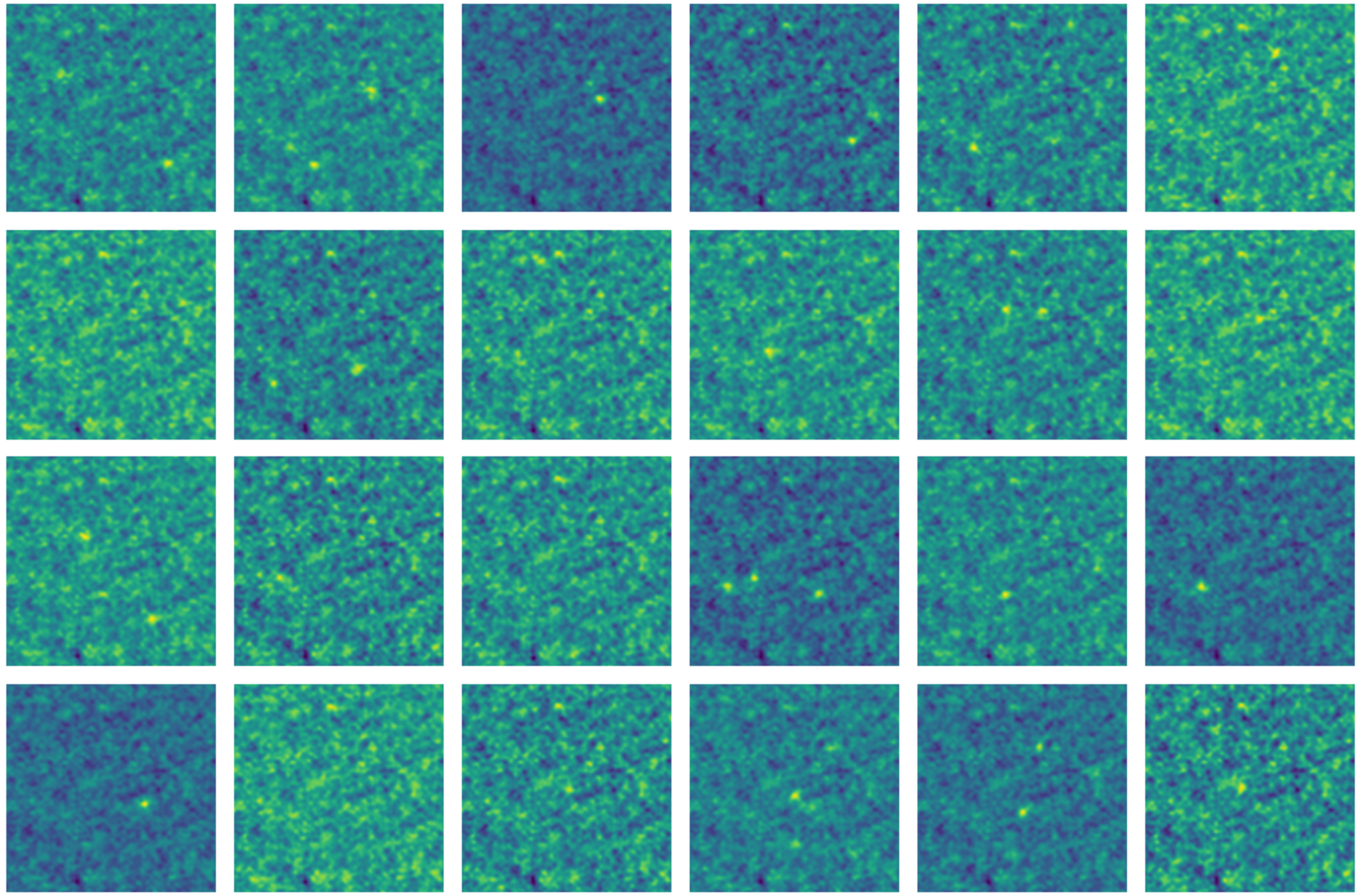

Conclusions and future work

- We introduced a stochastic generative model with a low complexity comparing to DDPM while maintaining high localization performance.
- STAR showed the ability to generate additional synthetic data.
- This hybrid model can be improved further by studying combinatorics for different losses
- We plan to add a generative network for styles (Implicit Autoencoder, FLOWs etc.)
- Investigate other methods for disentanglement between content and style.

Thank you! Questions?