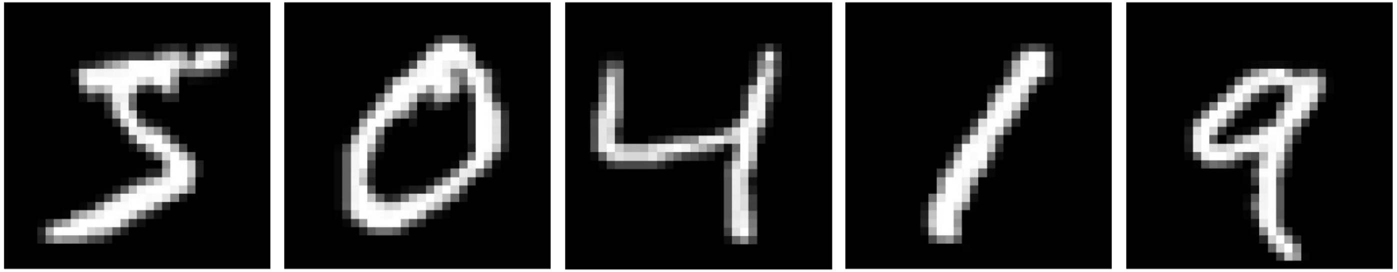
Image-to-Image Translation with Content-Style Disentanglement for Radio Astronomy

Mariia Drozdova, Vitaliy Kinakh, Yury Belousov, Omkar Bait, Davide Piras, Erica Lastufka, Taras Holotyak, Miroslava Dessauges-Zavadsky, Daniel Schaerer, Slava Voloshynovskiy

Introduction: let's talk about MNIST

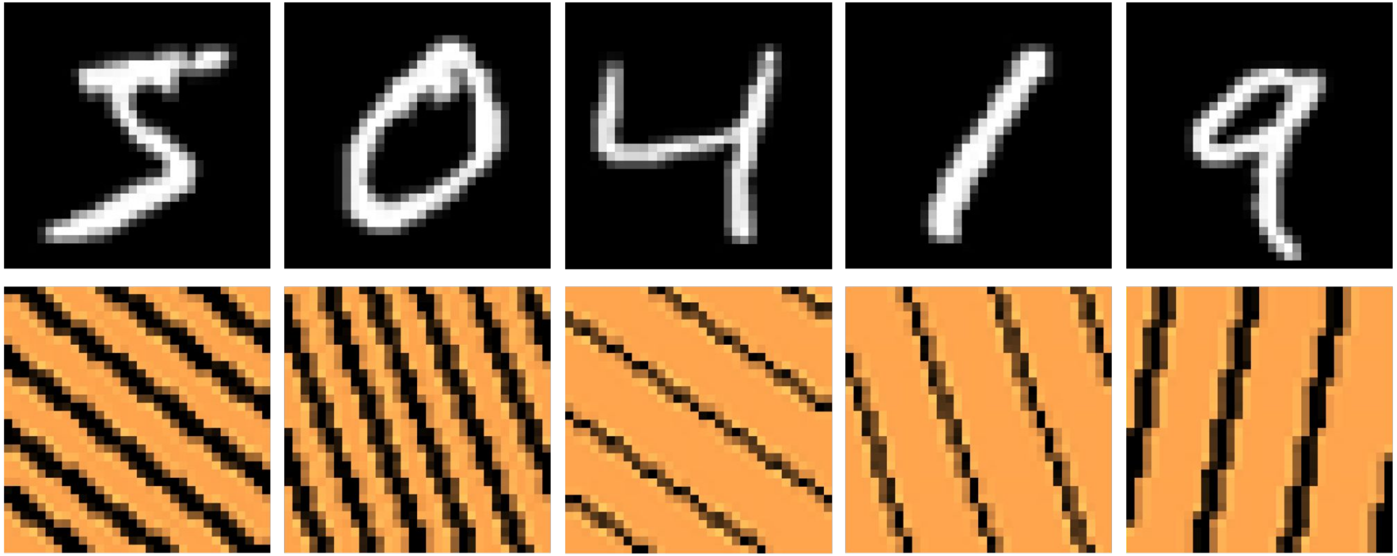
Content



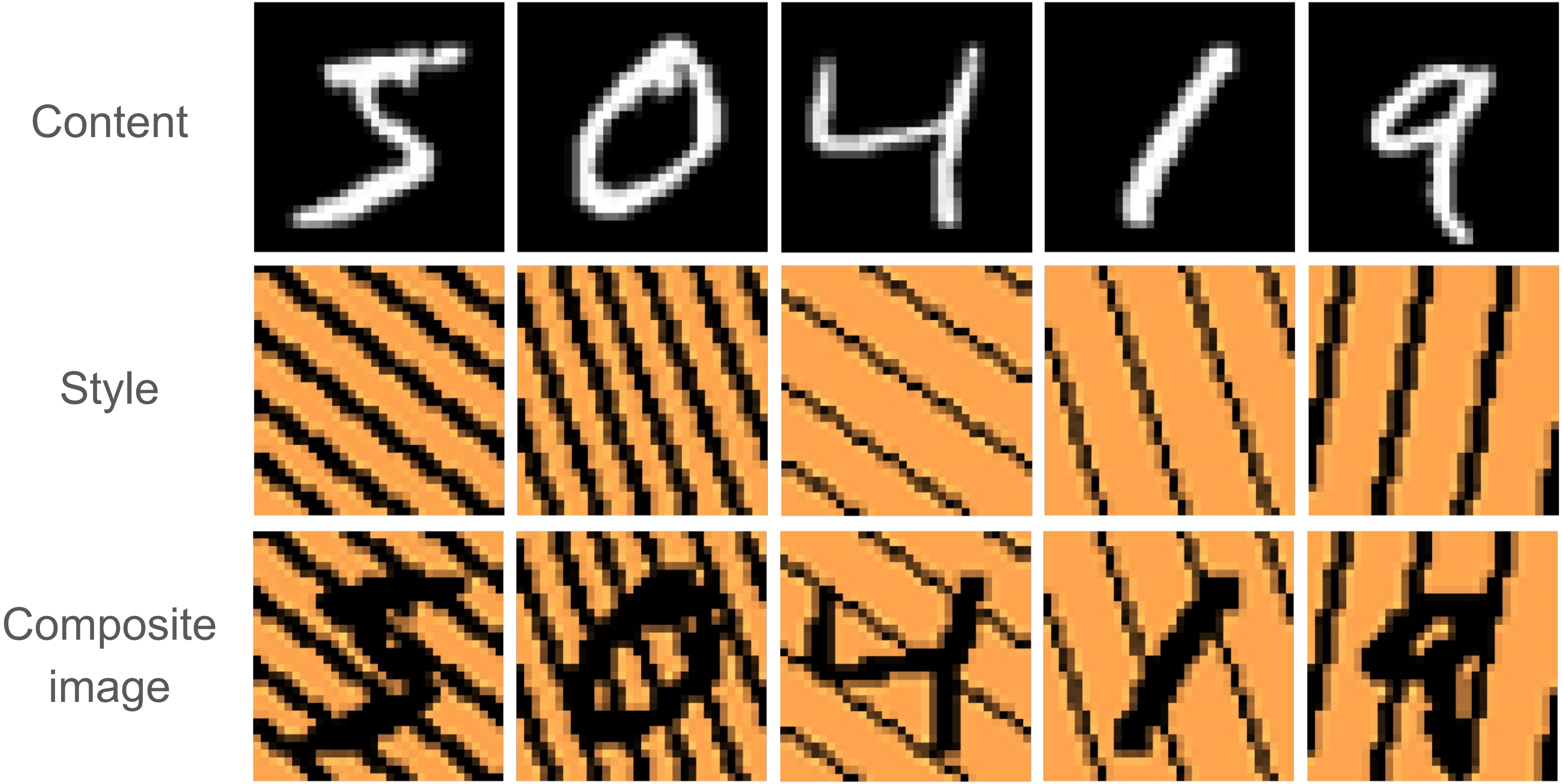
Introduction: let’s talk about MNIST

Content

Style



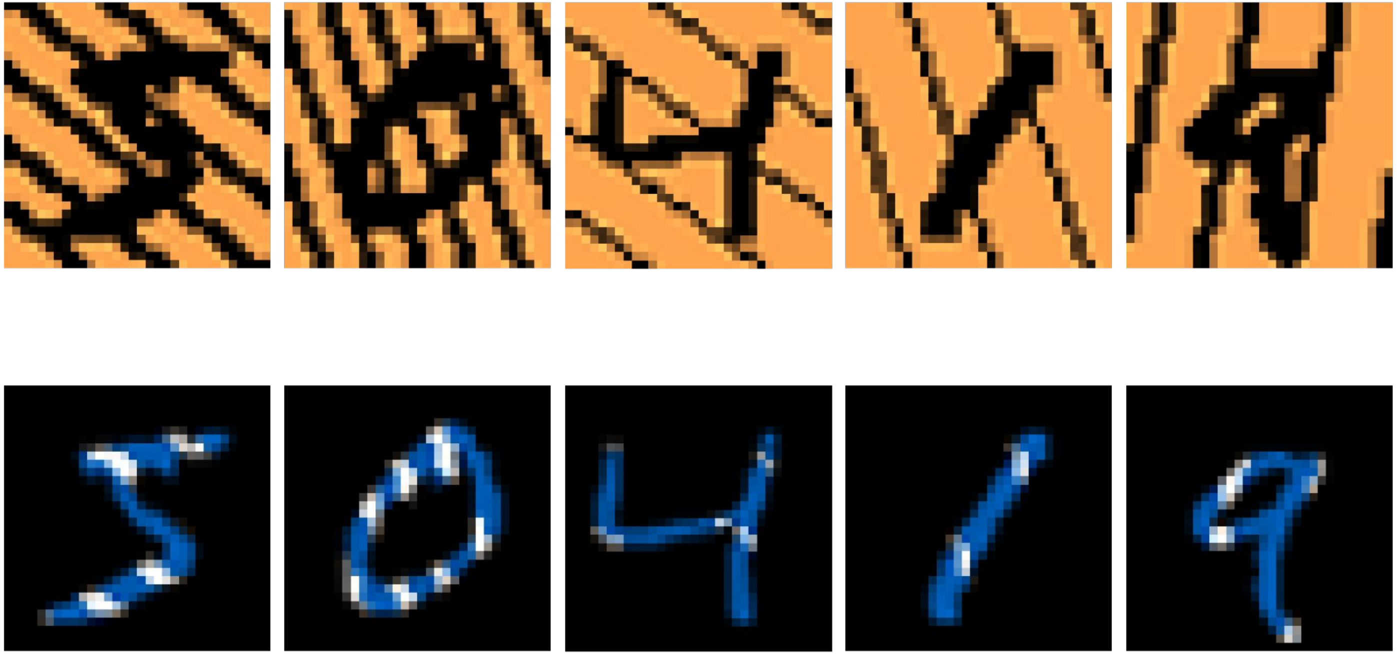
Introduction: let's talk about MNIST



Introduction: let's talk about MNIST

Composite image

Uncertain regions



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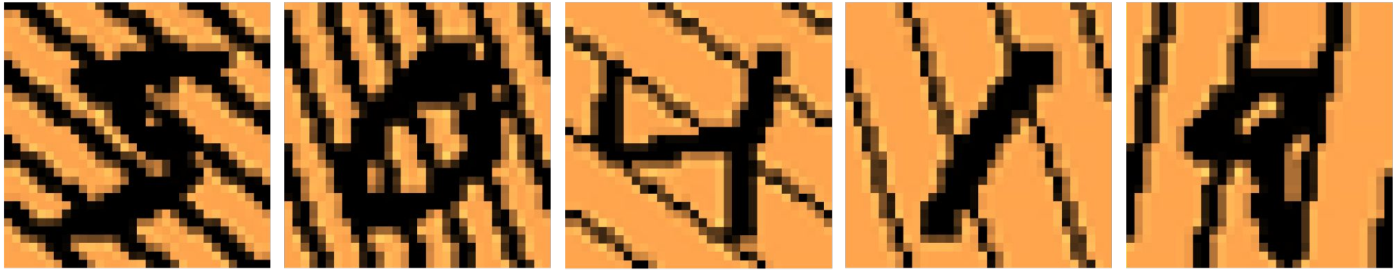
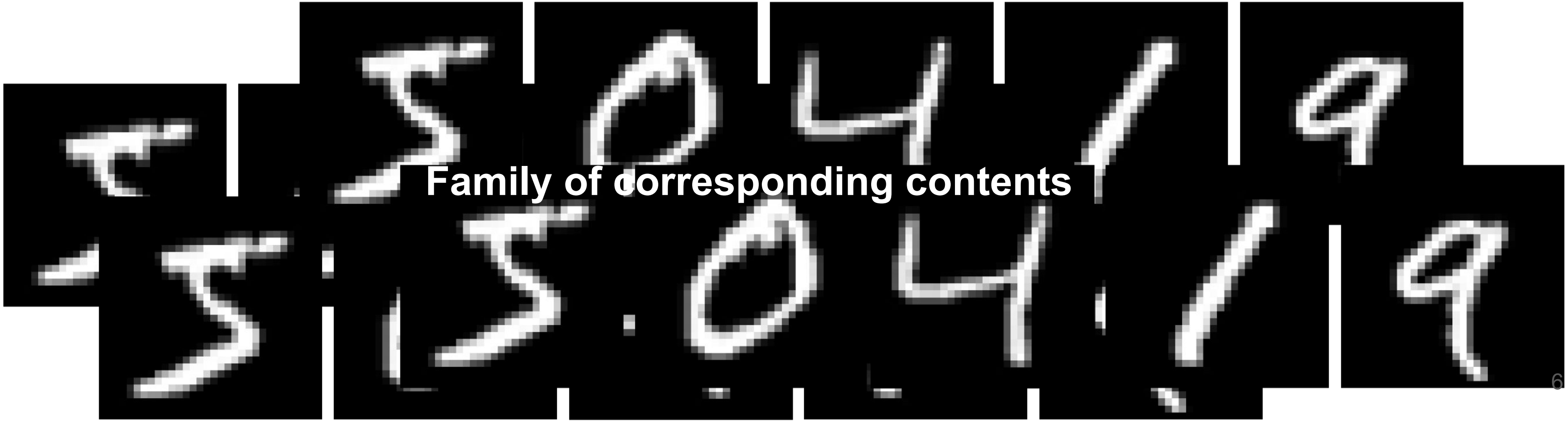
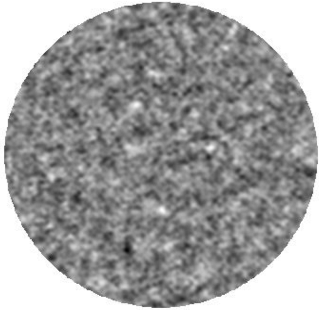




Radio Astronomy Dataset

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



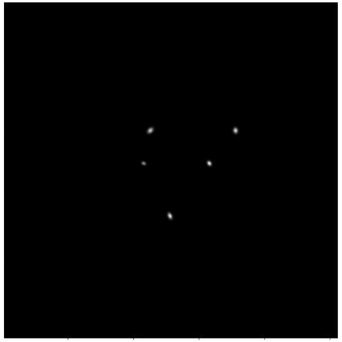


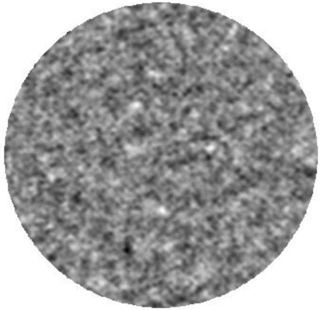
Image-to-image translation with uncertainty estimation

What is Image-to-Image Translation?

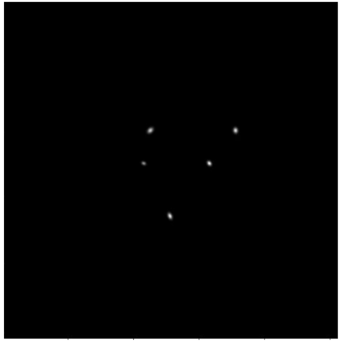
- Transforming one modality into another

Why Uncertainty Estimation?

- Critical for identifying reliable predictions
- Essential for interpretation



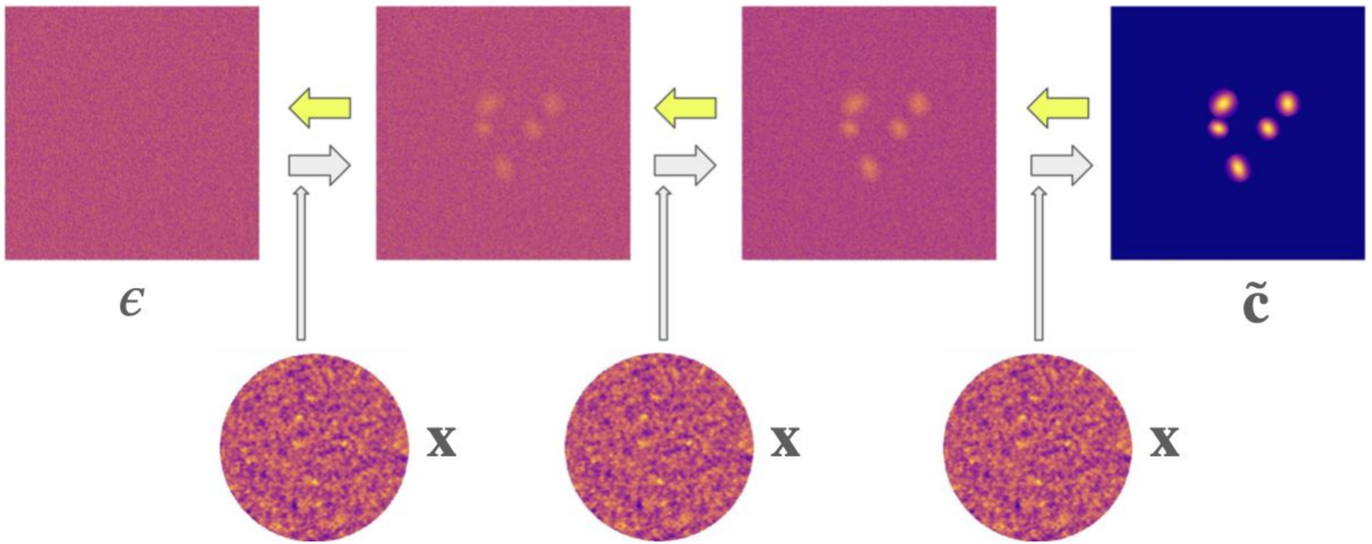
Dirty noisy image



Sky model image

Uncertainty estimation in DDPMs

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



Radio-astronomical image reconstruction with a conditional denoising diffusion model, M. Drozdova et al. 2024, Astronomy&Astrophysics

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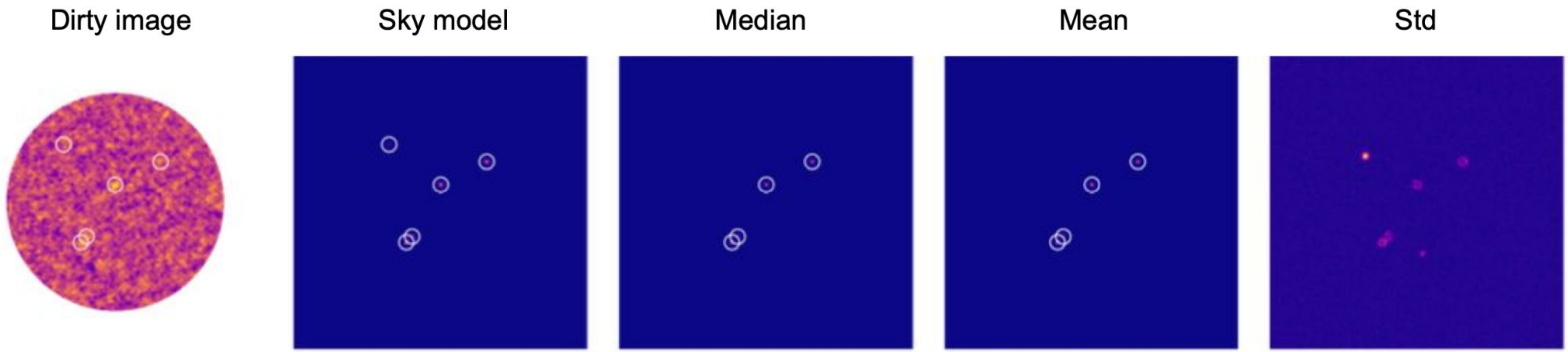

Radio-astronomical image reconstruction with a conditional denoising diffusion model, M. Drozdova et al. 2024, Astronomy&Astrophysics

Why new method?

Fast:

- Reduces computational time compared to methods like DDPMs.
- Efficient for large-scale data and real-time processing needs.

Interpretable:

- Aims to create a complete system where uncertainty is related to a non-visible variable: style.
- By mixing style with dirty image, we can generate the sky model and vice versa, giving insight into what the network understands as 'style'.
- This approach provides understandable uncertainty maps like DDPM.
- Easily integrated into classical paired settings, making it adaptable and user-friendly.

2-to-1 approach for radio astronomy data

If **sky model** and **astronomical & instrumental noise** are given, **dirty image** can be restored

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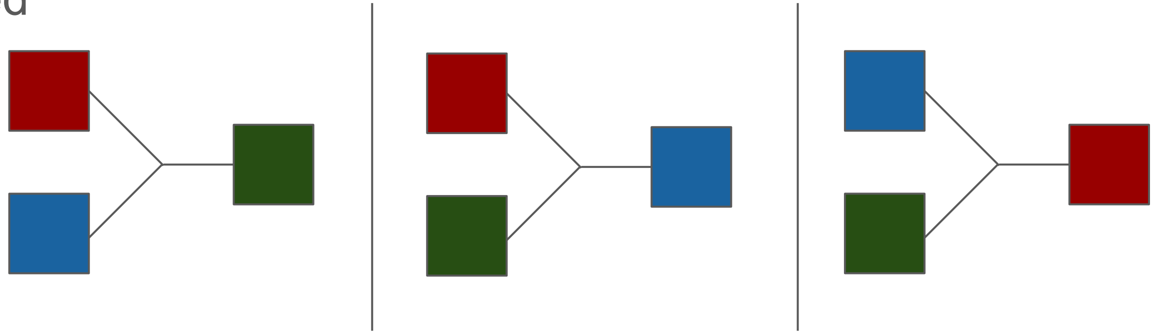
If **astronomical & instrumental noise** and **dirty image** are given, **sky model** can be restored



2-to-1 approach (general idea)

If **content** and **style** are given, **composite image** can be restored.

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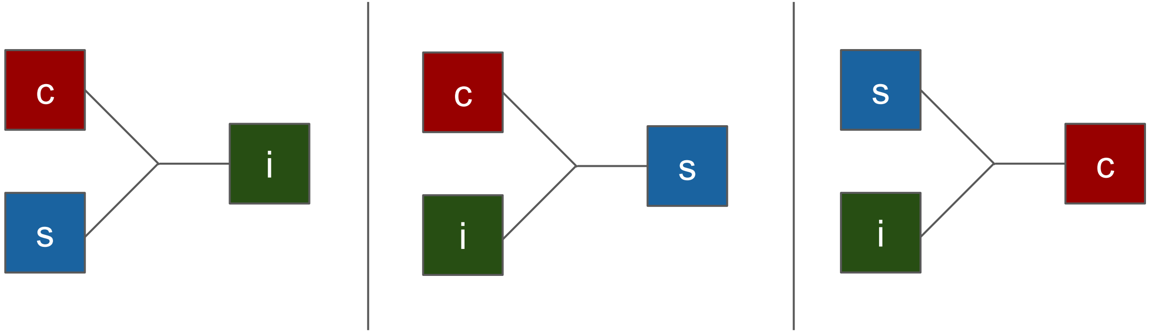

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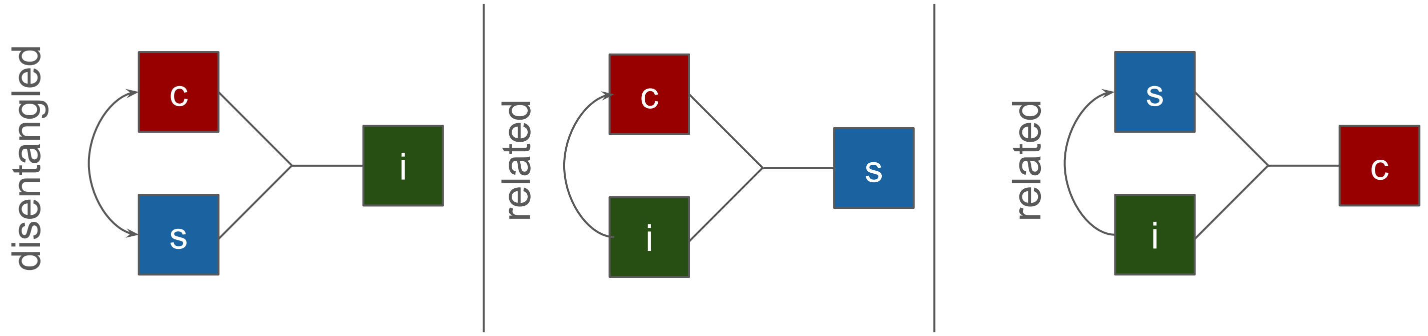

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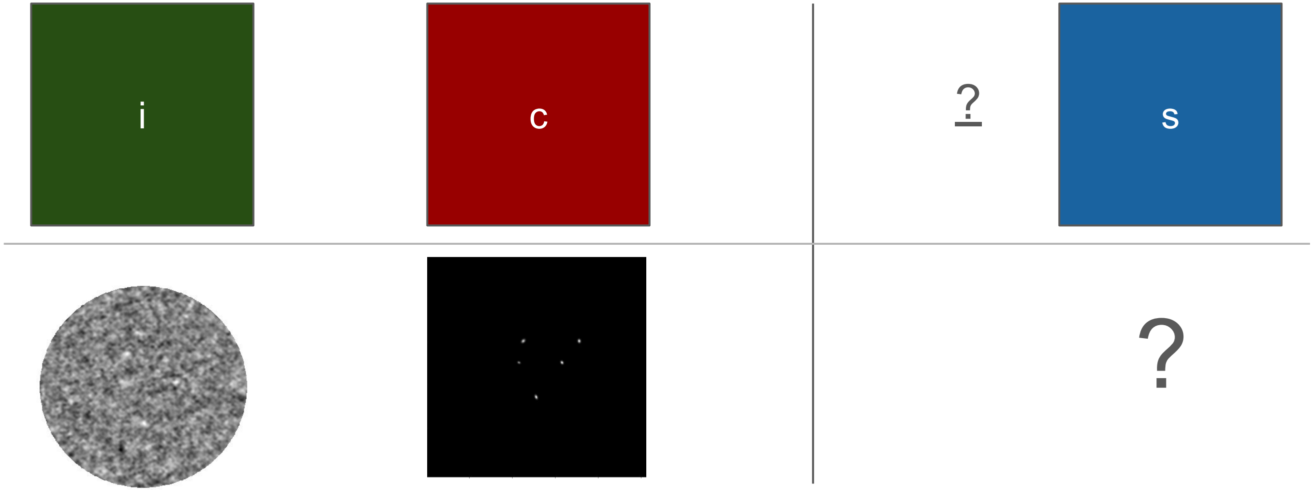
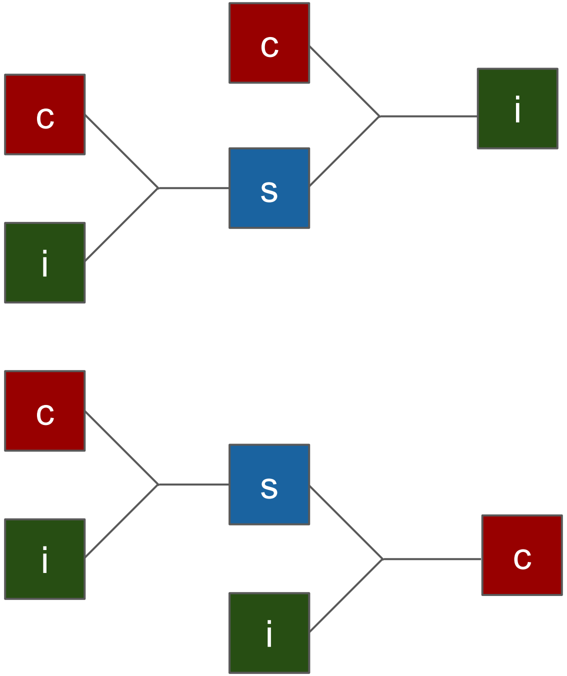
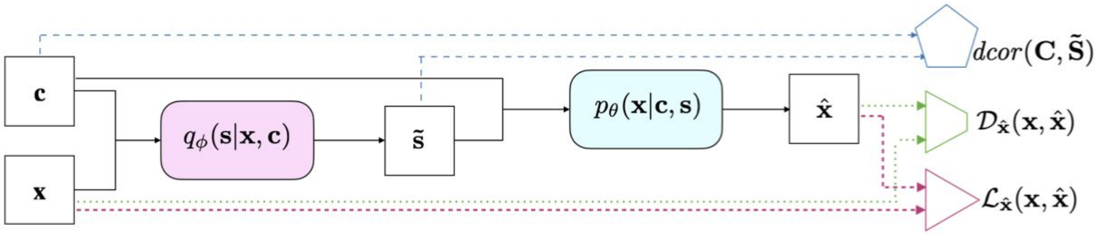
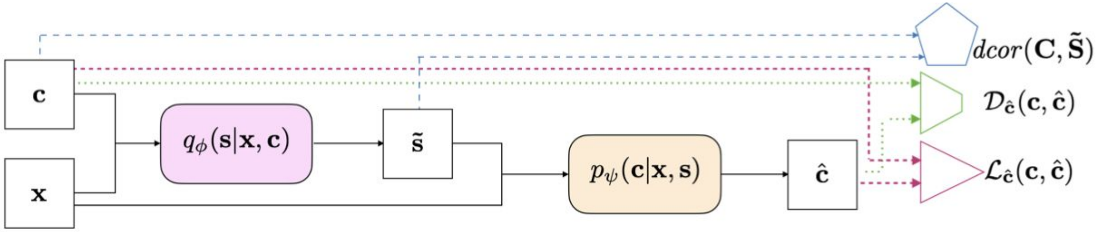


2-to-1 approach (reconstruction steps)



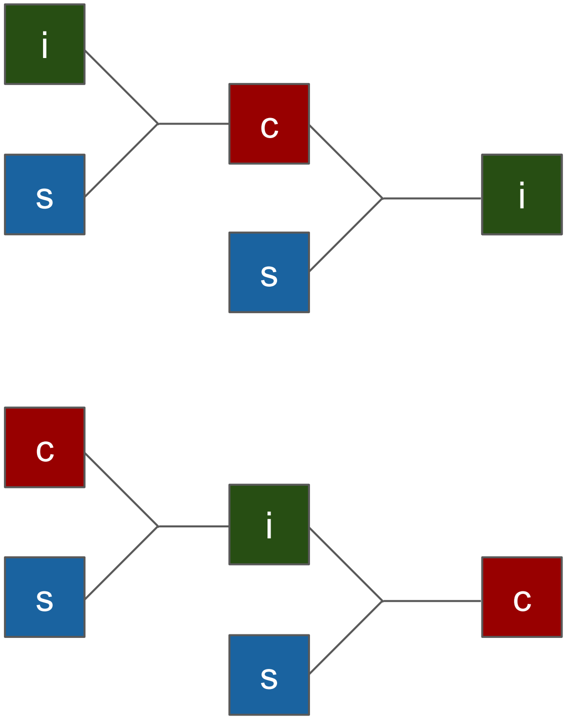


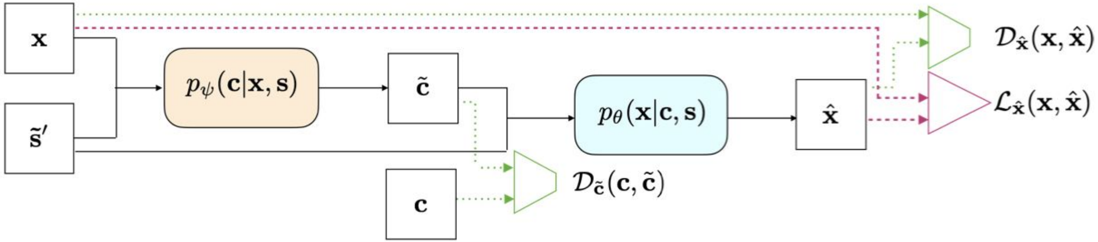
(a) Composite Image Reconstruction



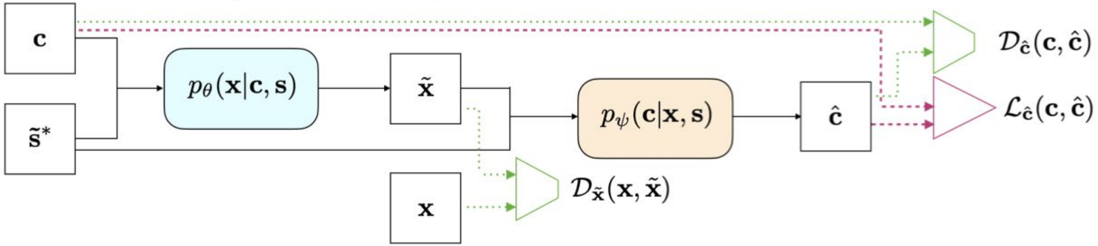
(b) Content Reconstruction

2-to-1 approach (generation steps)



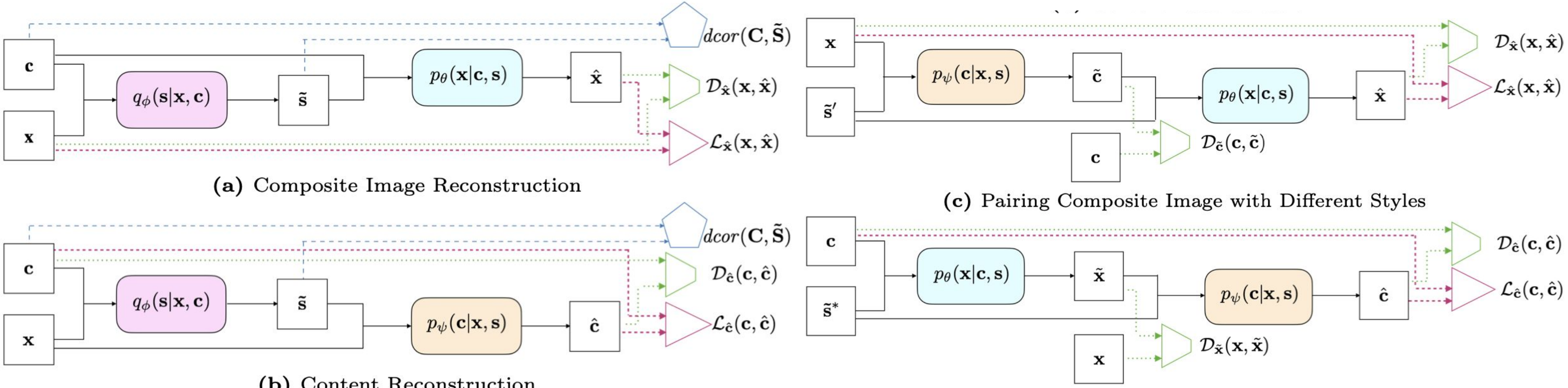


(c) Pairing Composite Image with Different Styles



(d) Pairing Content with Different Styles

Full architecture



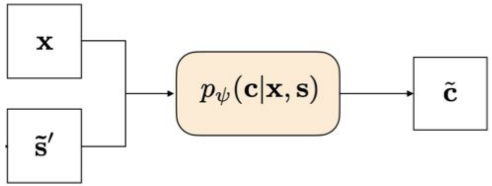
(a) Composite Image Reconstruction

(c) Pairing Composite Image with Different Styles

(b) Content Reconstruction

(d) Pairing Content with Different Styles

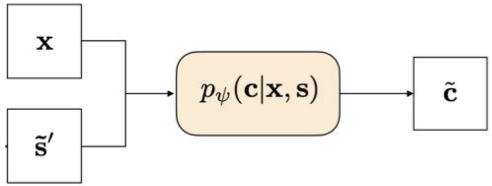
Uncertainty estimation in inference



Idea to measure Uncertainty:

- Pair given dirty image with different styles to get multiple predictions
- Aggregate the predictions

Uncertainty estimation in inference



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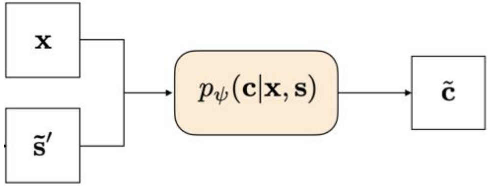
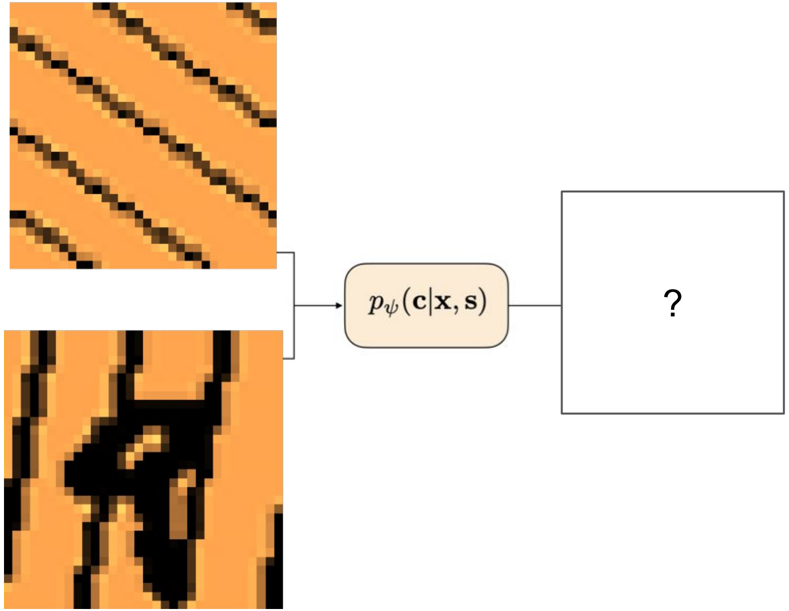
However, what if random style contradicts completely the given composite image?

Uncertainty estimation in inference





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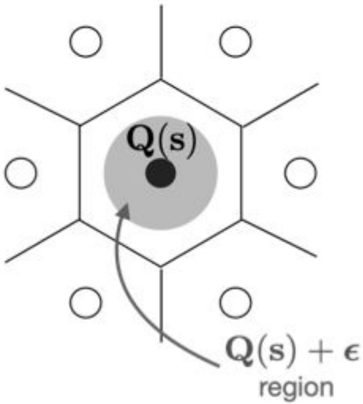
Uncertainty estimation in inference

We need to pair with only plausible styles:

- Find the style estimate (interpreted as plausible styles cluster center)
- Generate multiple styles by adding noise to style estimate



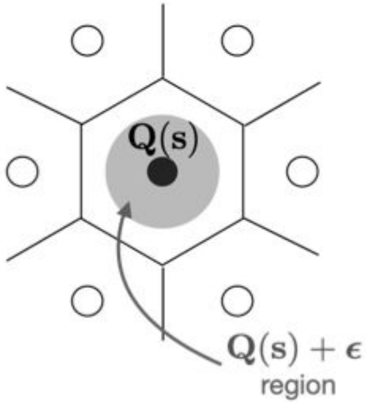
Uncertainty estimation in inference

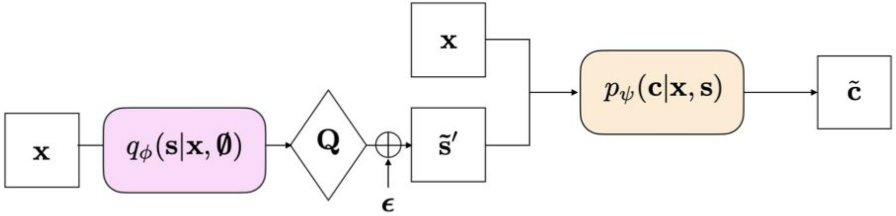
We need to pair with only <u>plausible</u> styles:

- Find the style estimate (interpreted as plausible styles cluster center)
- Generate multiple styles by adding noise to style estimate

After pairing, we get multiple predictions:

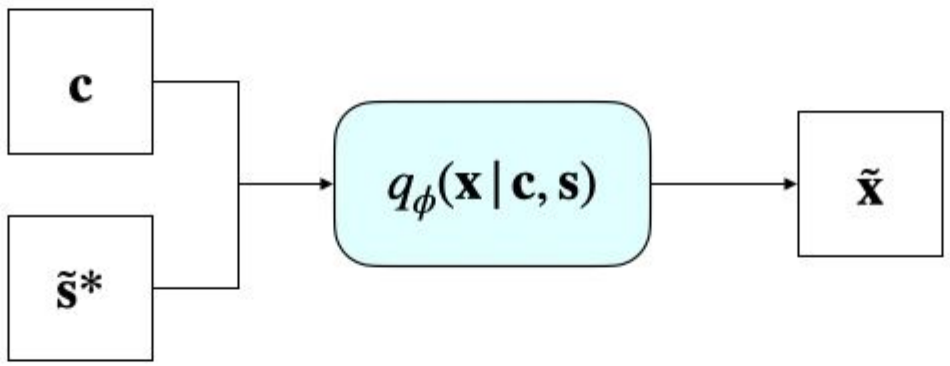
- Compute standard deviation to estimate uncertainty



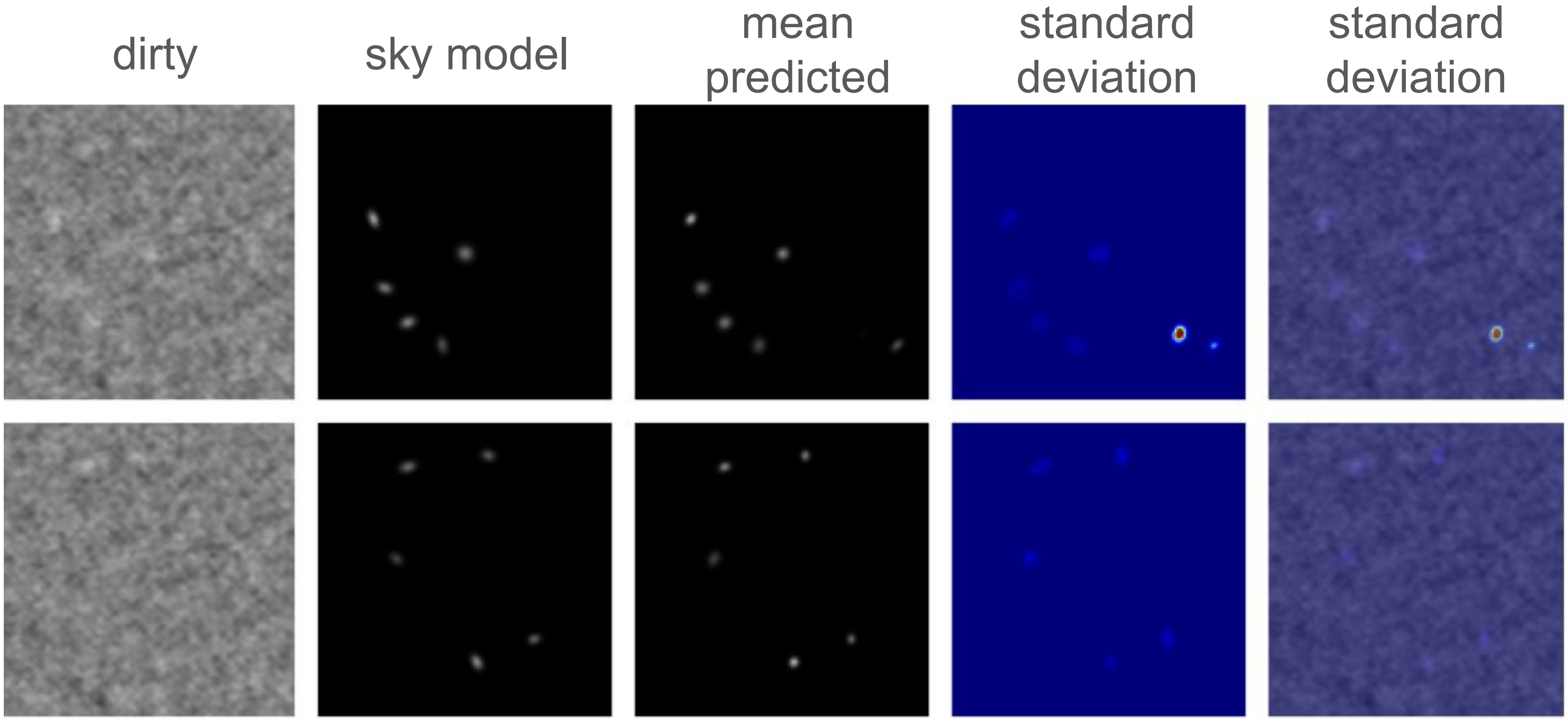


Generation in inference

- Style and content are disentangled, so we can pair any two to generate a new composite image.



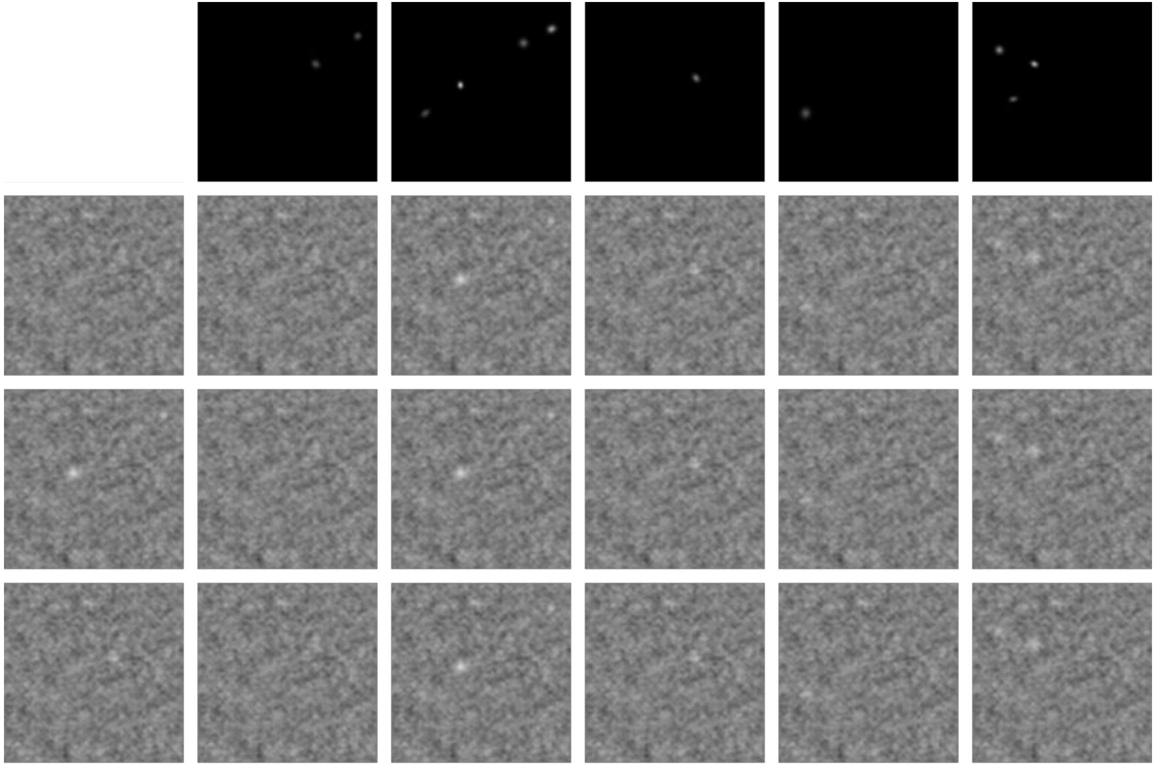
Experiments - Radio Astronomy Dataset



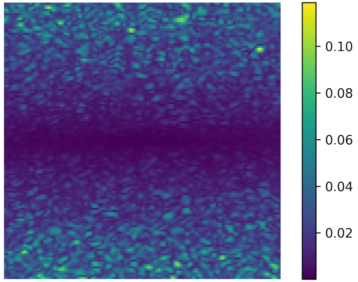
Experiments - Radio Astronomy Dataset

	Purity	Completeness	F1 Score	Network runs
Only MSE	93.23	93.60	93.41	1
DDPM	**99.30**	**97.05**	**98.16**	250*20
Ours, direct	96.69	94.89	95.78	1
Ours, multiple runs	**98.51**	**96.83**	**97.66**	**10**

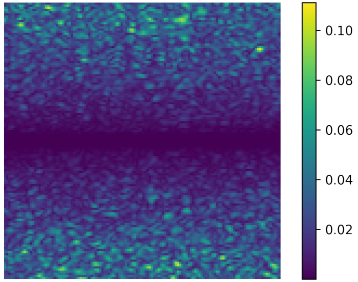
Experiments - Radio Astronomy Dataset



Standard deviation of the simulated dataset:



Standard deviation of the generated images:



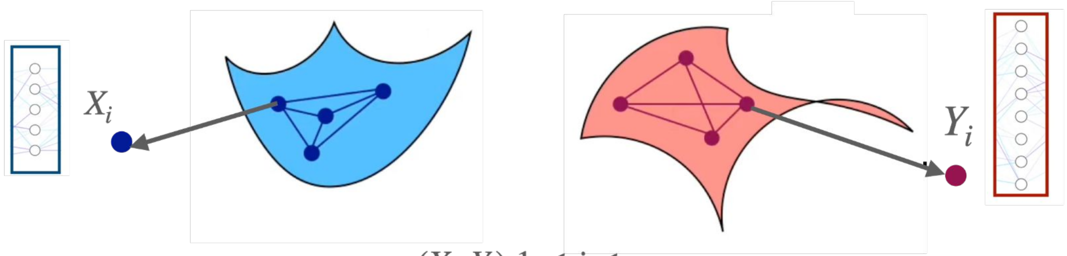
Summary

We introduced a **2-to-1 prediction method** for image-to-image translation in radio astronomy which combines **content-style disentanglement** with uncertainty estimation.

- **Fast:** Reduces computational time compared to traditional deep learning models like DDPMs.
- **Interpretable:** Provides clear uncertainty maps by linking uncertainty to style variability.
- **Future Directions:** Applying the method to more complex datasets, exploring semi-supervised learning approaches for broader applicability.

Questions

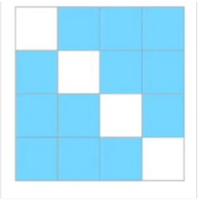
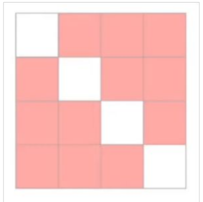
Distance correlation



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

Distance matrix: $a_{k,l} = ||X_k - X_l||$ $\quad$ $b_{k,l} = ||Y_k - Y_l||$:

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

$A =$  $\longleftrightarrow$ 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