APC, CNRS, FRANCE

MADNESS

Maximum-A-posteriori solution with Deep generative NEtworks for Source Separation

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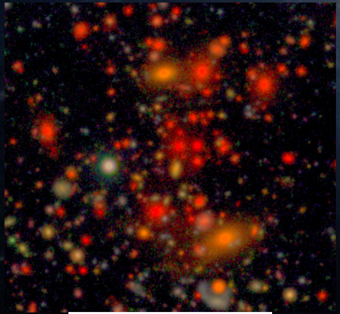
Surveys and Challenges

Large survey of Space and Time (LSST) at Vera Rubin Observatory:

- Ground-based
- constrain Dark Energy
- 3.2 billion pixel camera
- 6 observation bands in visible range

more depth + area of coverage ⇒ More statistics!

Surveys and Challenges



HSC ultradeep image

Large survey of Space and Time (LSST) at Vera Rubin Observatory:

- Ground-based
- constrain Dark Energy
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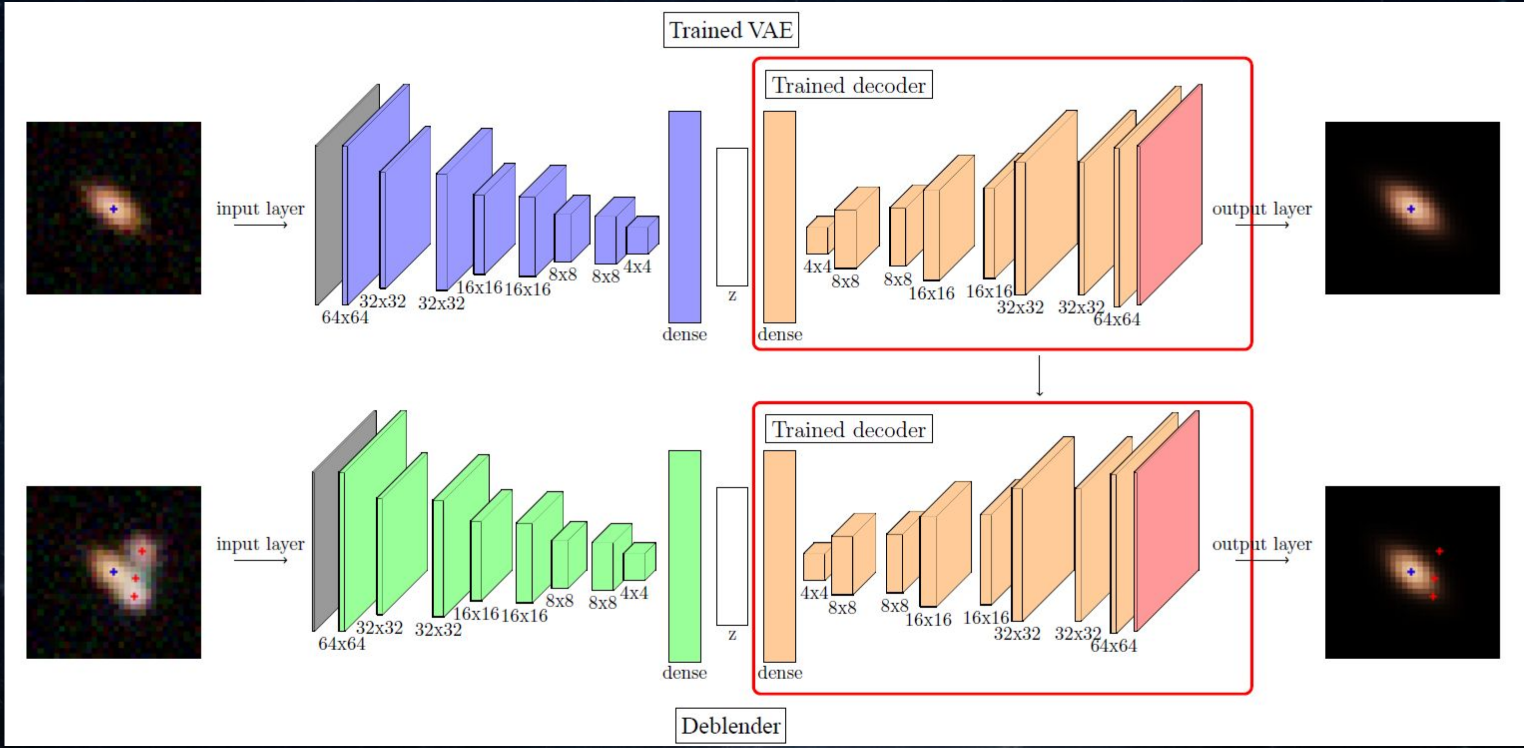
more depth + area of coverage ⇒ More statistics!

greater depth means more complex data!

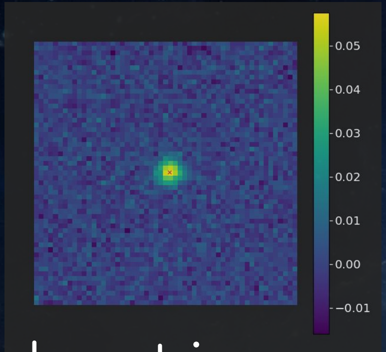
~ Galaxies (60% in LSST) are expected to overlap (blending) in images due to increased depth

ML for Deblending

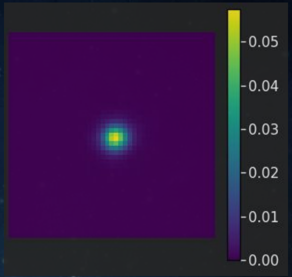


Arcelin et al (arXiv:2005.12039)

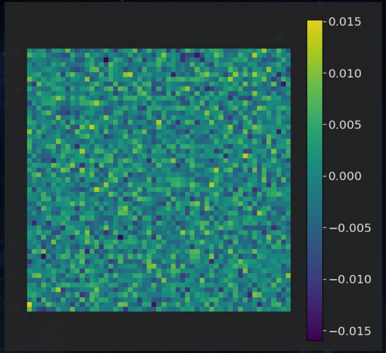
Denoising (Single source)



Input image (y)



Predicted image (x)



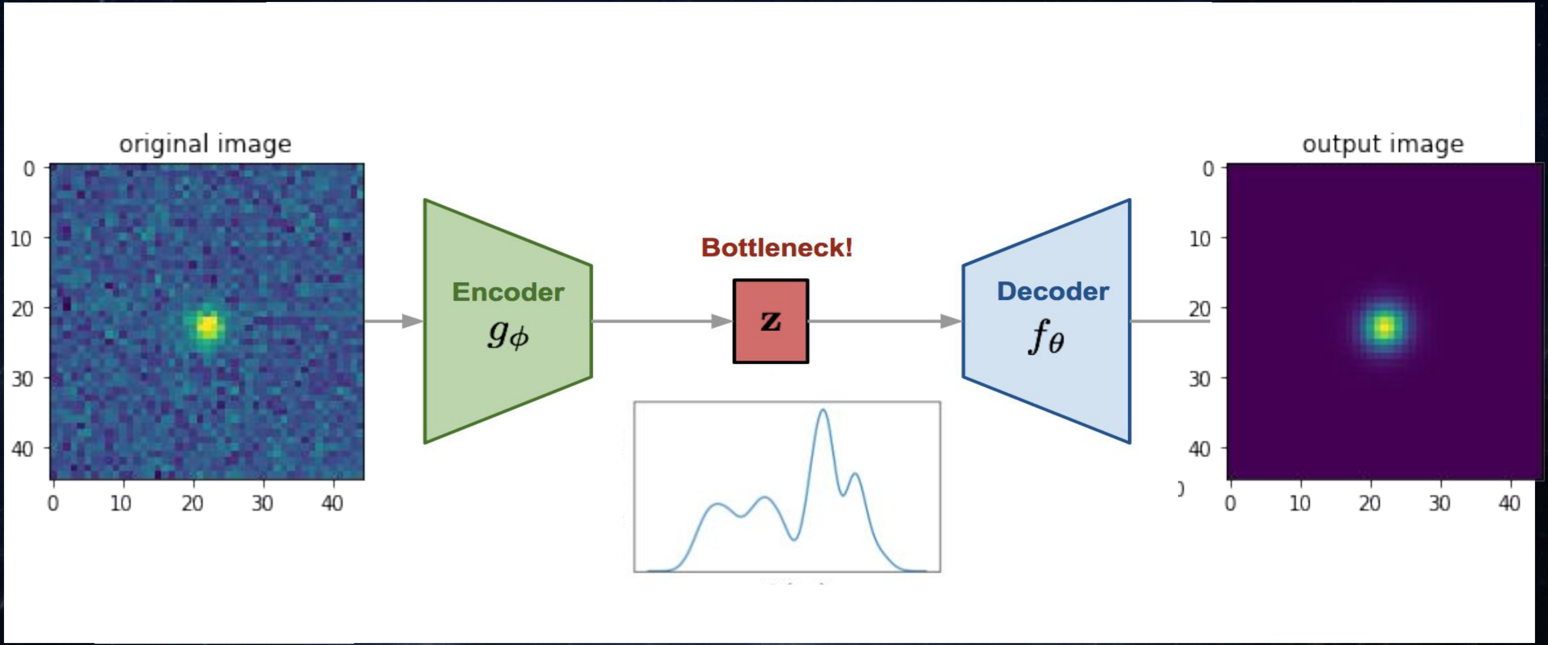
Residual (y-x)

$$x^* = \arg\min_x \; -\log p(y|x) - \log p(x)$$

$$x^* = \arg\min_x \; \frac{|| y - x ||^2}{2\sigma^2_{noise}} - \log p(x)$$

Where, $x*$ is the maximum a posteriori probability (MAP) estimate

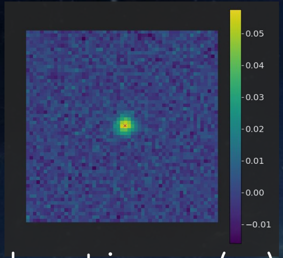
Train VAE as generative model



For example: Lanusse et al (arXiv:2008.03833)

Training: $$\underbrace{-\mathbb{E}_{\mathbf{z}\sim q_\phi(\mathbf{z}|\mathbf{x})} \log p_\theta(\mathbf{x}|\mathbf{z})}_{\text{Reconstruction term}} + \underbrace{D_{\mathrm{KL}}(q_\phi(\mathbf{z}|\mathbf{x}) \| p_\theta(\mathbf{z}))}_{\text{Regularization term}}$$

MAP estimate in latent space

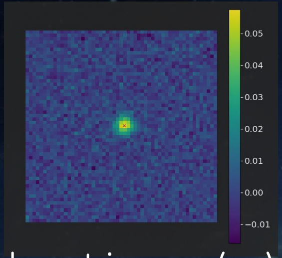


Input image (y)

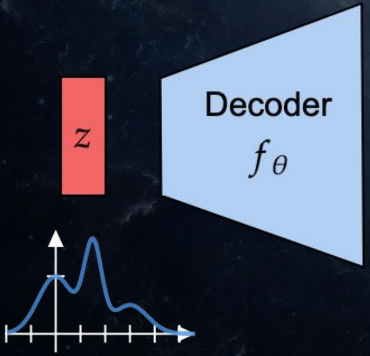
$$x^* = \arg\min_x \frac{\| y - x \|^2}{2\sigma_{noise}^2} - \log p(x)$$

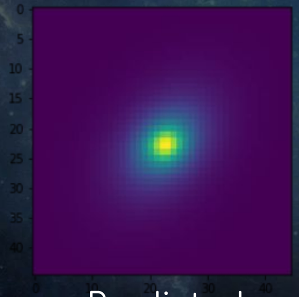
Predicted galaxy (x)

MAP estimate in latent space



Input image (y)





Predicted galaxy (x)

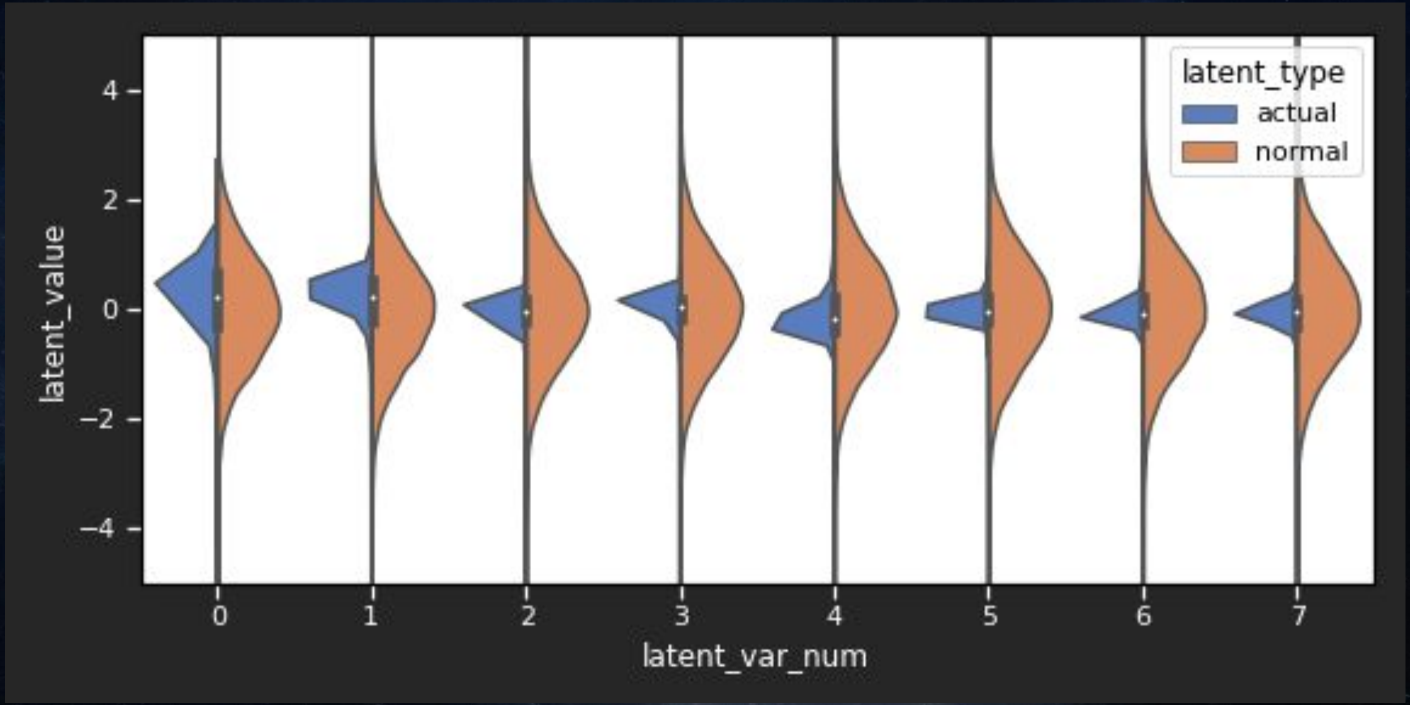
$$x^* = \arg\min_x \frac{\| y - x \|^2}{2\sigma_{noise}^2} - \log p(x)$$

Going to the latent space

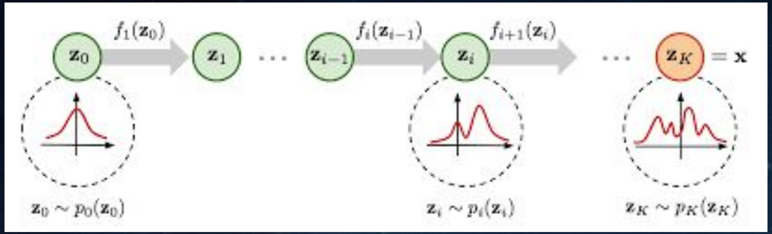
$$z^* = \arg\min_z \frac{\| y - f_\theta(z) \|^2}{2\sigma_{noise}^2} - \log p(z)$$

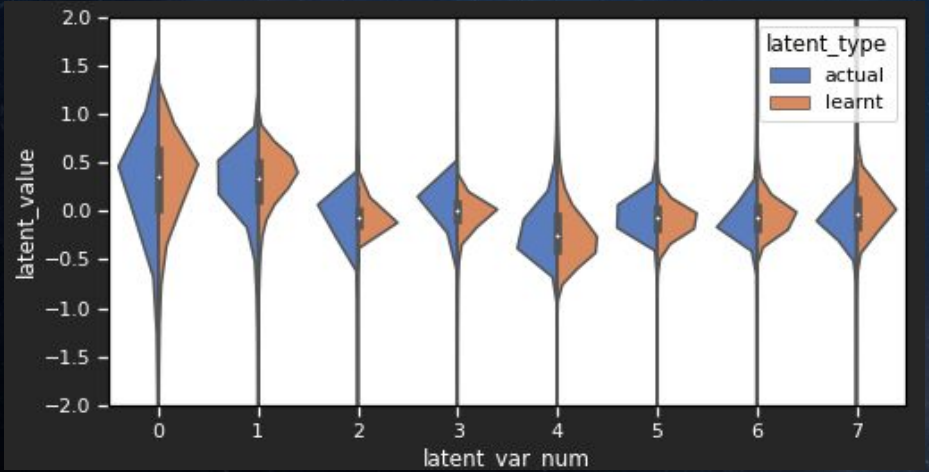
Where, z^* is the maximum a posteriori probability estimate in the latent space

How to choose a prior?



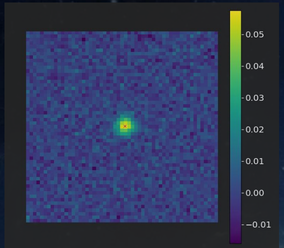
Normalizing flow



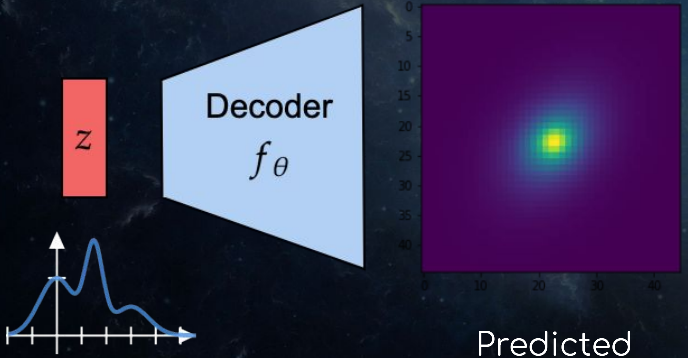


- The Normalizing Flows is trained to map the underlying latent space distribution
- We can evaluate log prob in the learned latent space distrib.

Minimization



Input image (y)



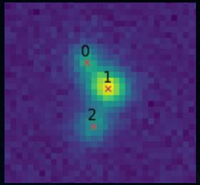
Predicted galaxy (x)

- Start with random z
- Do gradient descent in the latent space to minimize the objective function

$$z^* = \arg\min_z \frac{\| y - f_\theta(z) \|^2}{2\sigma^2_{noise}} - \log p(z)$$

Where, z^* is the maximum a posteriori probability estimate in the latent space

Deblending (Multiple sources)



$$Z = \left\{ z_i \mid z_i \textit{ being the latent space representation of } i^{th} \textit{ galaxy} \right\}$$

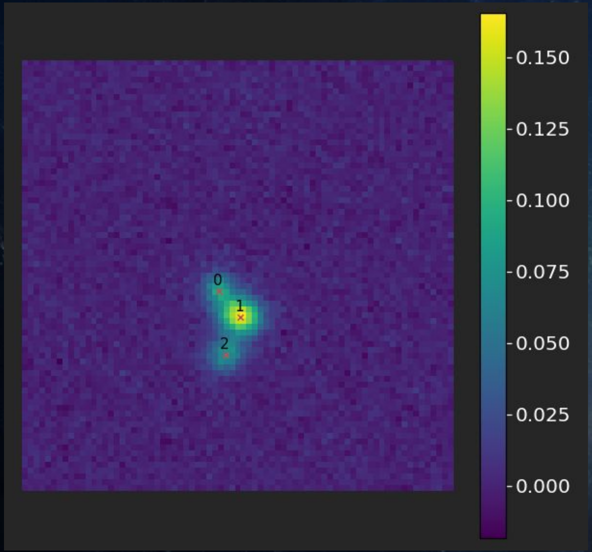
$$Z^* = \arg\min_{Z} \; -\log p(y|Z) - \log p(Z)$$

Reconstructed field

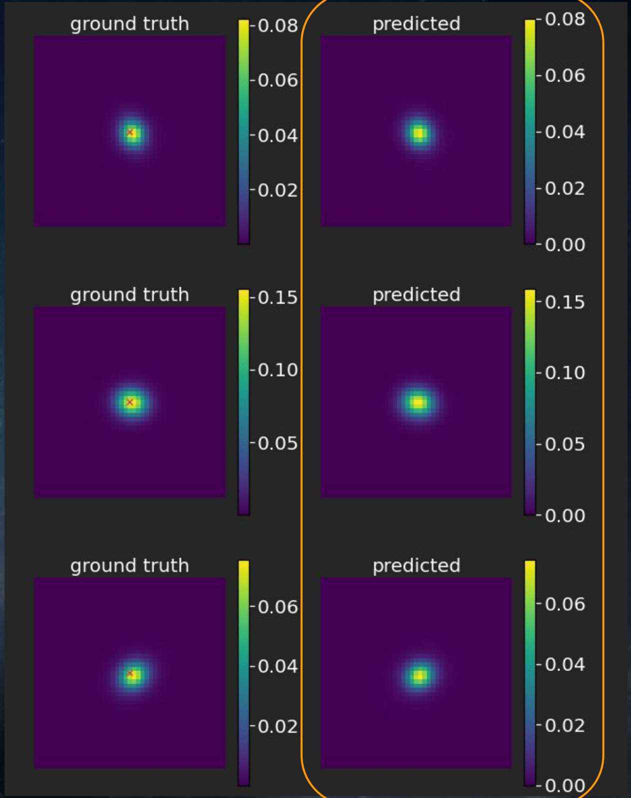
Probability that predictions are galaxies!

$$Z^* = \arg\min_{Z} \frac{\| y - \sum_i f_\theta(z_i) \|^2}{2\sigma^2_{noise}} - \sum_i \log p(z_i)$$

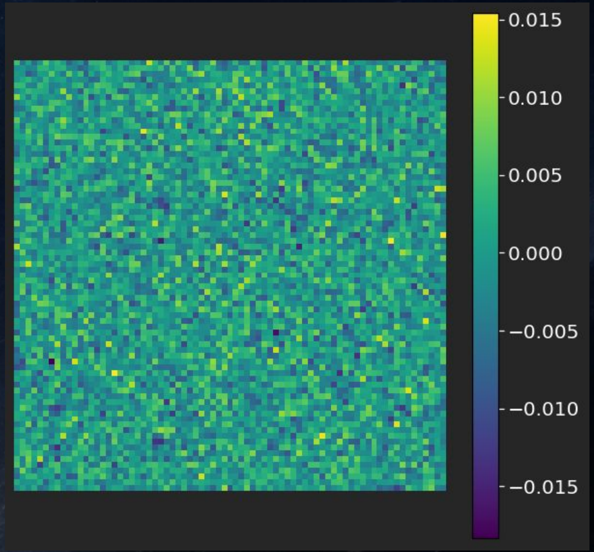
Deblending Example



Input image

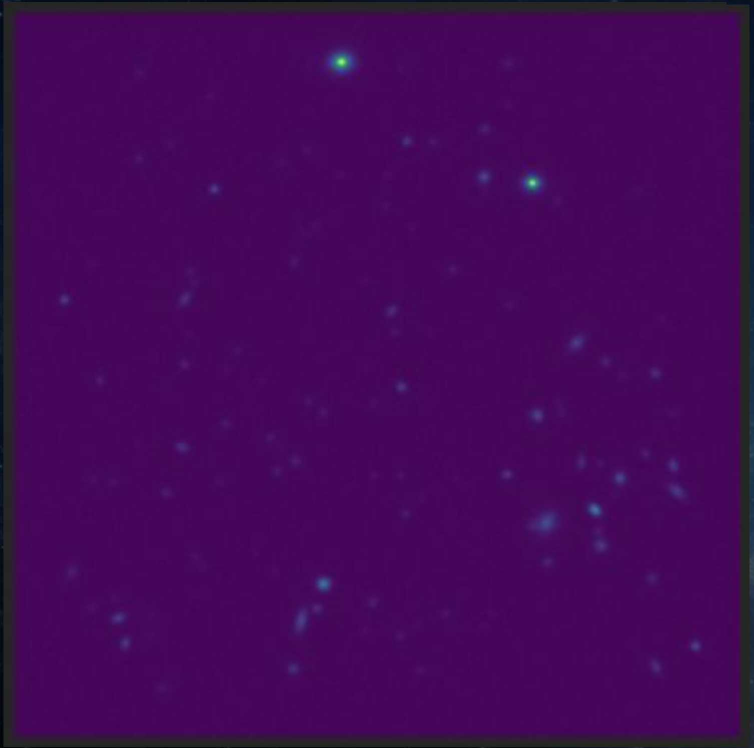


Predictions

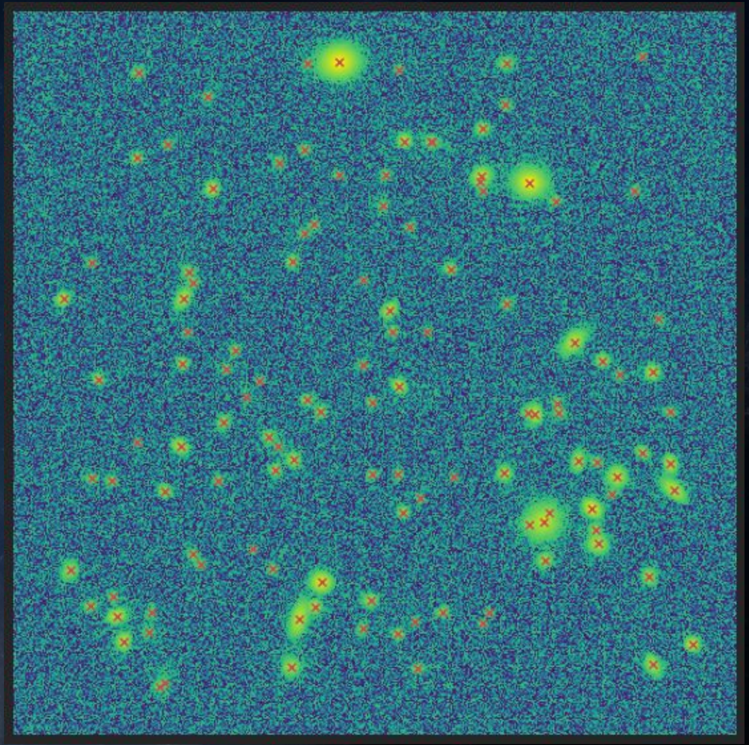


Residual image
(input - predictions)

Moving to a larger field...

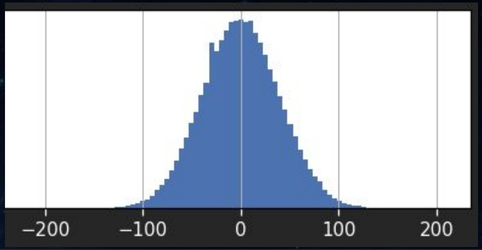


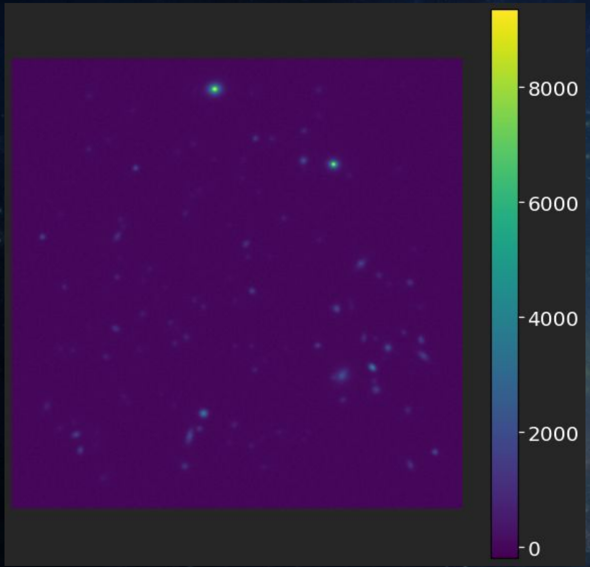
Input field (501 x 501)



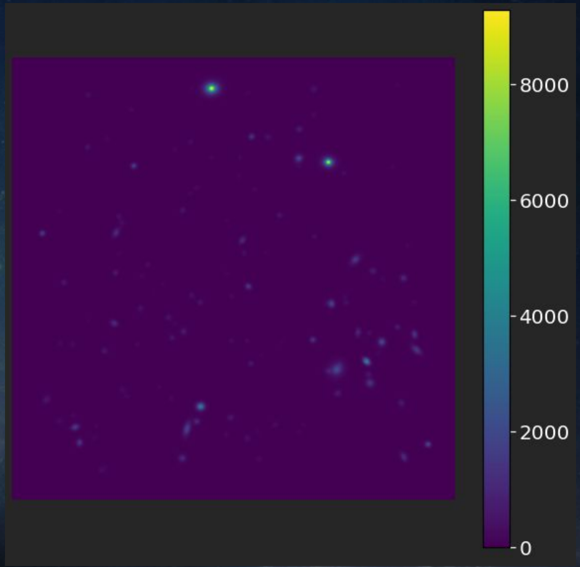
$\sinh^{-1}$(Input field)

Moving to a larger field...

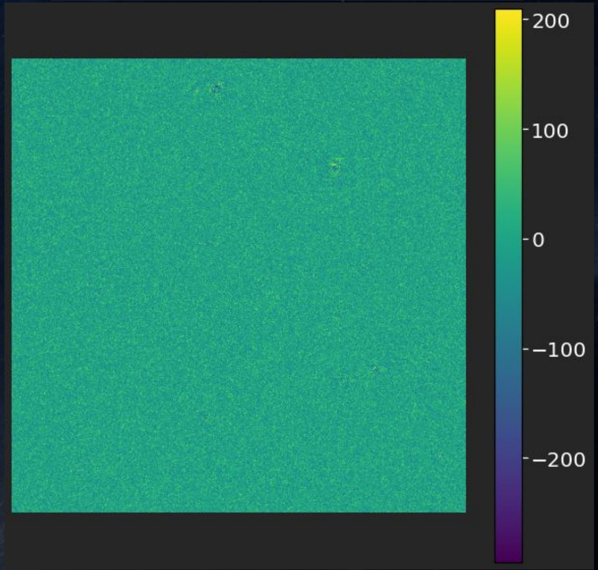




Input field



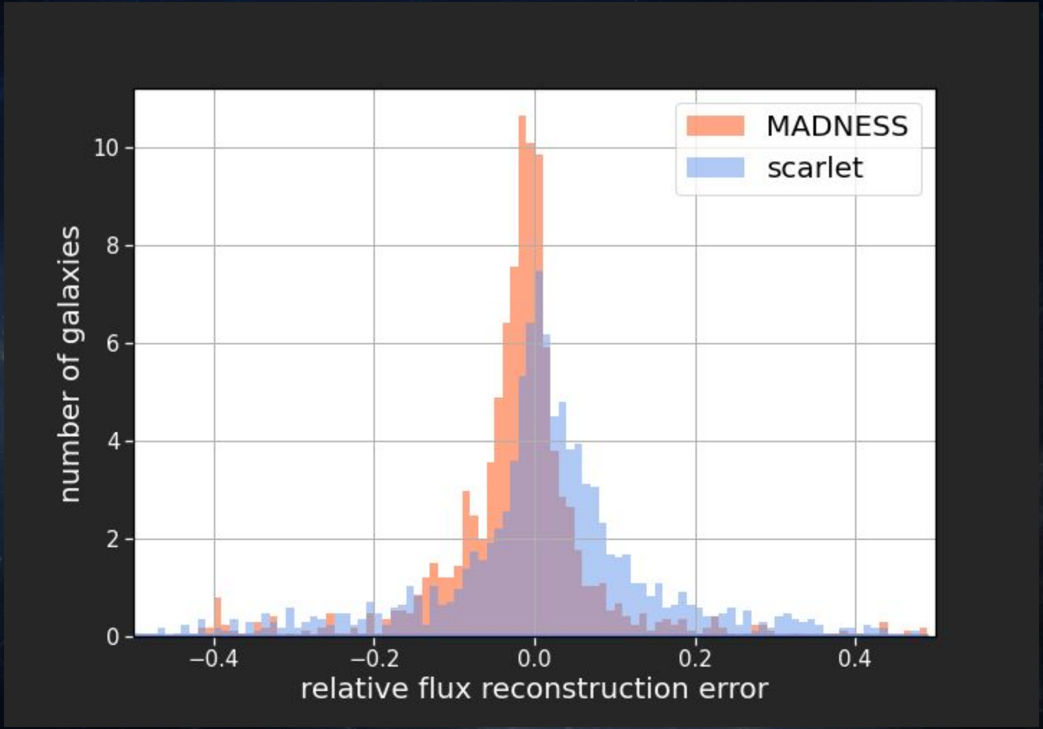
predicted field



residual field
(Input - predicted)

Preliminary results*

Compare with SOTA



Preliminary results*

Conclusion and Future work

- Developed source separation algorithm using VAEs, NF
- Deblending performance at-par with SOTA
- Next steps:
  - Handle artifacts in real data
  - Evatulate systematics in science results, eg. probes such as weak lensing
  - Paper in progress (code to be available soon)

Thank you!