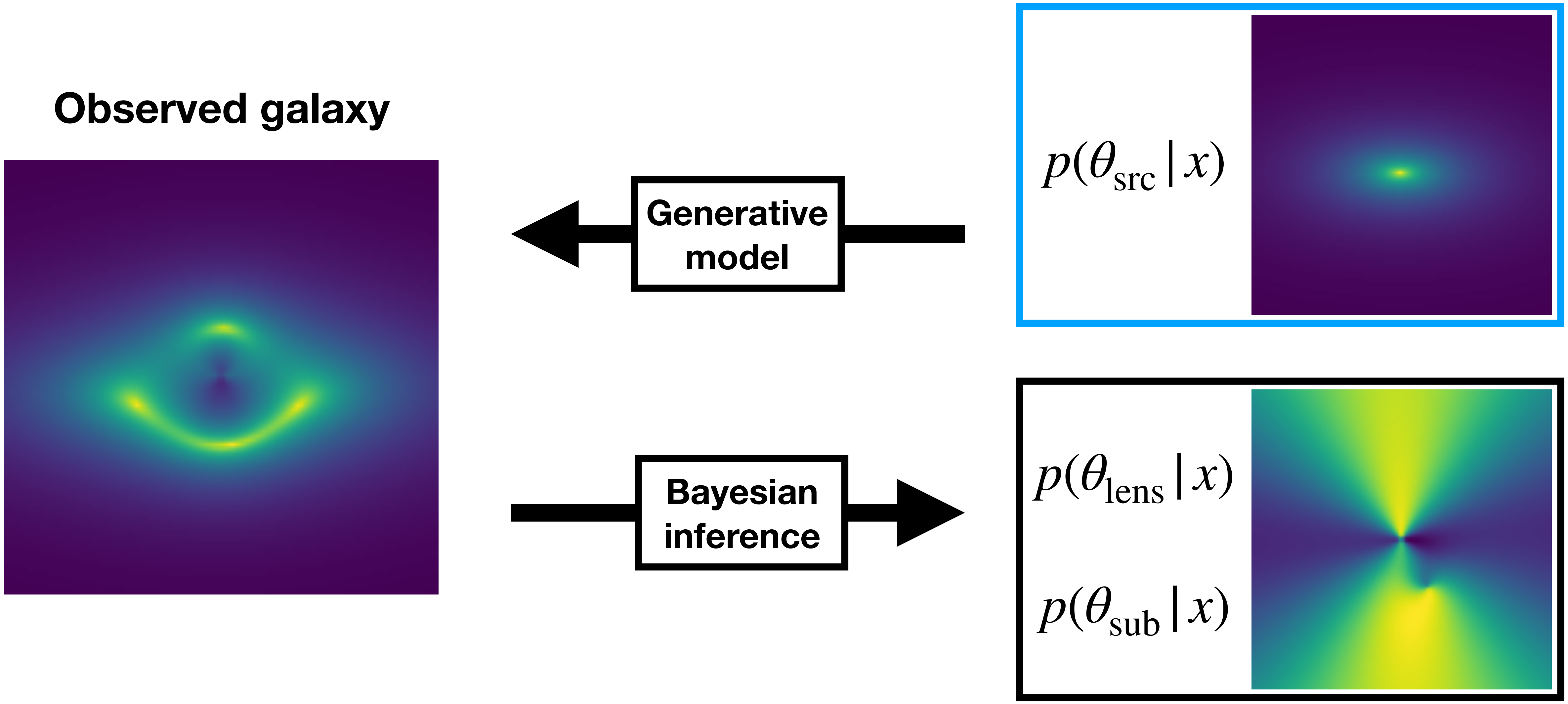
Strong Gravitational Lensing and ML: generative models for galaxies

Adam Coogan

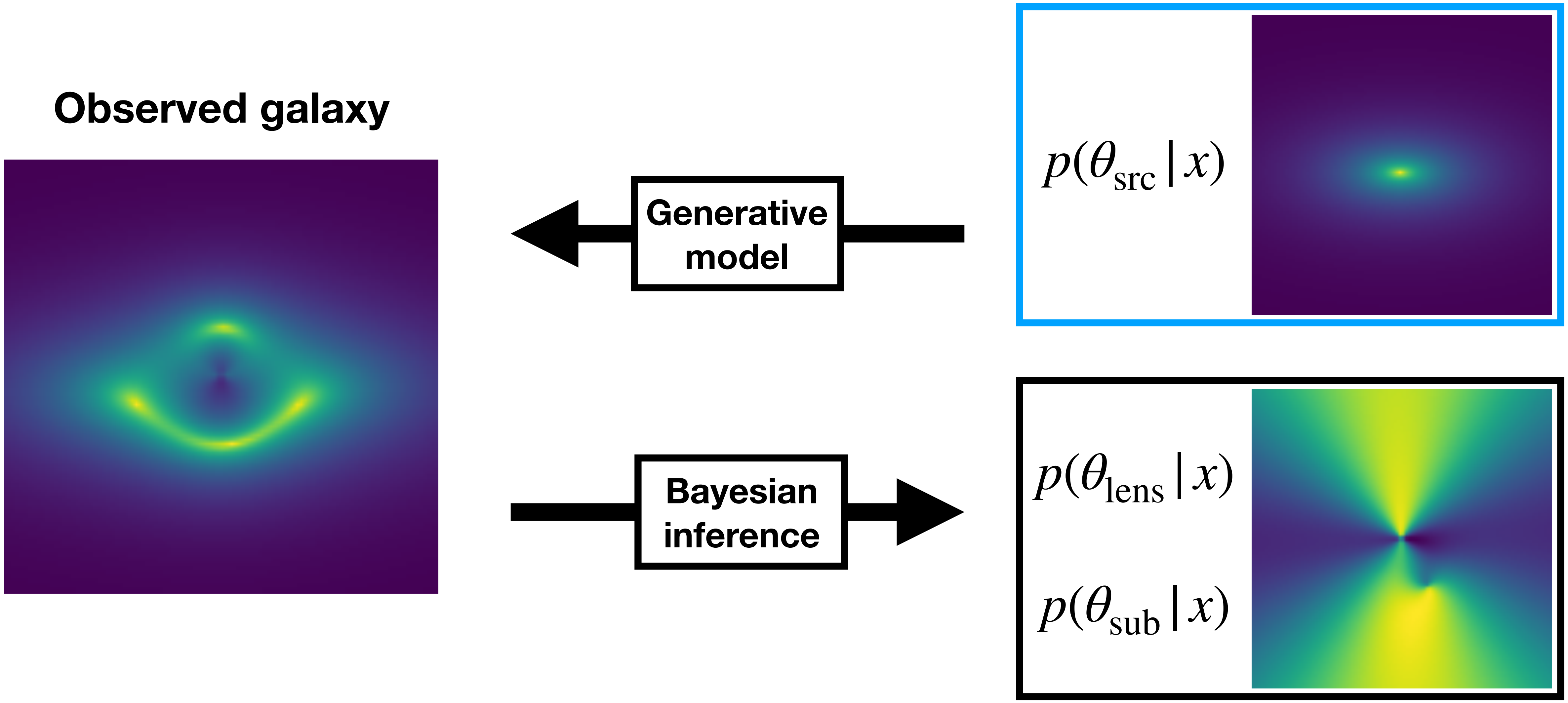
Dark Machines workshop
ICTP, 8-12 April 2019

University of Amsterdam

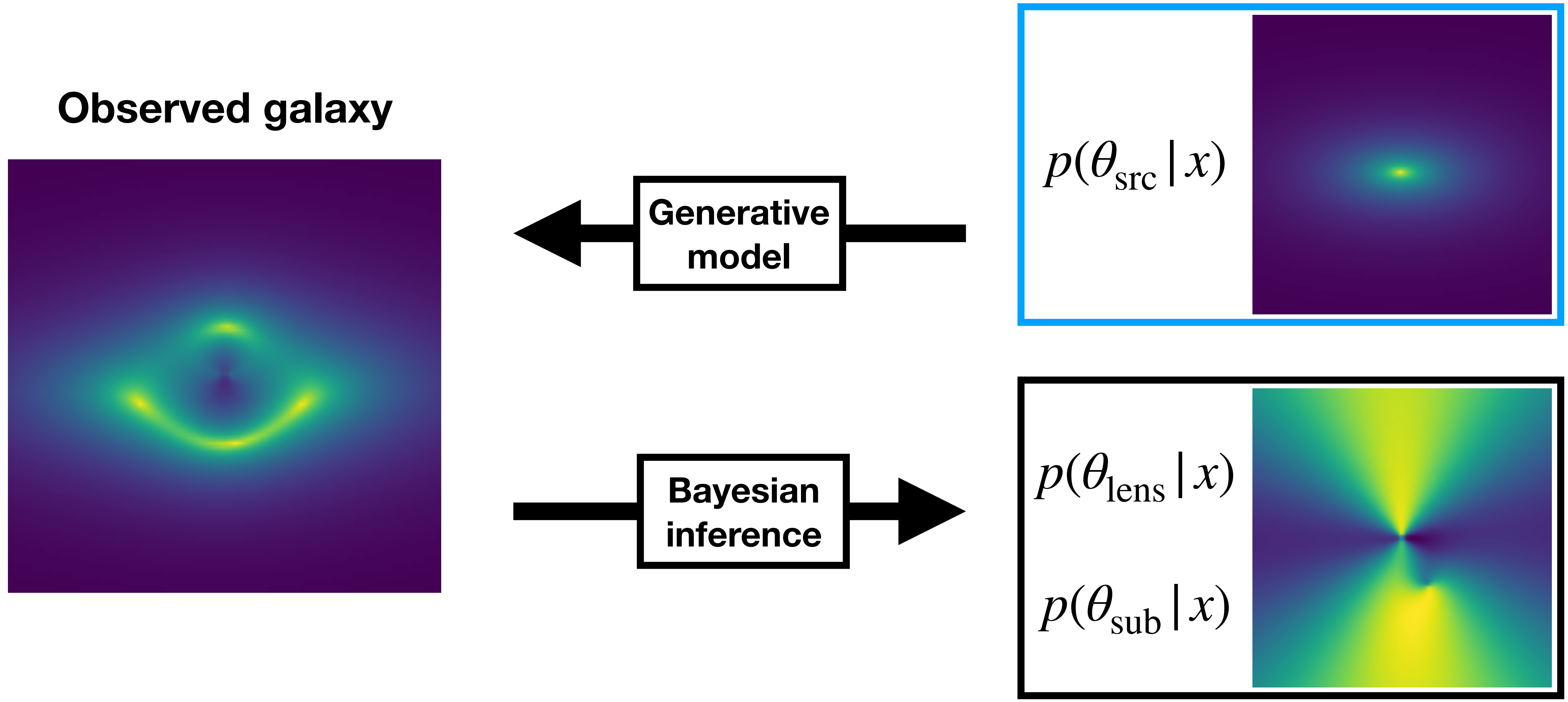
GRAPPA
GRavitation AstroParticle Physics Amsterdam



Model physics when possible, use machine learning for the rest

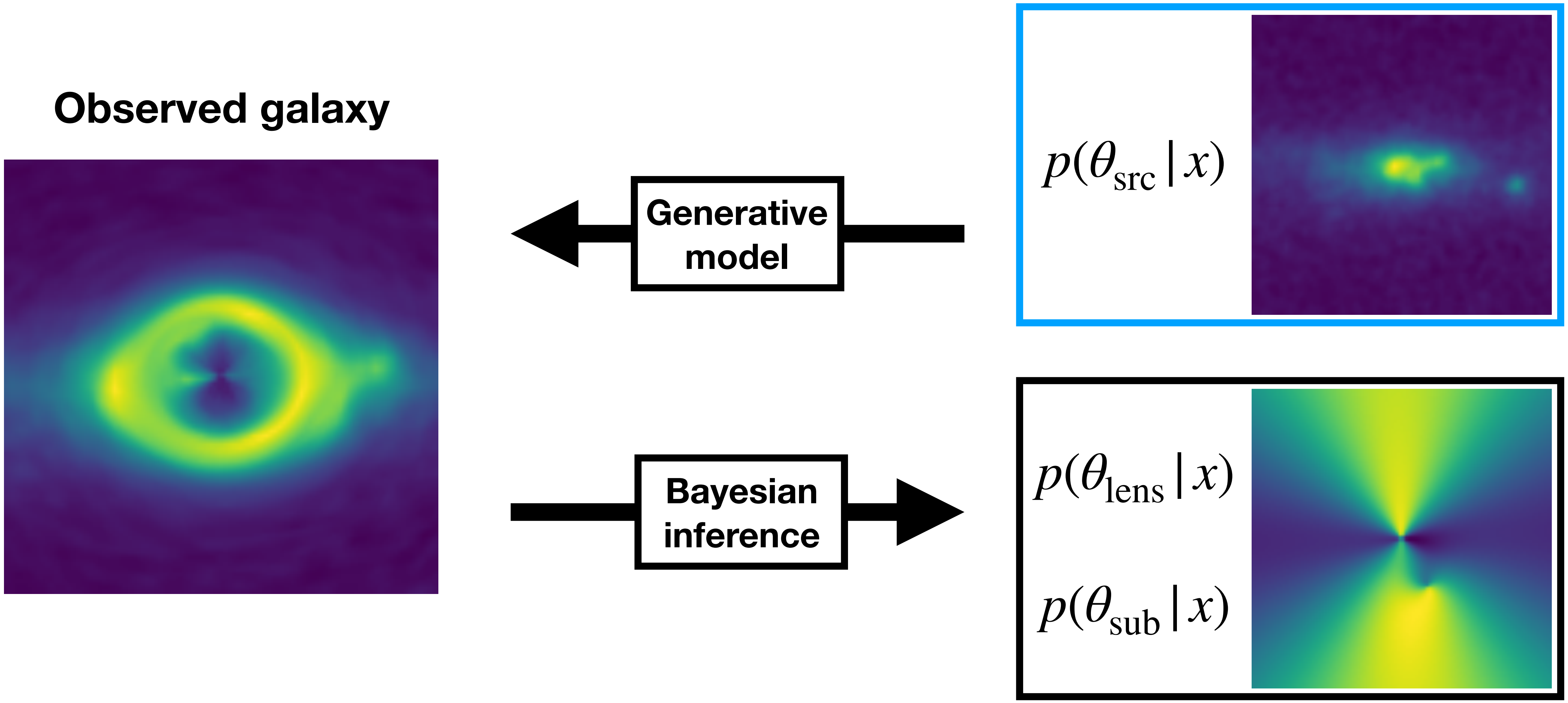


http://great3.jb.man.ac.uk/



Machine learning for generatively modeling the source light

http://great3.jb.man.ac.uk/



Machine learning for generatively modeling the source light

- Galaxies have diverse, complex morphologies (especially z≳2)

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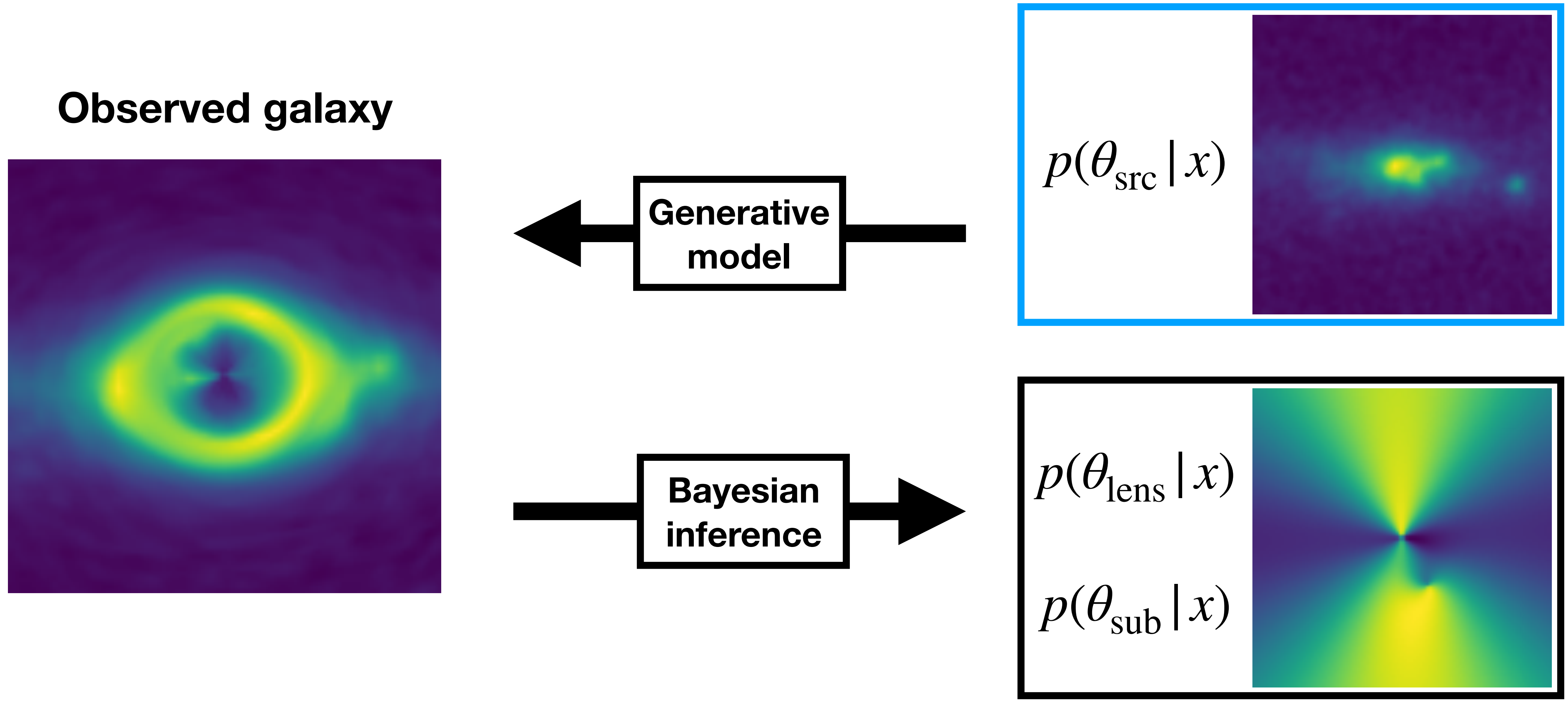

Machine learning for generatively modeling the source light

- Galaxies have diverse, complex morphologies (especially $z \gtrsim 2$)
- Complex source → more accurate lens parameter inference

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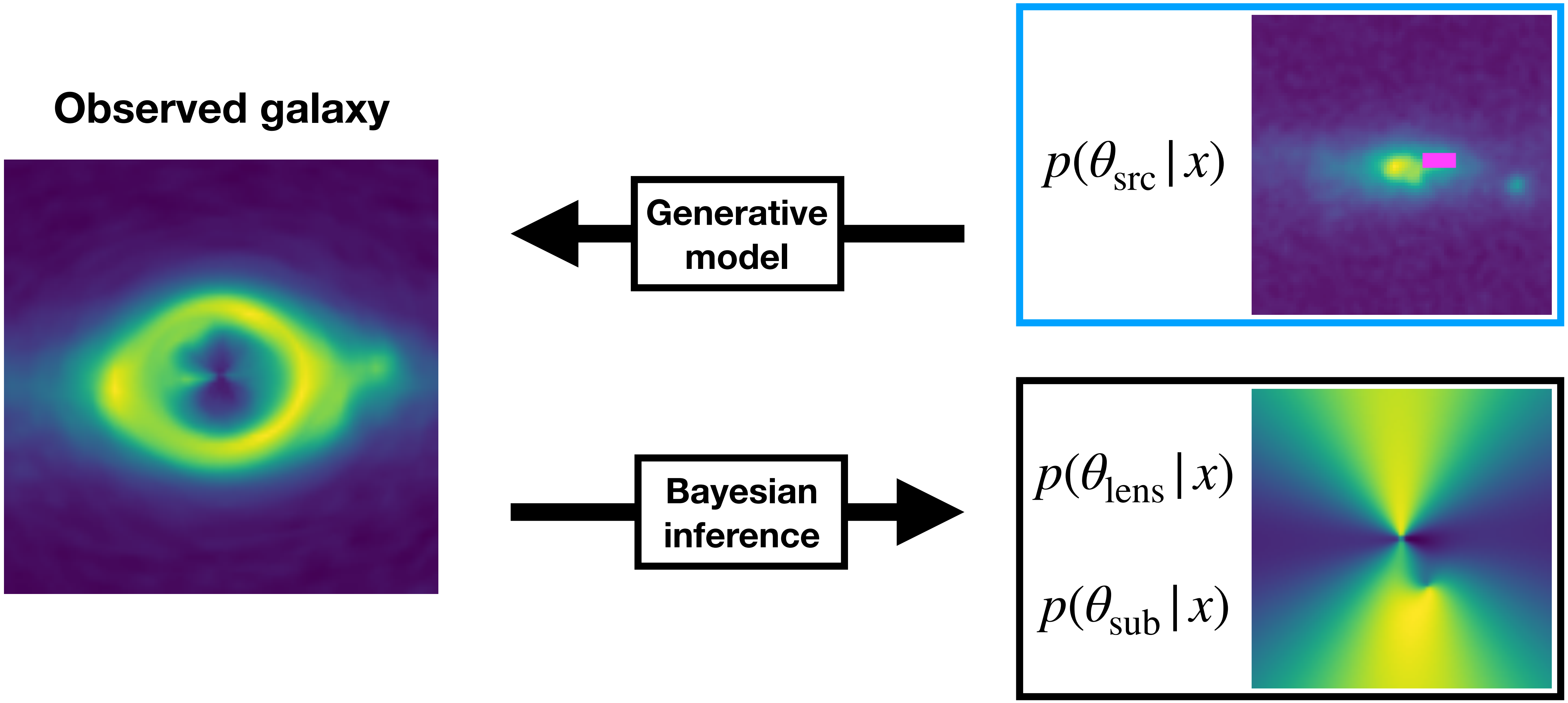

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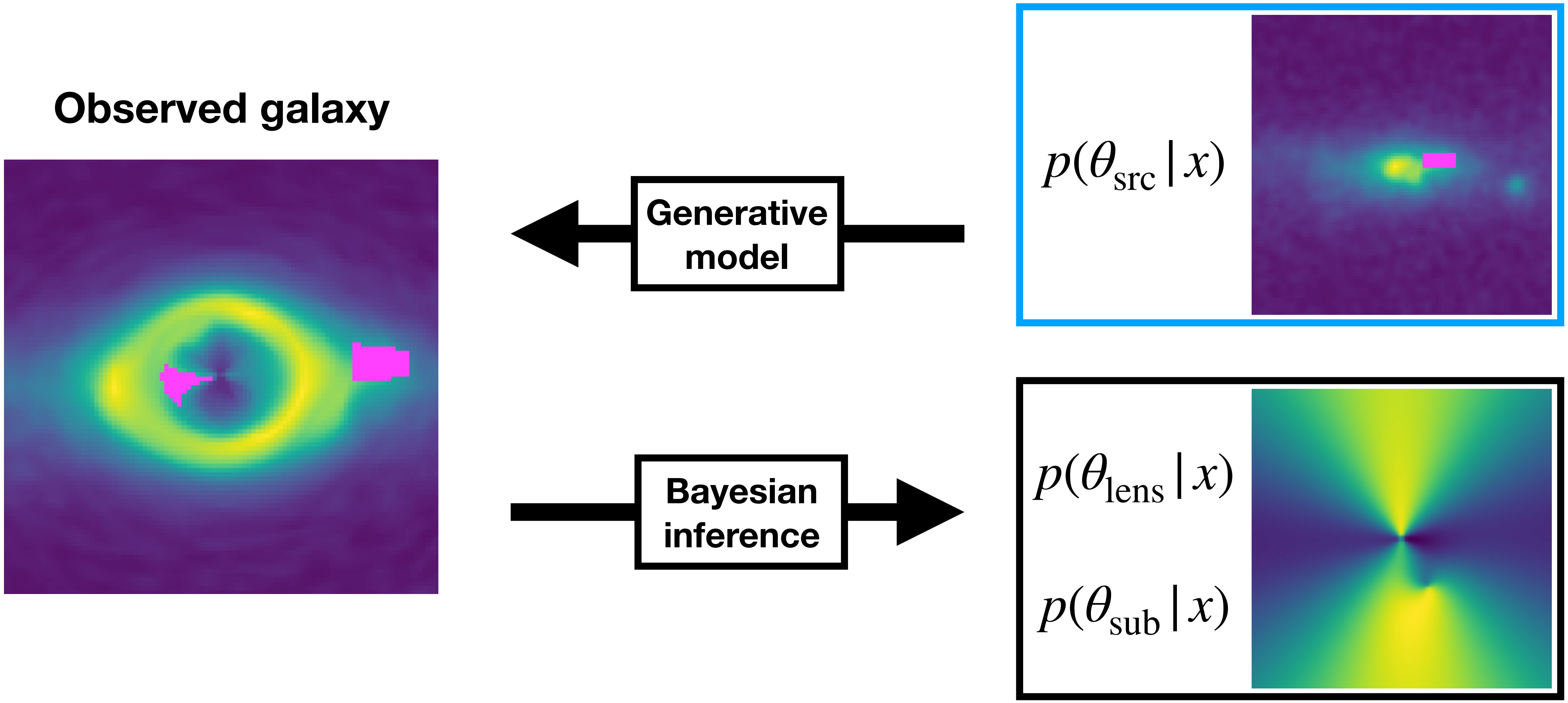

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Source model

- Low-dimensional representation of data that:
  - ➡ Captures range of galaxy morphologies
  - ➡ Has a latent space compatible with Bayesian inference

Kingma & Welling 2013, Rezende et al 2014

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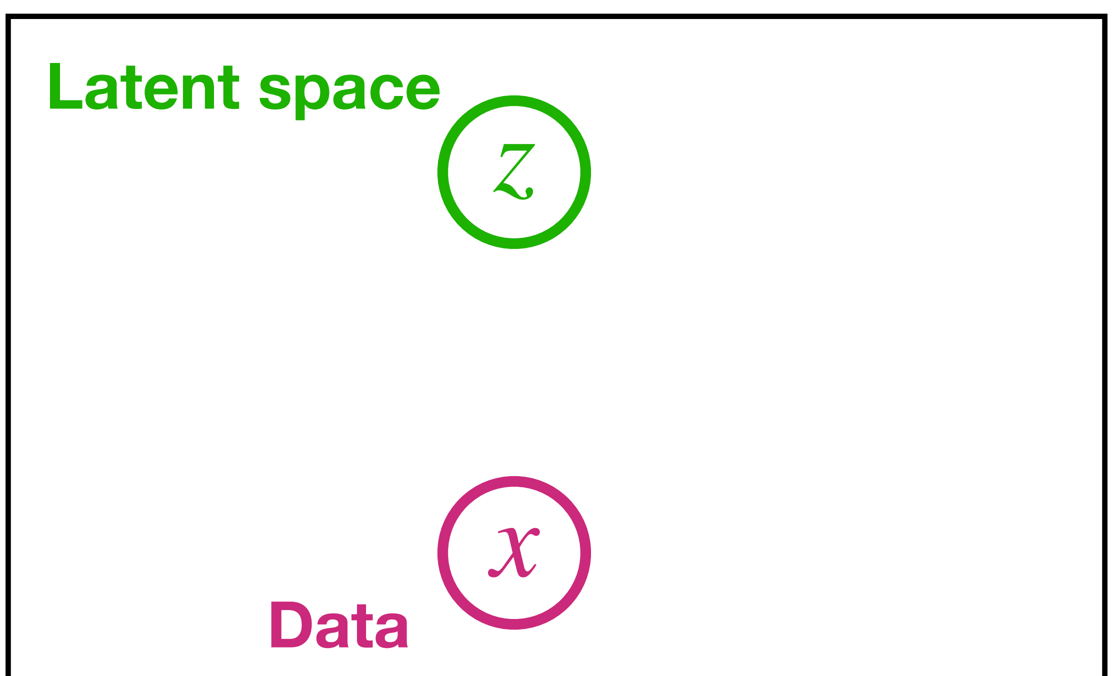
Variational autoencoder



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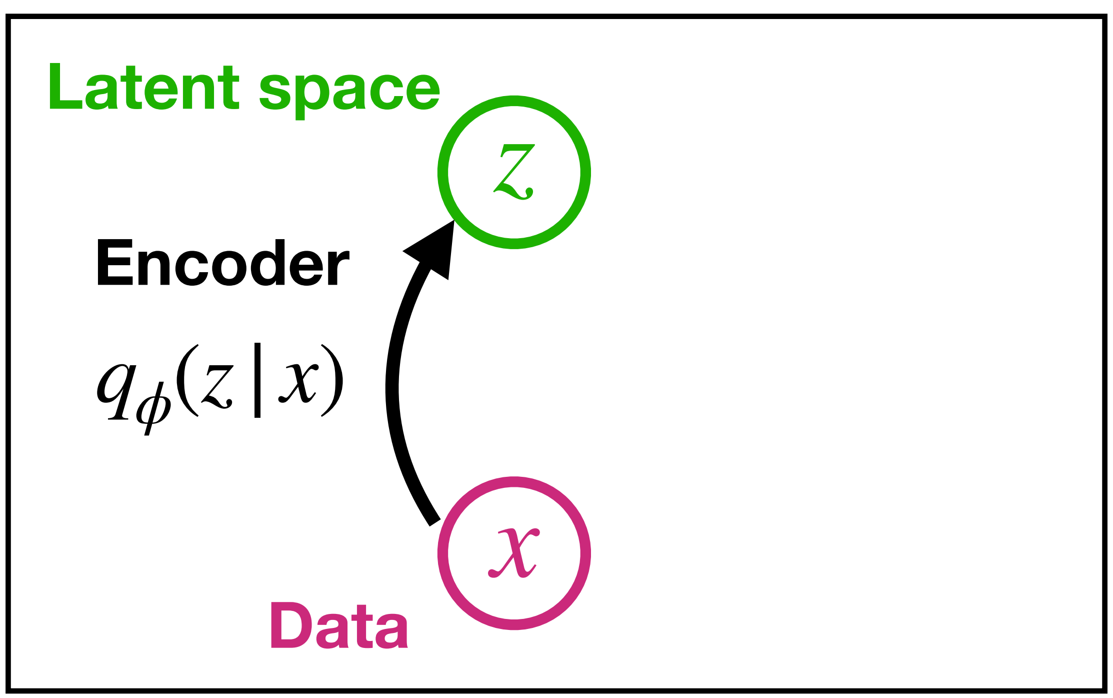

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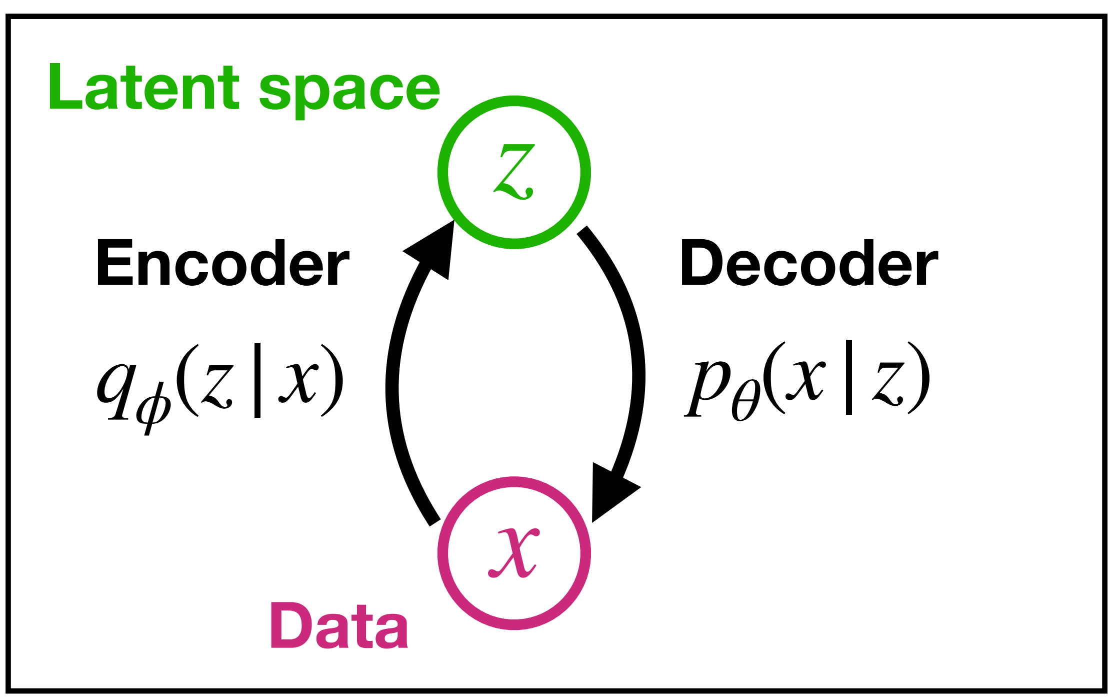

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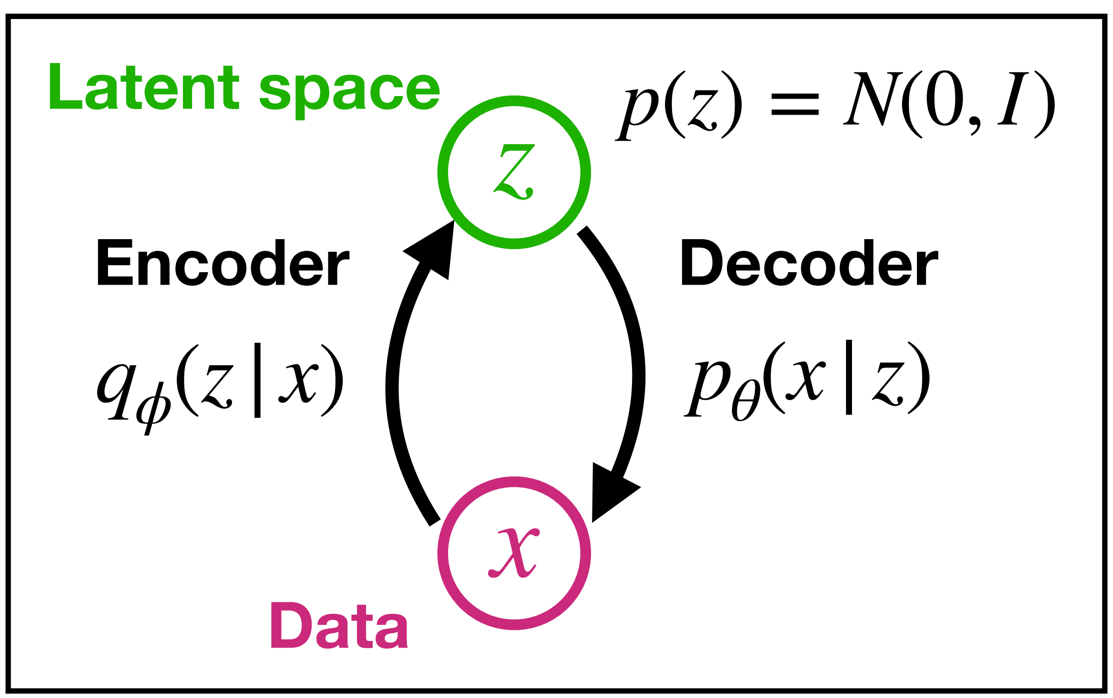

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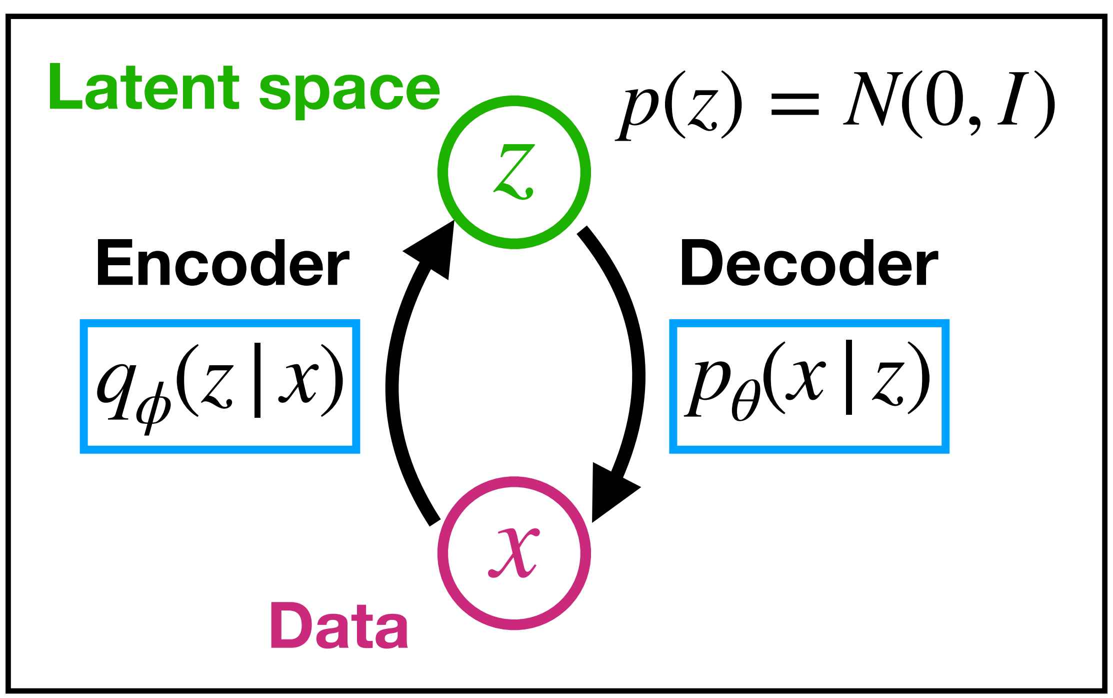

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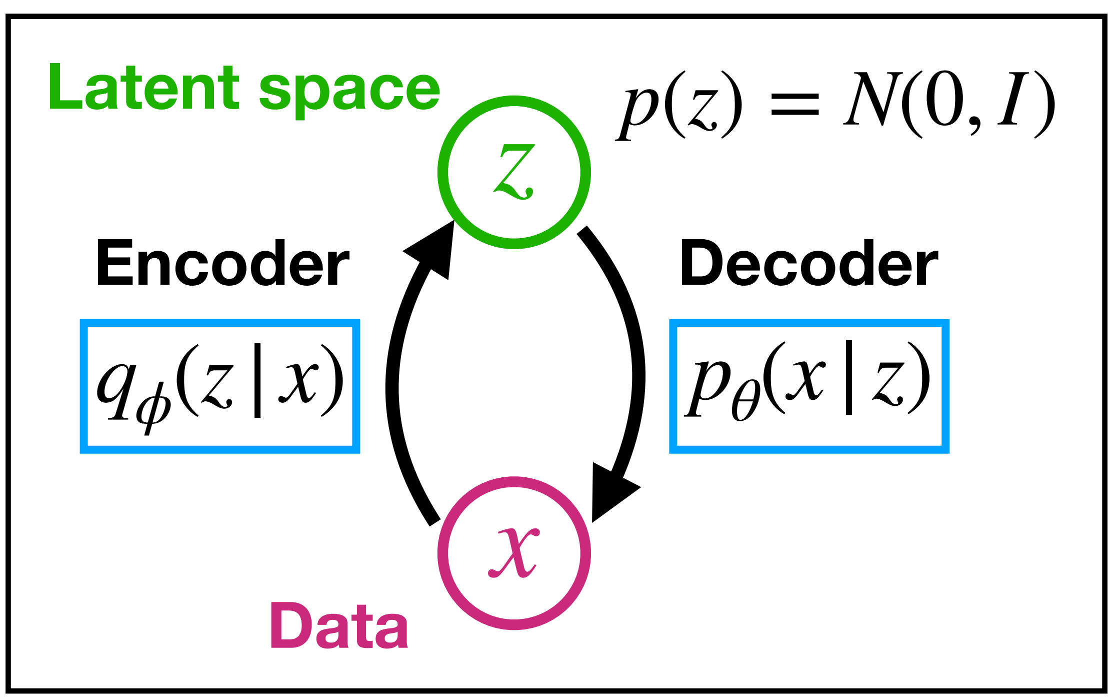

Train encoder, decoder by maximizing lower bound on p(data)

Kingma & Welling 2013, Rezende et al 2014

Galaxy VAE

- Dataset: ~56,000 galaxies, redshifts ~ 1

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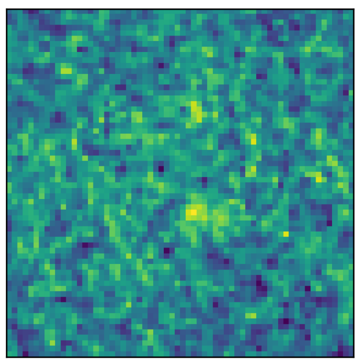
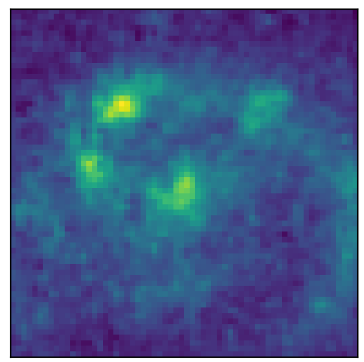
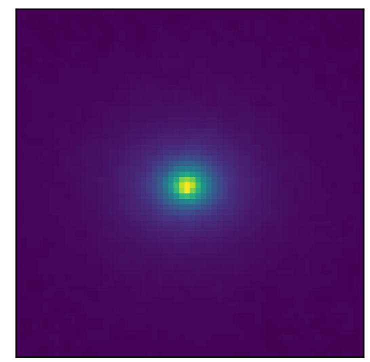


S/N < 10



S/N ~ 20



S/N > 100

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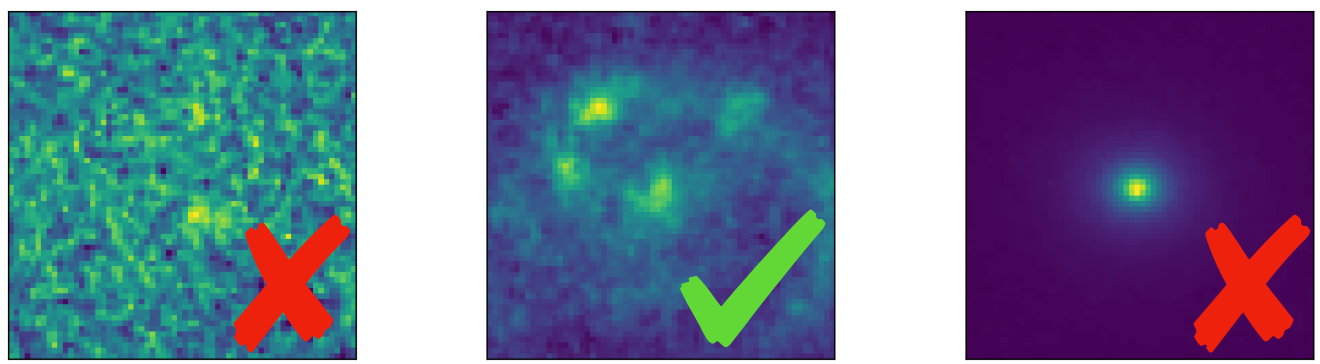
Galaxy VAE

- Dataset: ~56,000 galaxies, redshifts ~ 1



S/N < 10 S/N ~ 20 S/N > 100

This talk: train on ~10,000 images with S/N = 15 - 50

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Galaxy VAE

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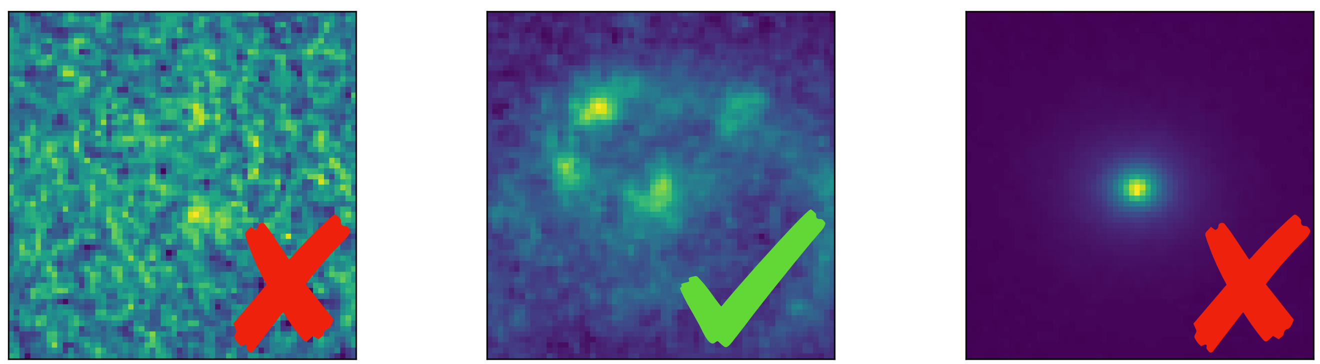
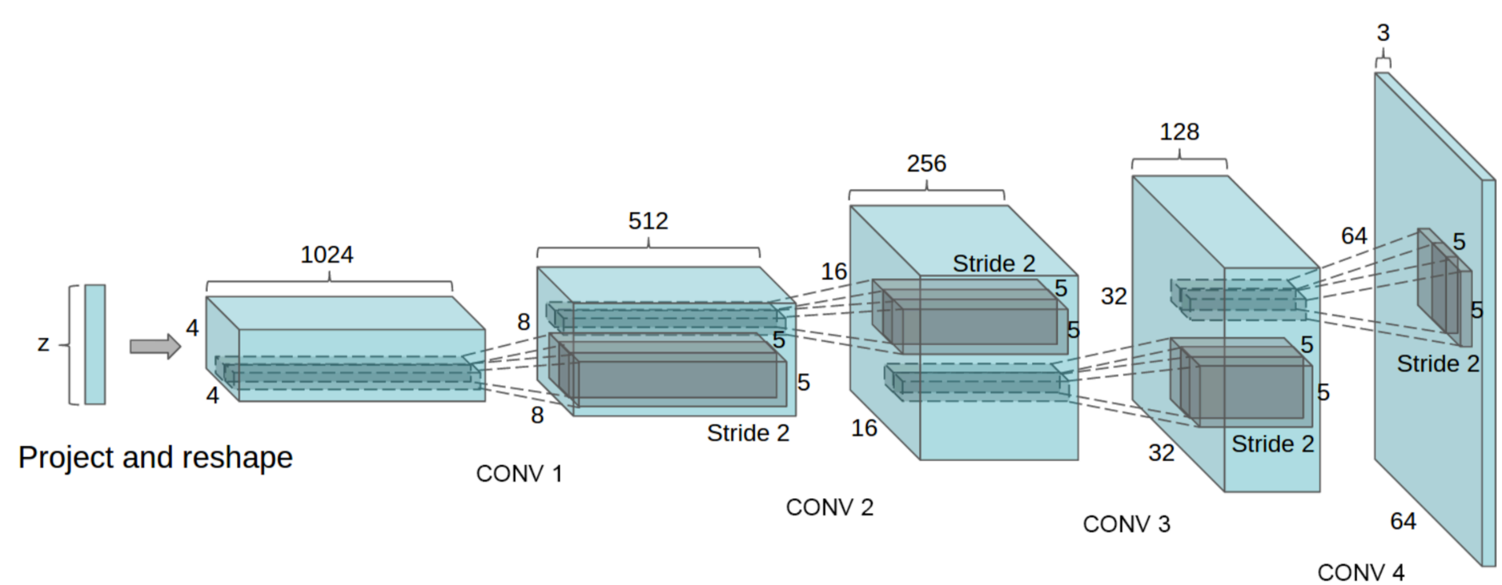


S/N < 10 S/N ~ 20 S/N > 100

This talk: train on ~10,000 images with S/N = 15 - 50

- Encoder, decoder: deep convolutional neural networks

Eg, decoder:



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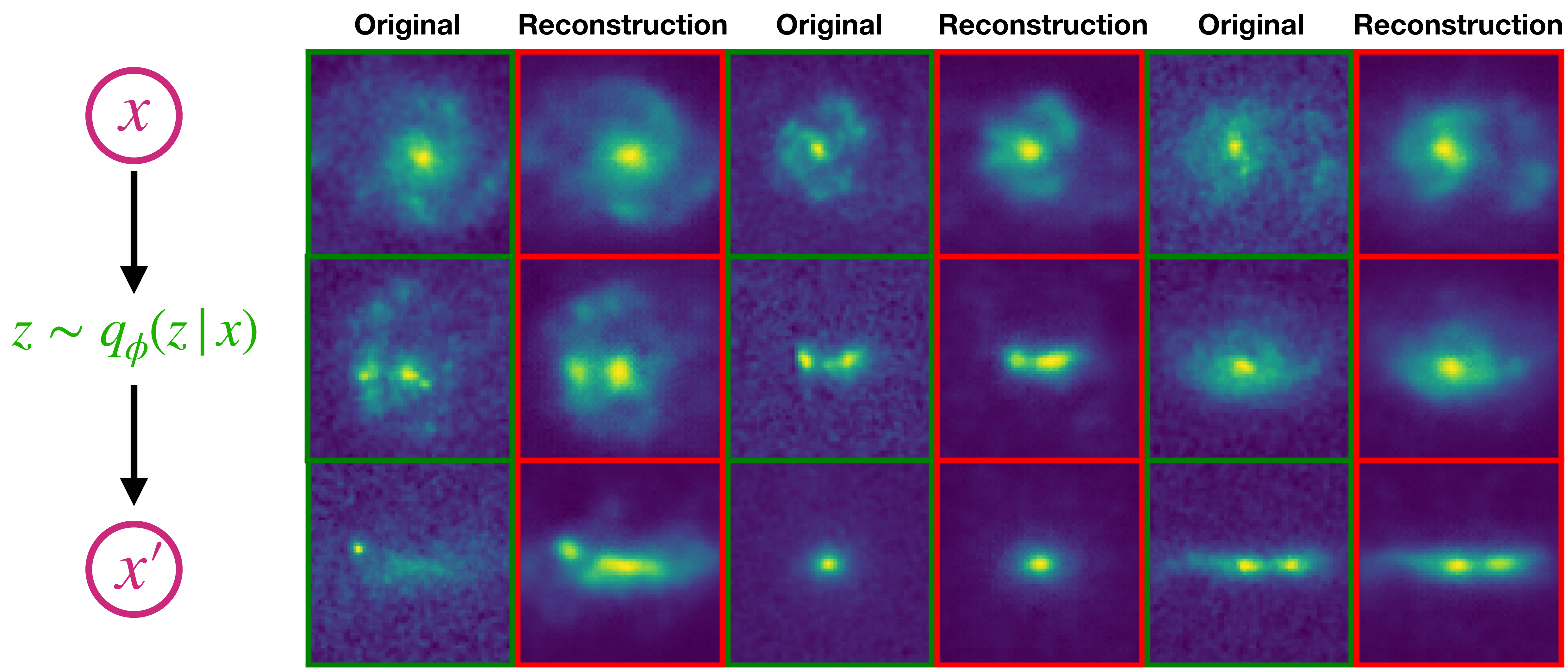
Radford et al 2015 (DCGAN)

Galaxy VAE: reconstructions

$$\begin{tikzcd} x \arrow[d] \\ z \sim q_\phi(z \mid x) \arrow[d] \\ x' \end{tikzcd}$$

Galaxy VAE: reconstructions



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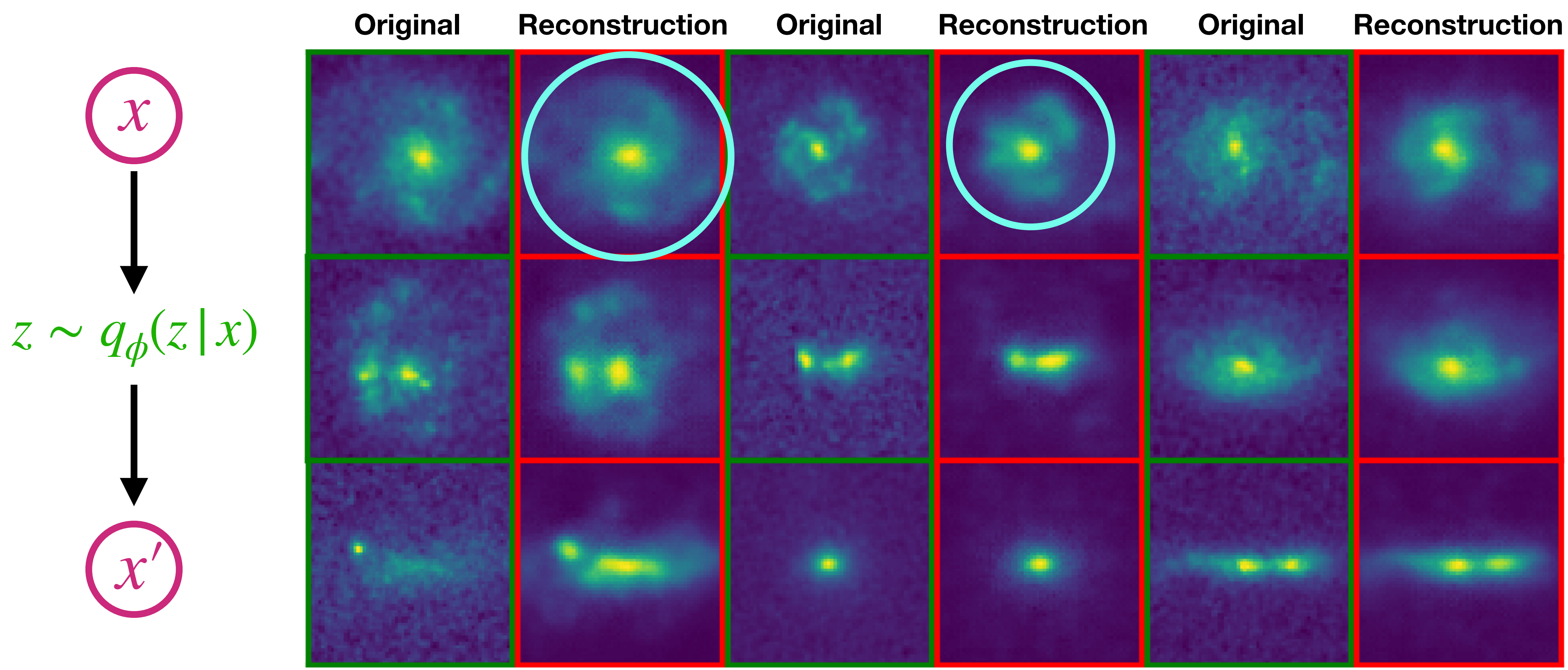
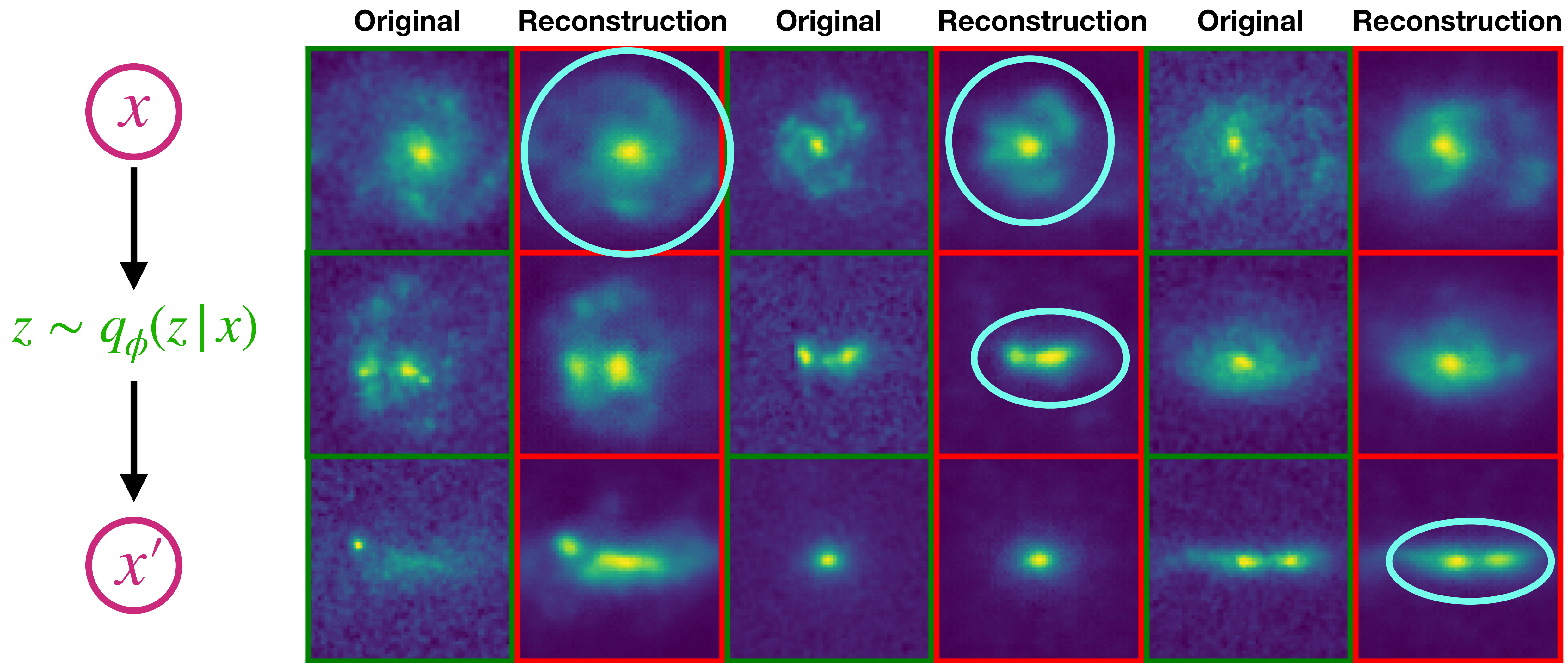


Galaxy VAE: reconstructions



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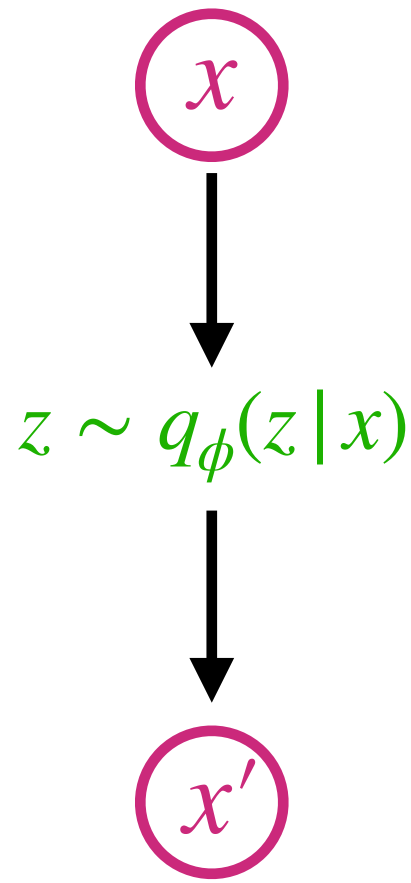

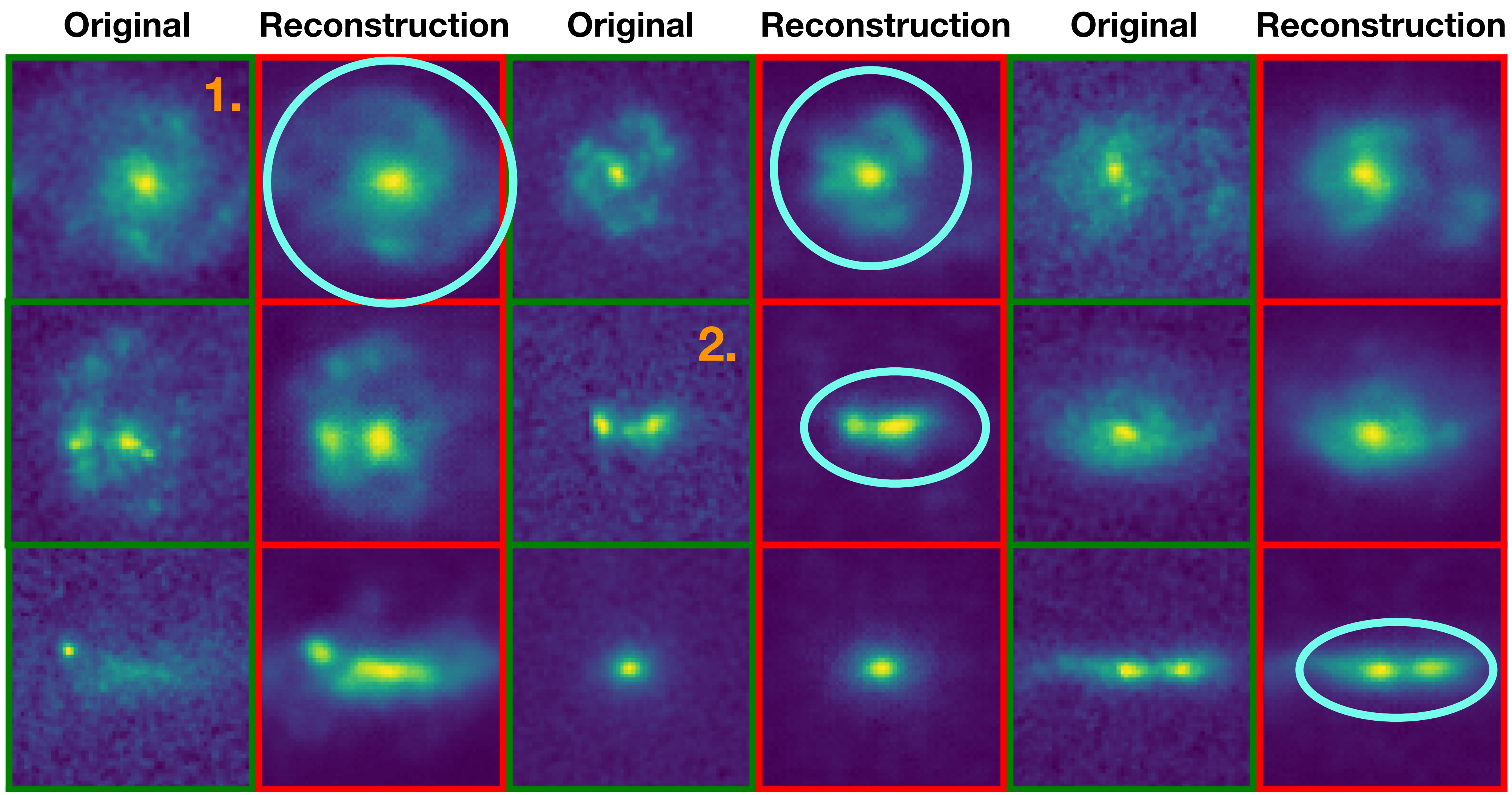

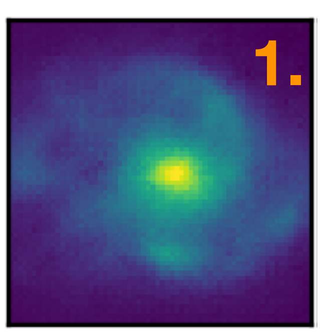

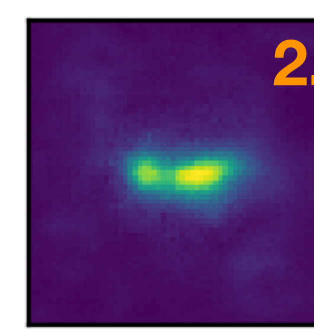

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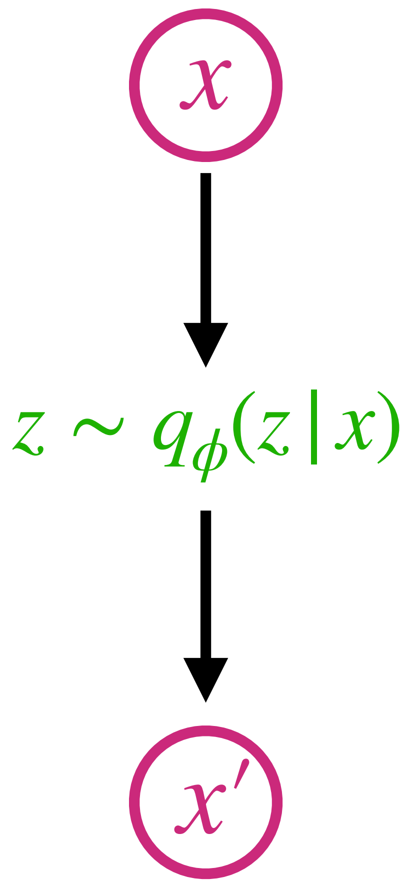

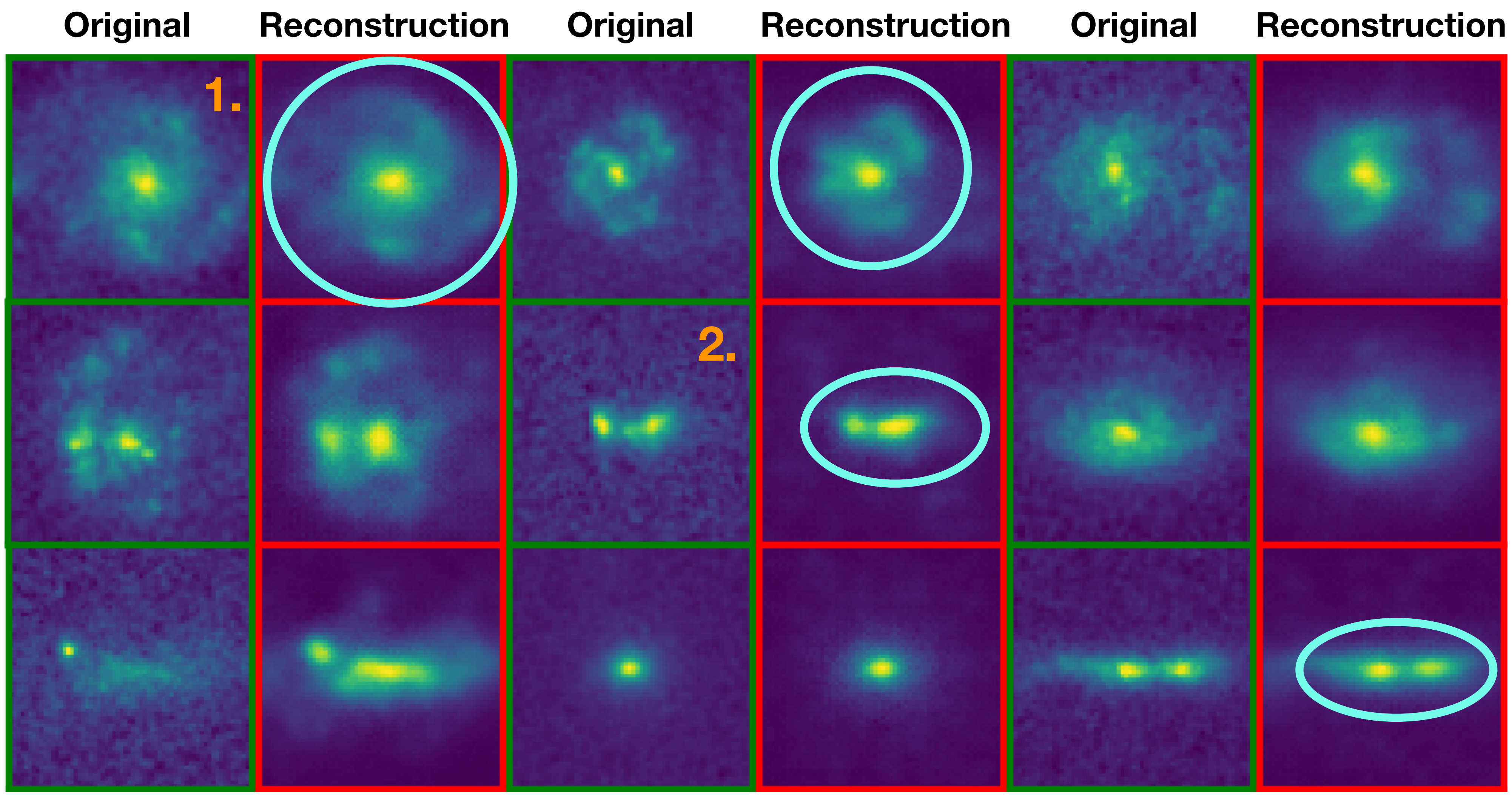

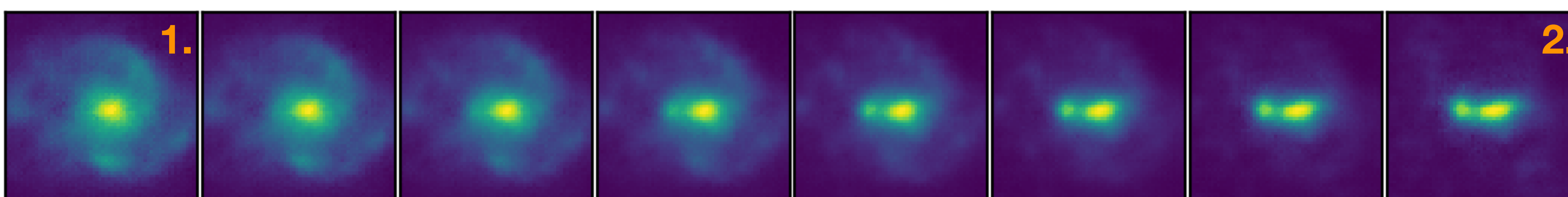

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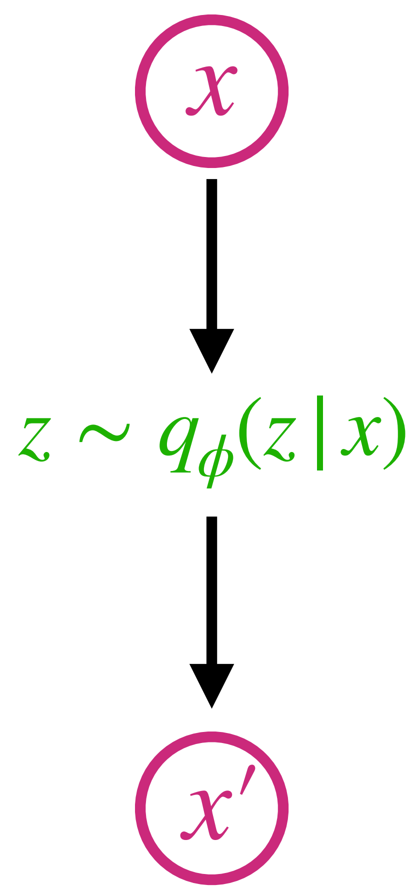

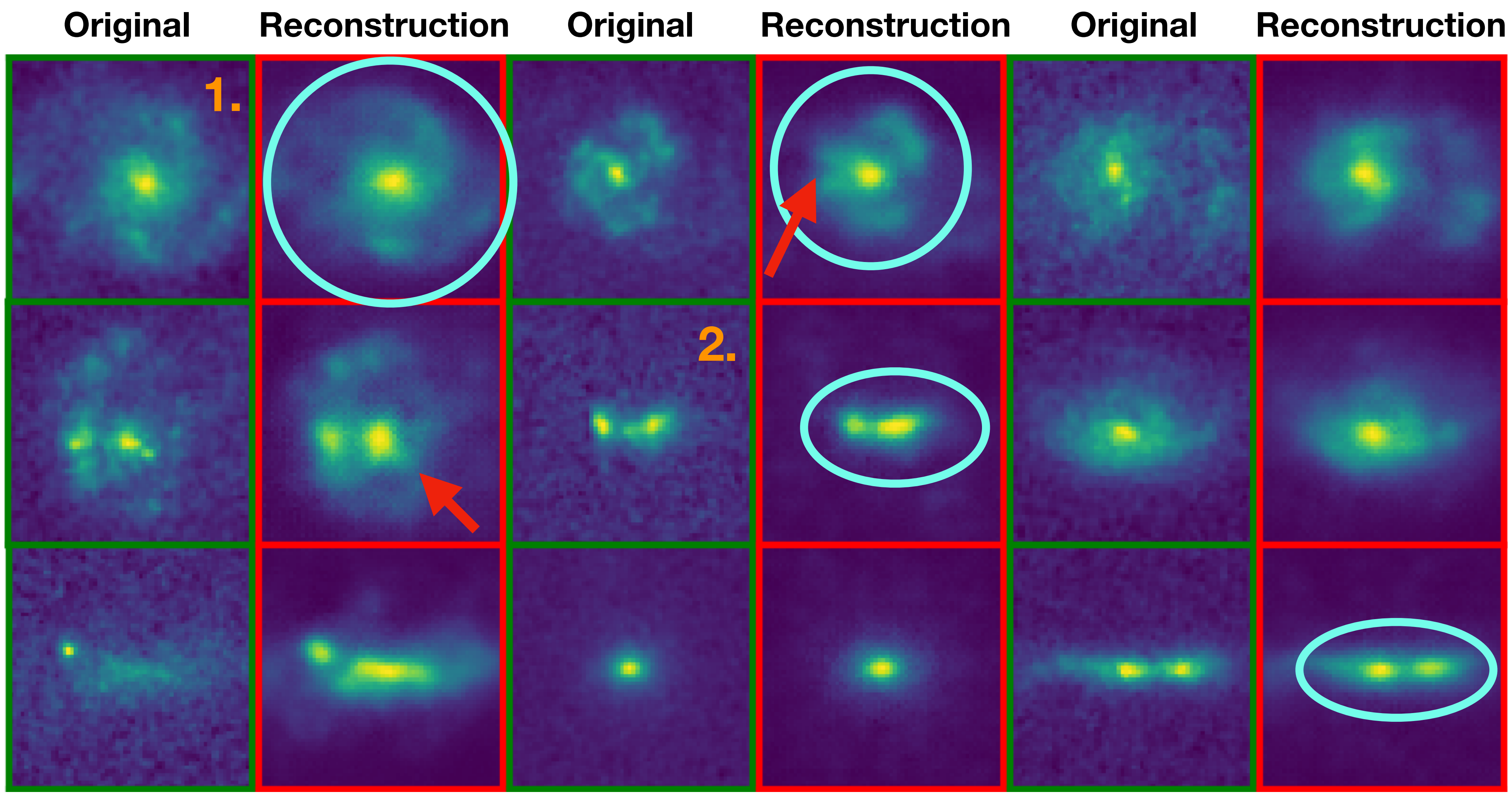

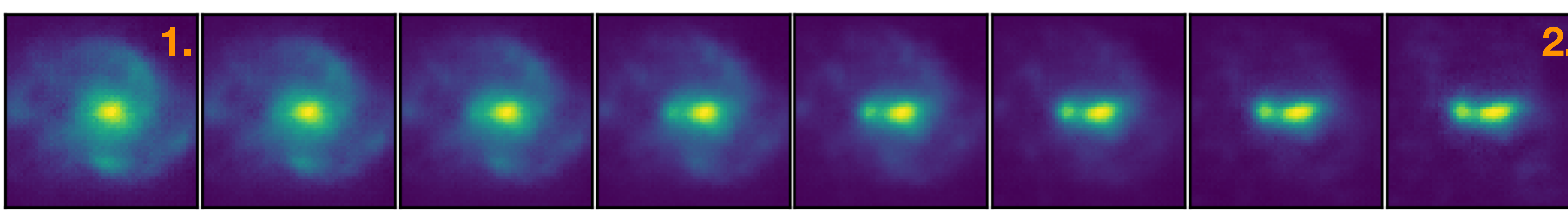

Rezende & Viola 2018, Zhao et al 2017

Galaxy VAE: samples

$z \sim p(z) = N(0, I)$

Hoffman & Johnson 2016, Alemi et al 2018

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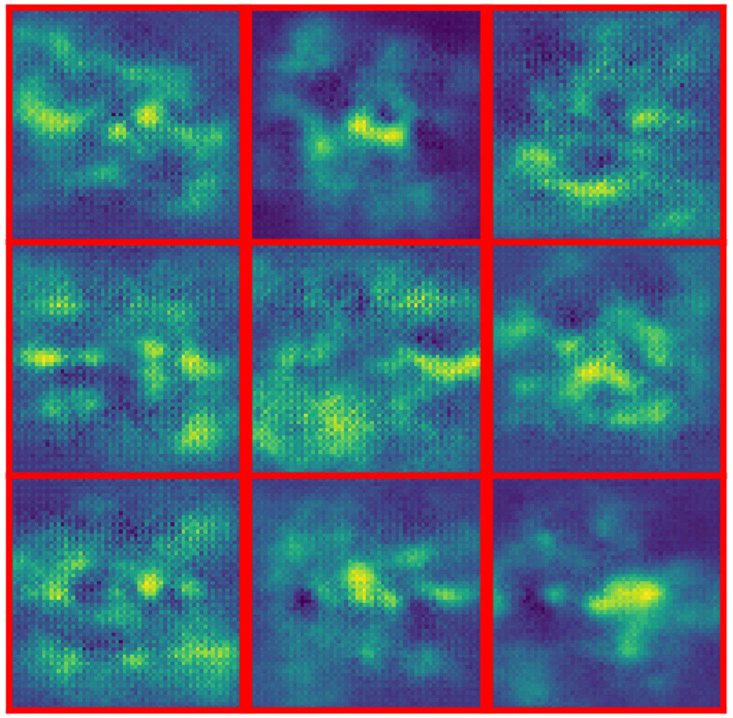

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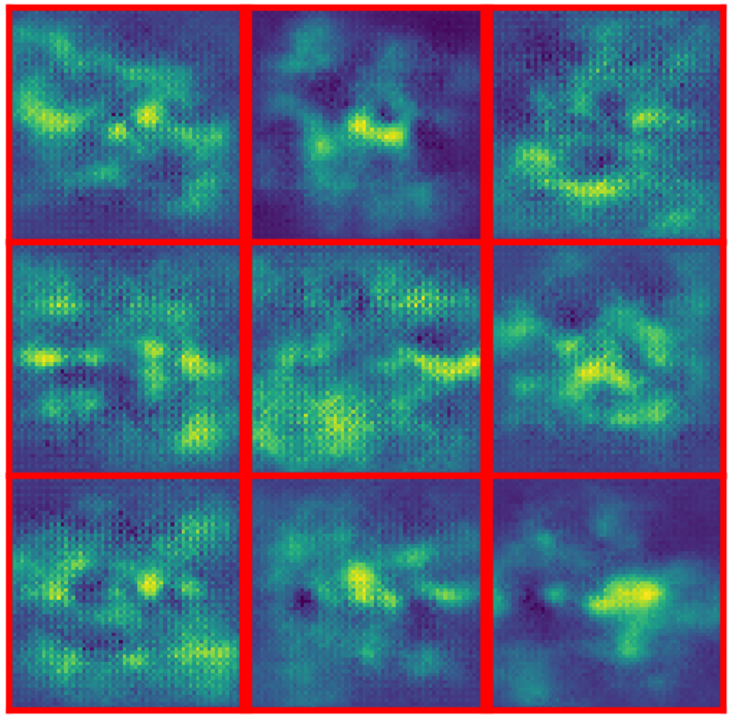

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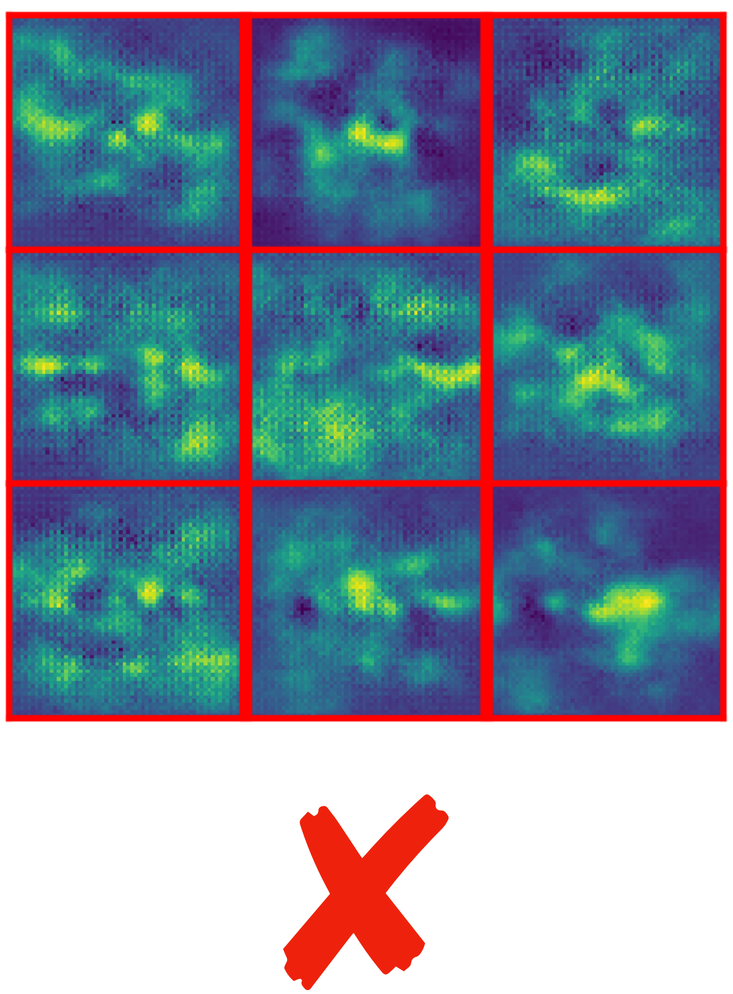
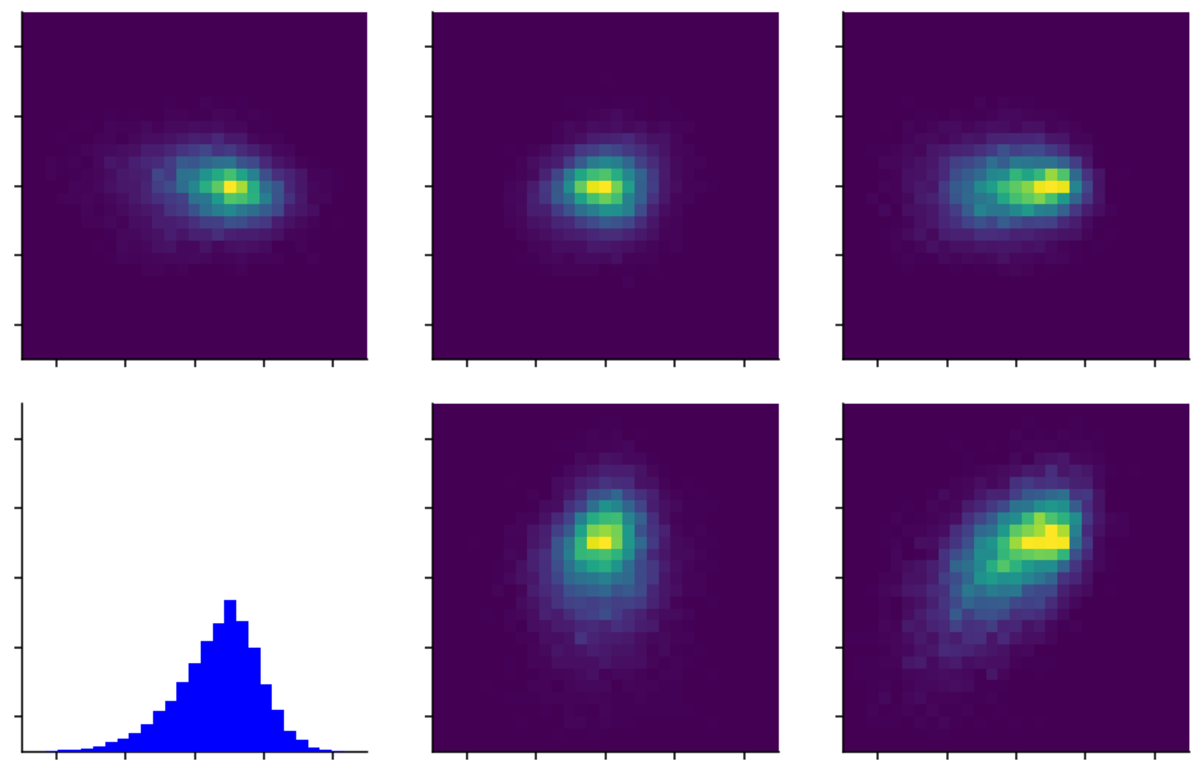


z distribution for training data



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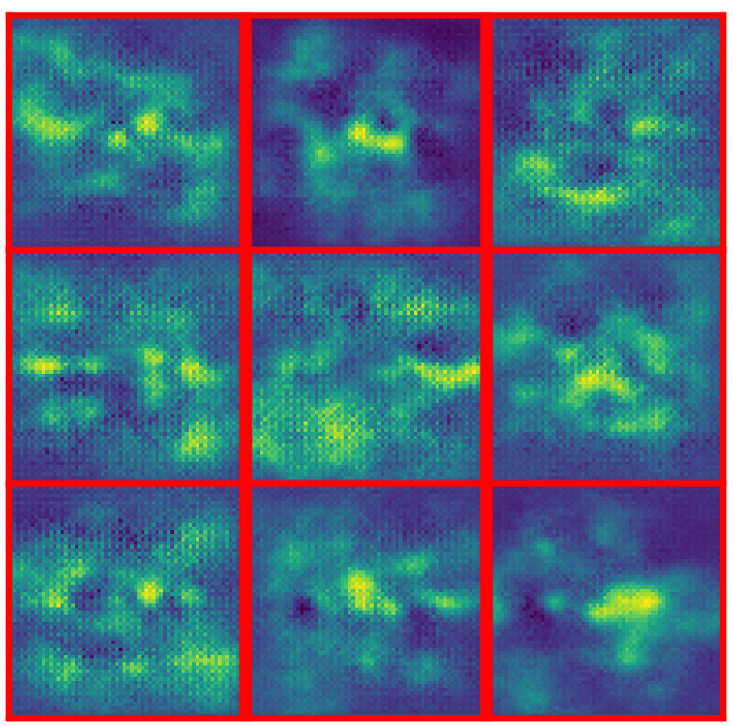

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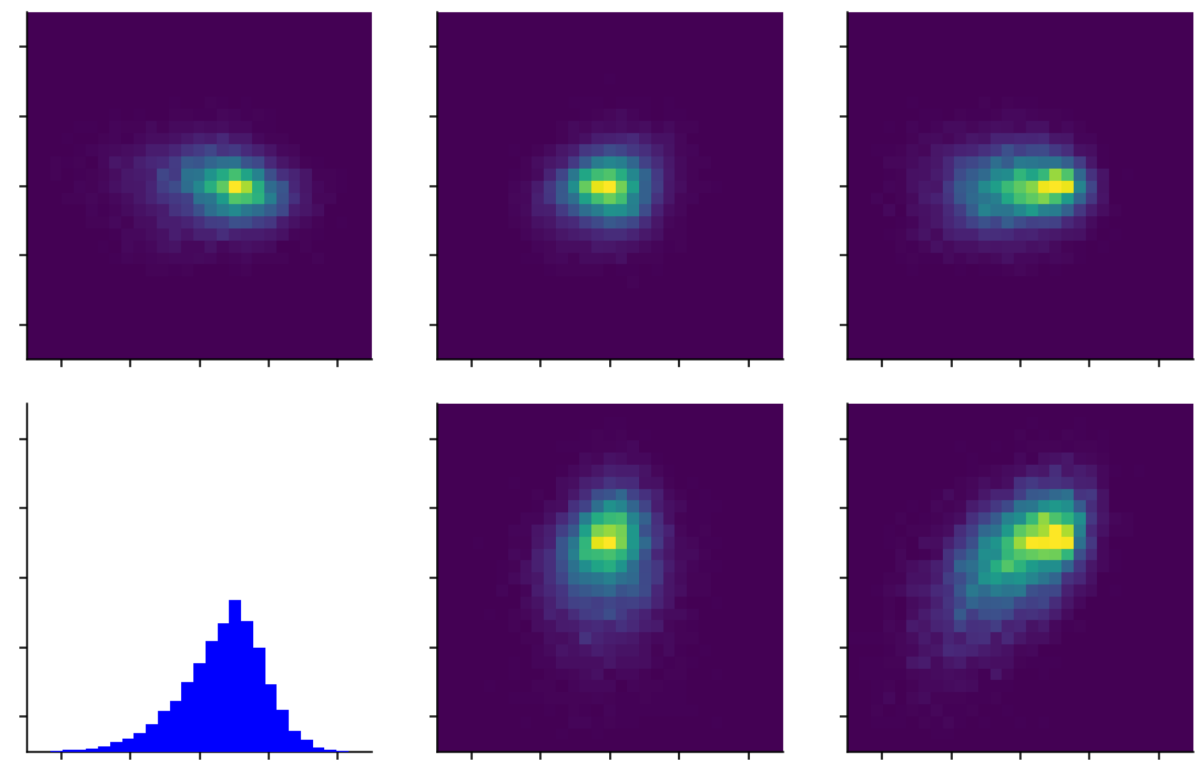

$\neq N(0, I)$ →**open issue with VAEs!**

Hoffman & Johnson 2016, Alemi et al 2018

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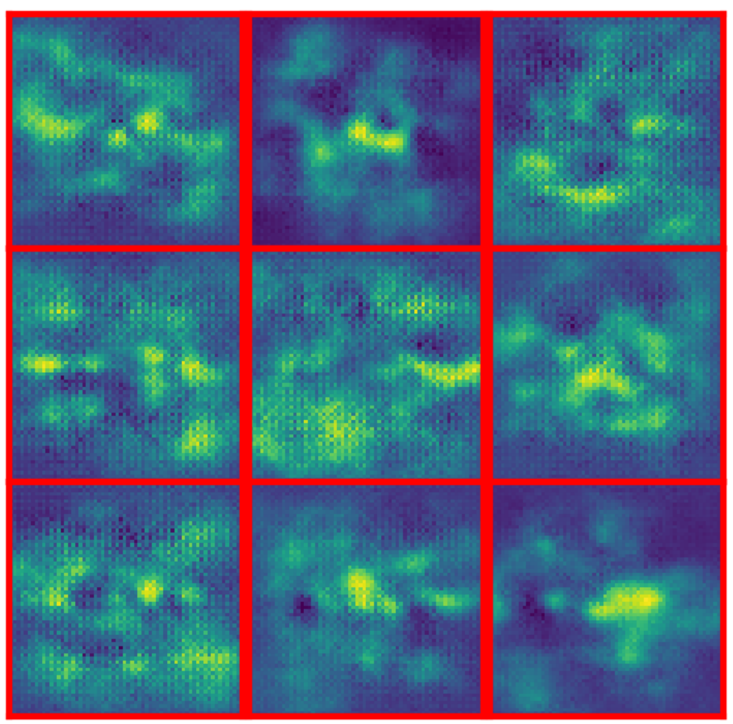

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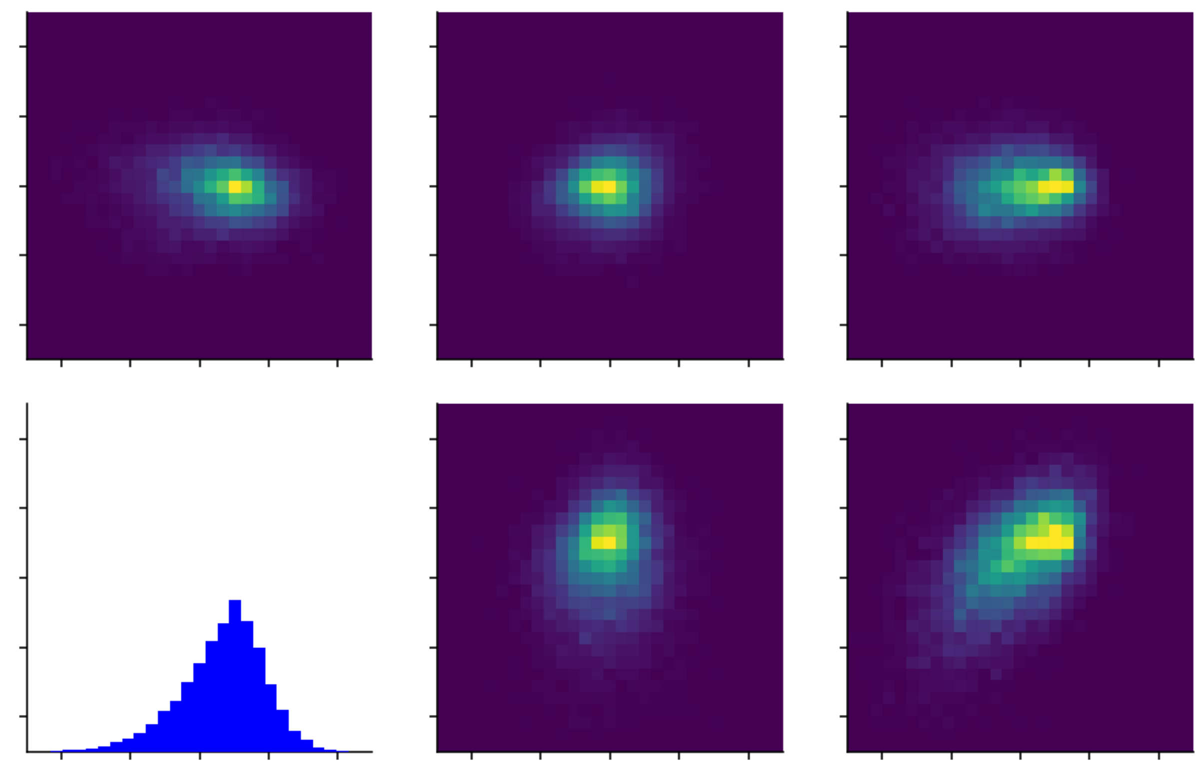
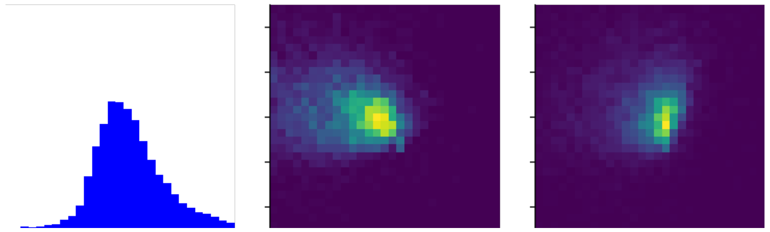


$\neq N(0, I)$ → **open issue with VAEs!**

Our approach: sample z from here to generate better galaxies

Hoffman & Johnson 2016, Alemi et al 2018

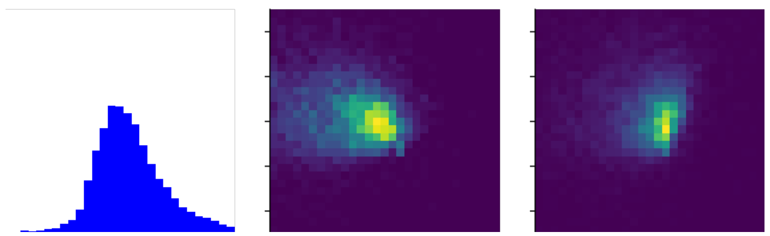
Normalizing flows

$z \sim N(0, I) \longrightarrow z' \sim$ 

Rezende & Mohamed 2015, Kingma et al 2016, …

Normalizing flows

$$z \sim N(0, I) \xrightarrow{f_T \circ \ldots \circ f_2 \circ f_1(z)} z' \sim$$



- Compose **invertible transformations** with **simple Jacobians** to reshape distributions

Rezende & Mohamed 2015, Kingma et al 2016, …

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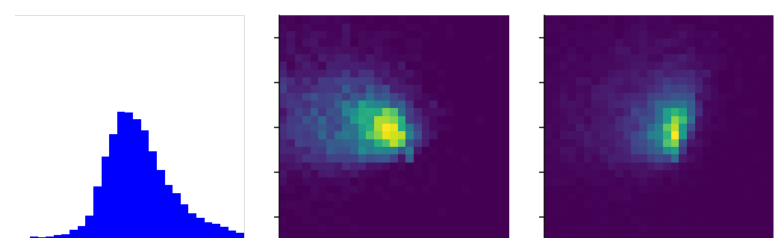

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- Parametrize with neural networks

Rezende & Mohamed 2015, Kingma et al 2016, …

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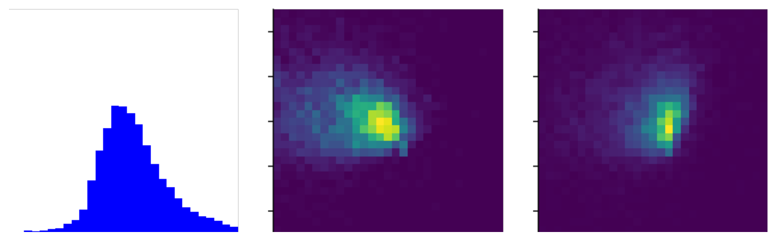


- Compose **invertible transformations** with **simple Jacobians** to reshape distributions

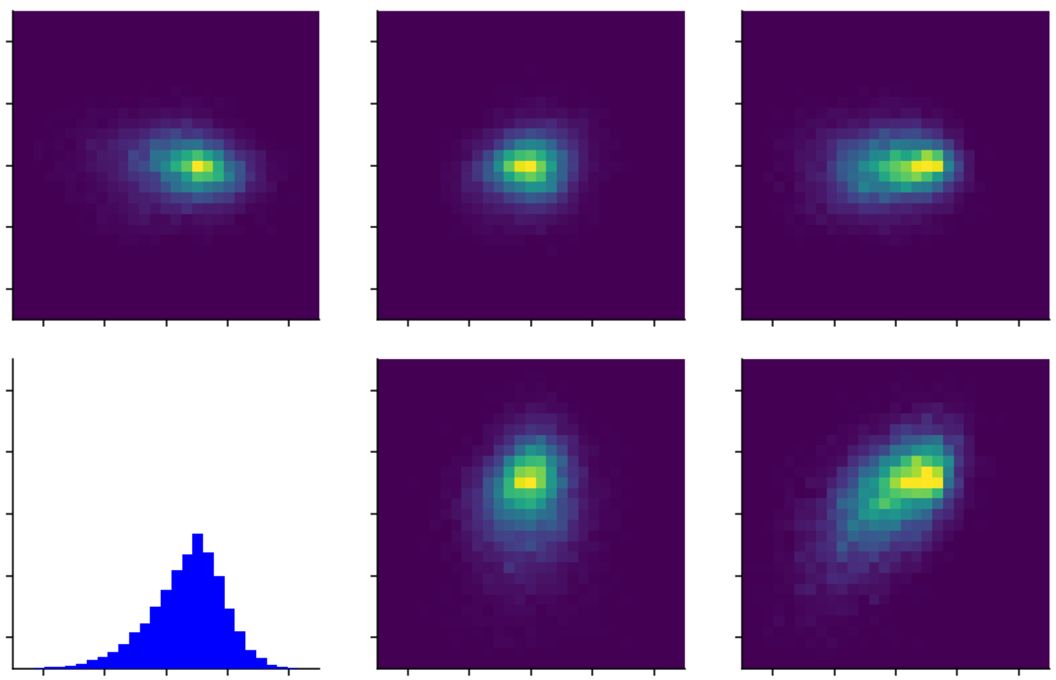
- Parametrize with neural networks

- For our purposes: inverse autoregressive flows (**IAFs**), which enable efficient sampling of the latent variable

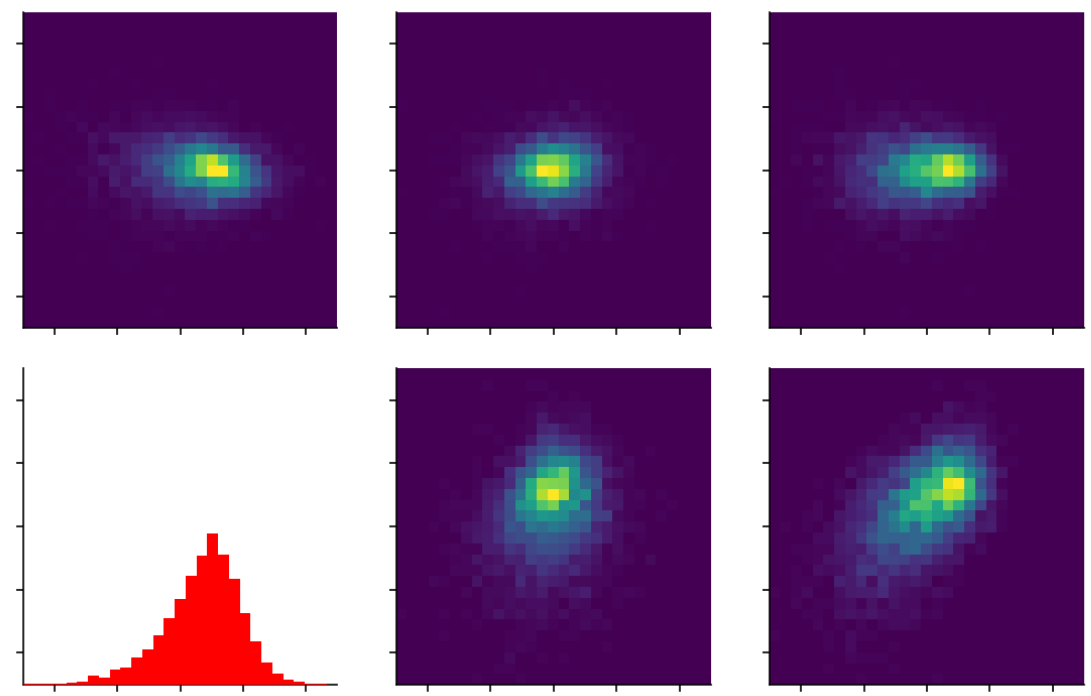
Rezende & Mohamed 2015, Kingma et al 2016, …

Galaxy VAE: samples

z distribution for training data



z samples from IAF fit



$z \sim \mathrm{IAF}(z)$

$\downarrow$

x

Galaxy VAE: samples

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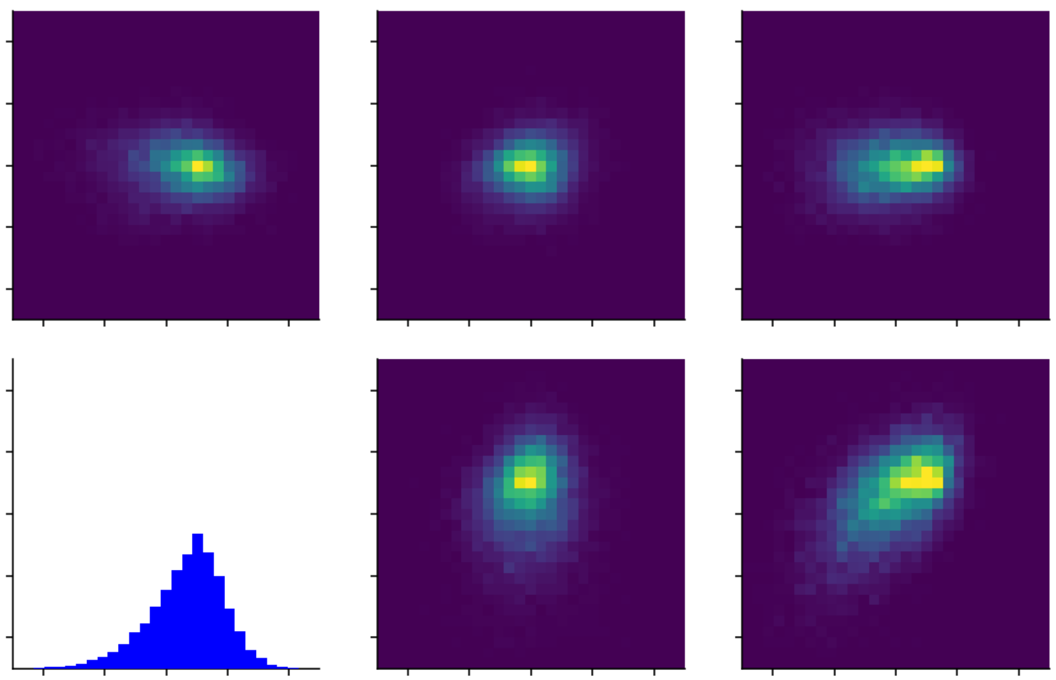

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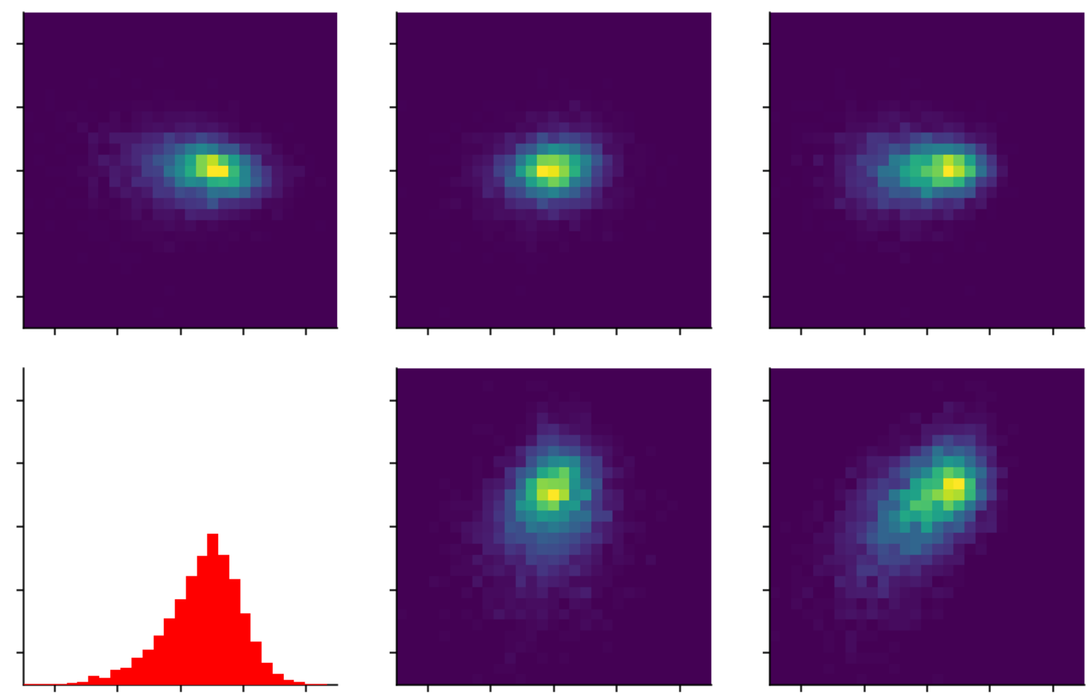

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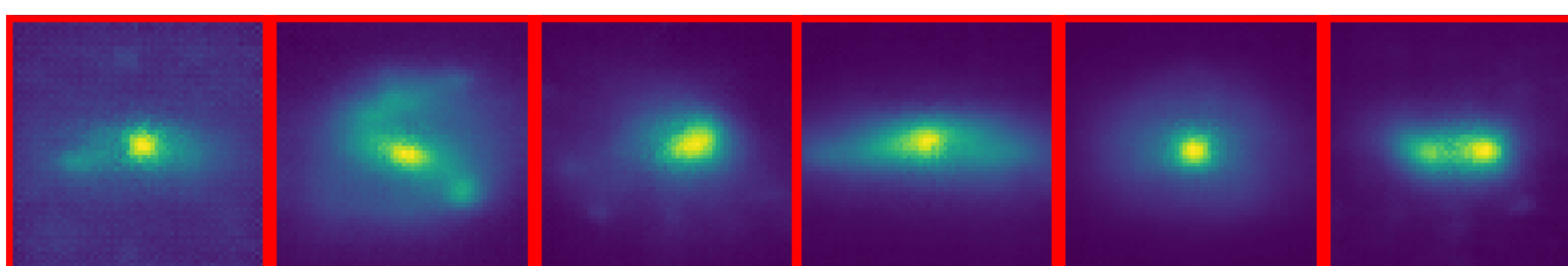
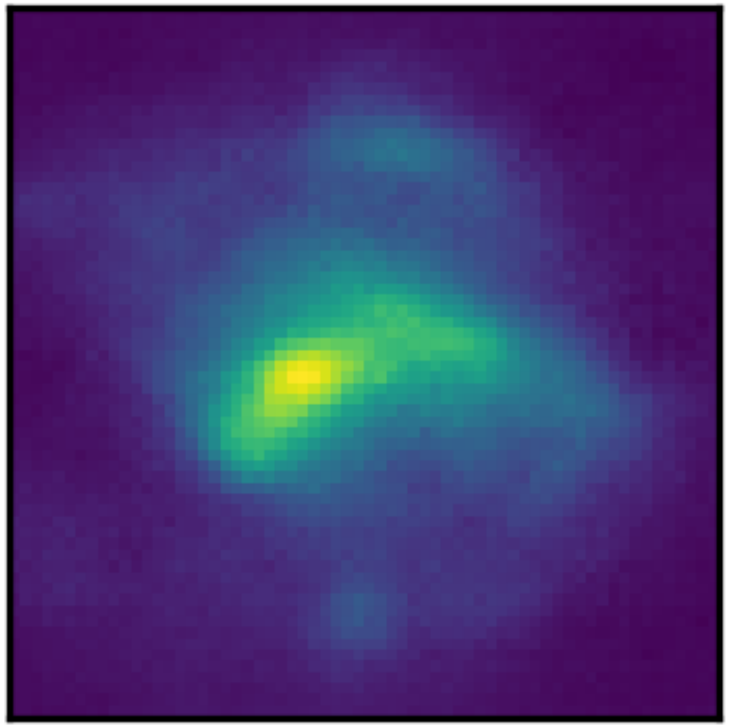
x

Generated galaxies

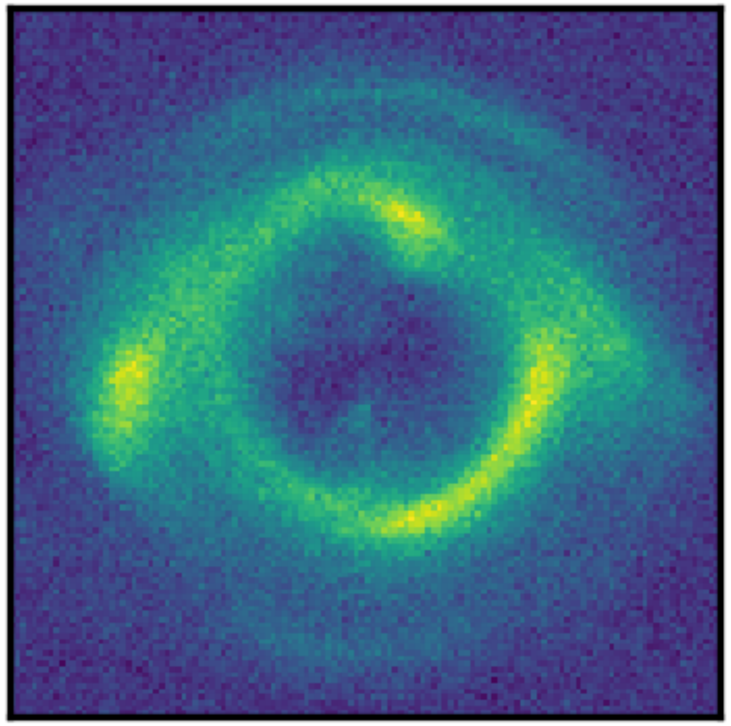


Lensing galaxies

True source



Observation



*Very preliminary, simplified analysis

Lensing galaxies

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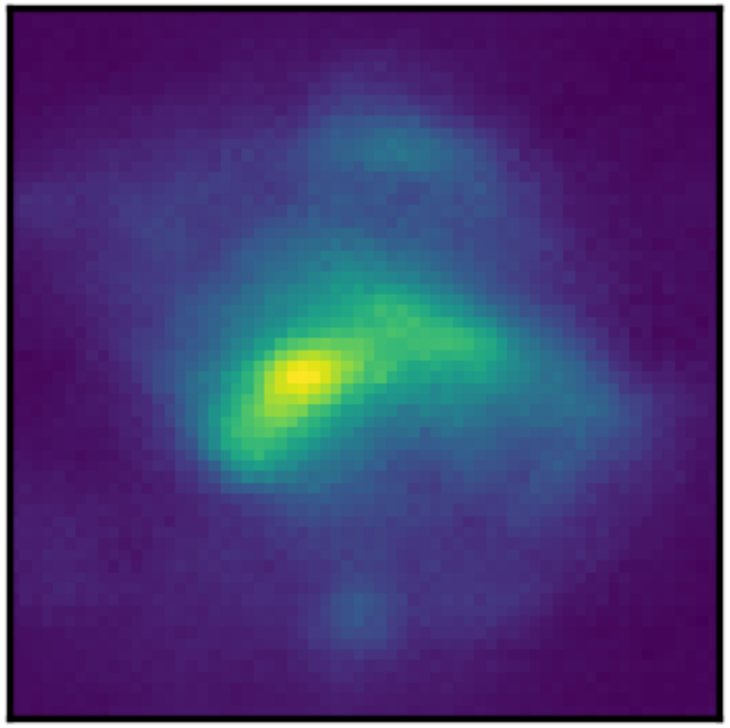

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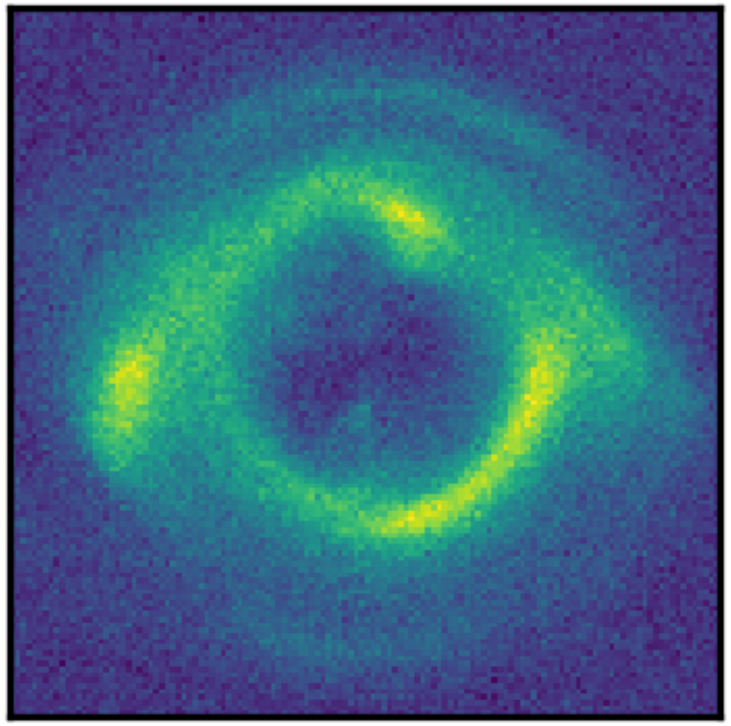
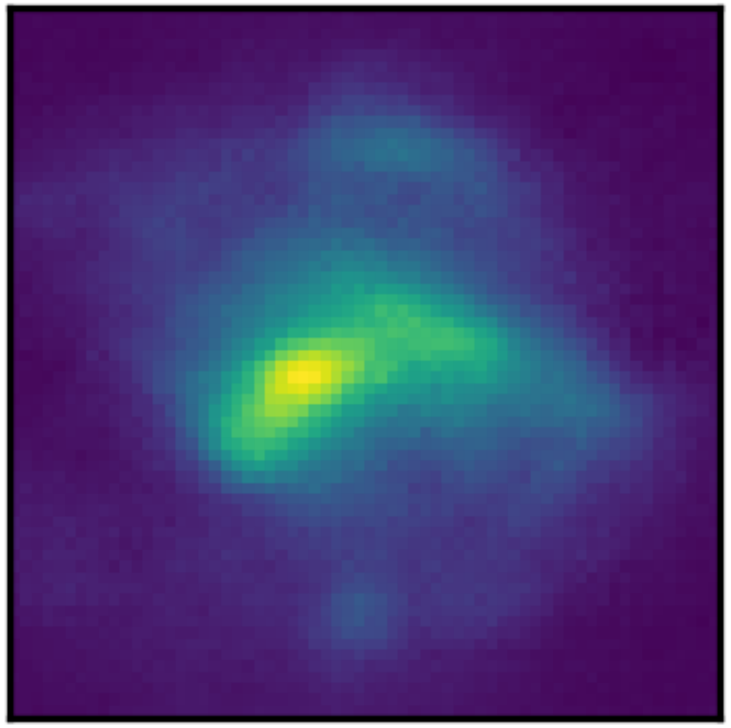


Best-fit source



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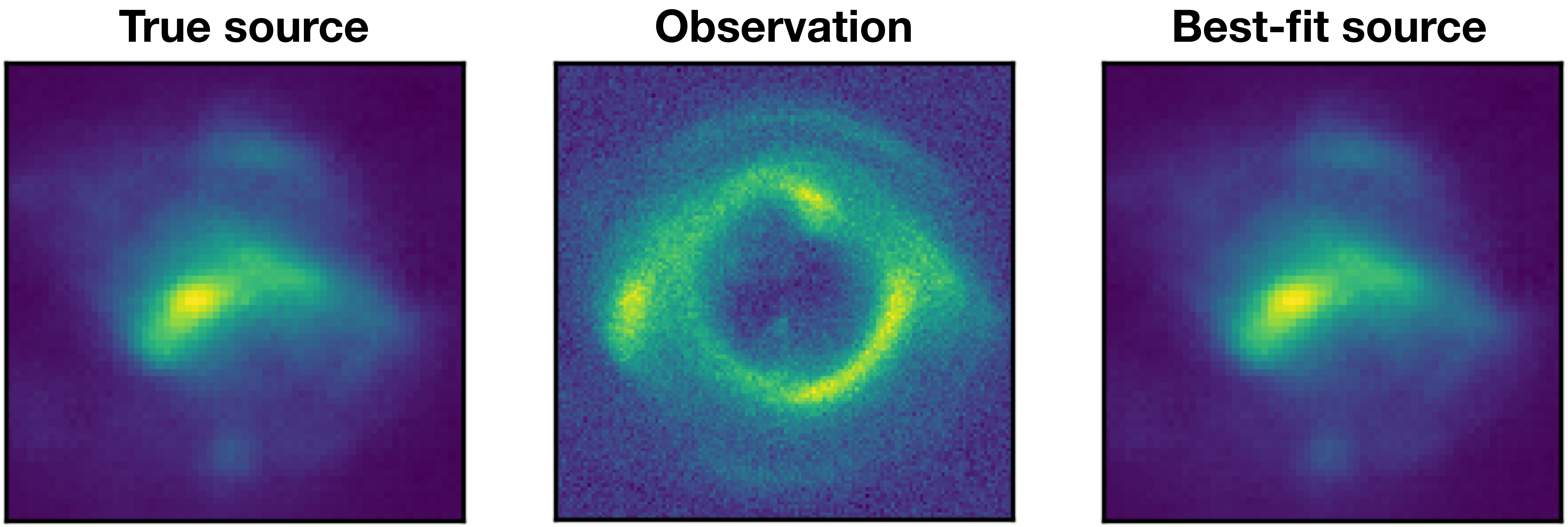
Lensing galaxies



True Einstein radius: 2.3
Best-fit value: 2.29

*Very preliminary, simplified analysis

Conclusions

- Integrate galaxy VAE with full analysis pipeline
- Improve prior/latent distribution mismatch:
  - Fully incorporate flows with VAE
- Fix blurriness:
  - More flexible encoder? β/conditional-VAE, …?
- Example of “differentiable programming” for physics + ML

Tomczak & Welling 2018

Higgins et al 2017

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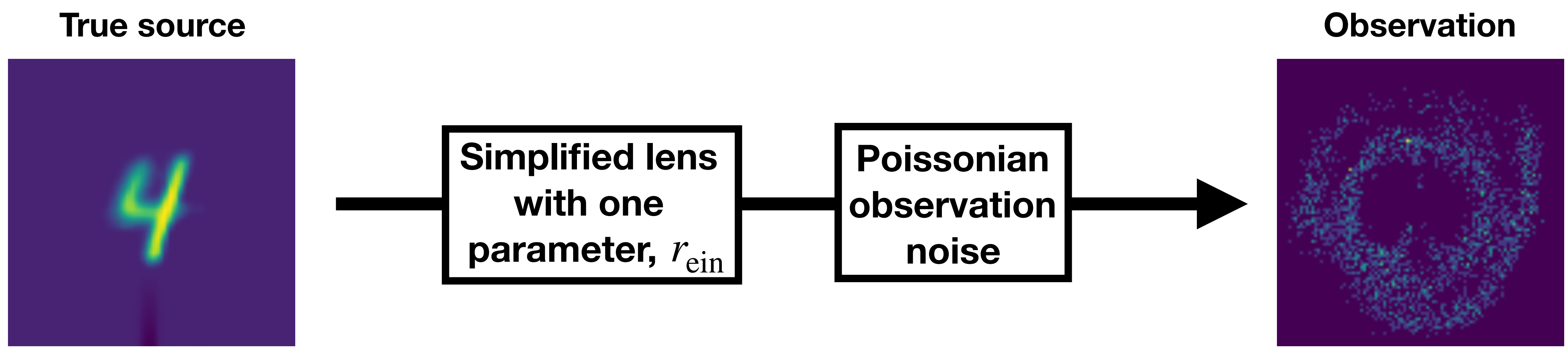
Thanks!

Tomczak & Welling 2018

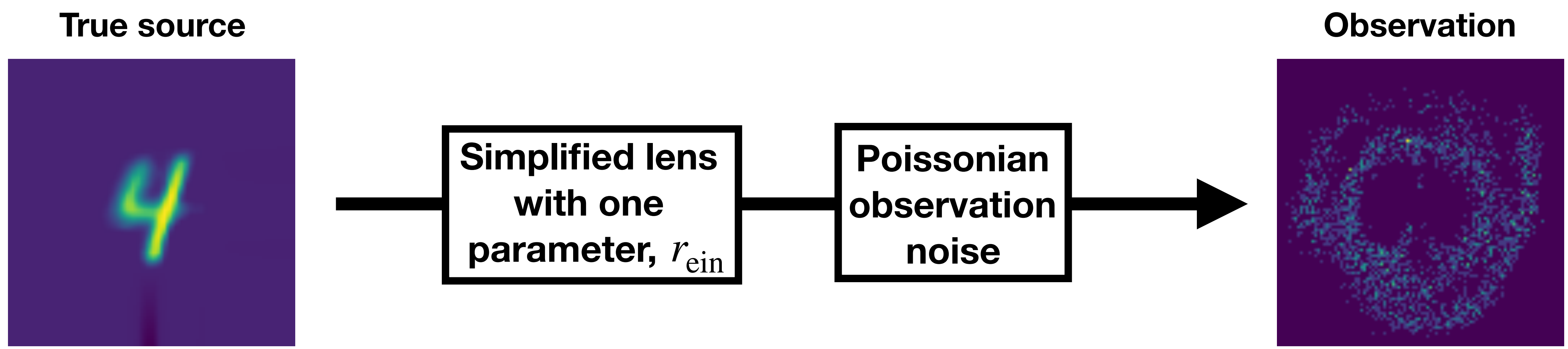
Higgins et al 2017

Lensing MNIST digits



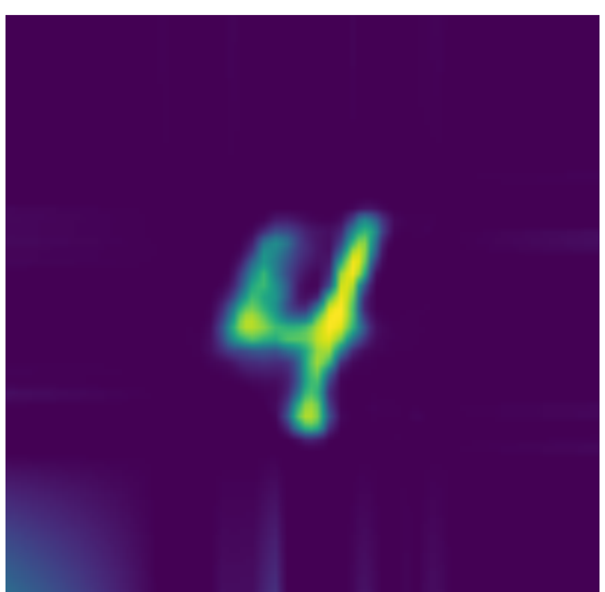
Outputs from simplified analysis

Lensing MNIST digits



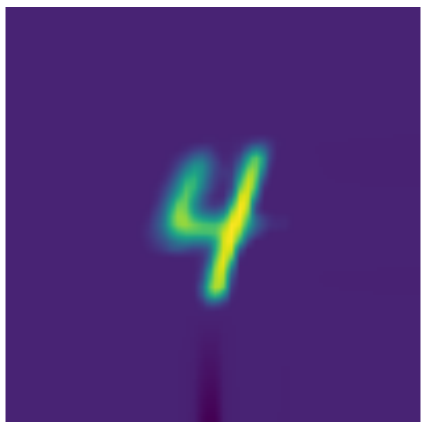
Outputs from simplified analysis

Best-fit source
from VAE



Lensing MNIST digits

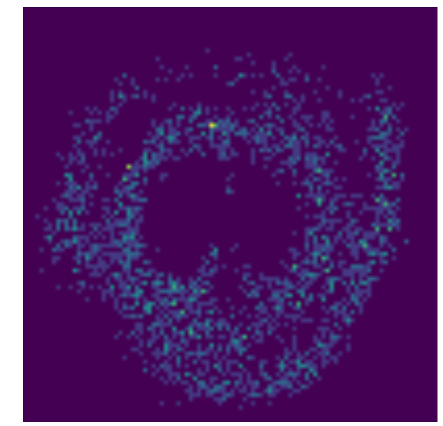
True source



Simplified lens with one parameter, r_{ein}

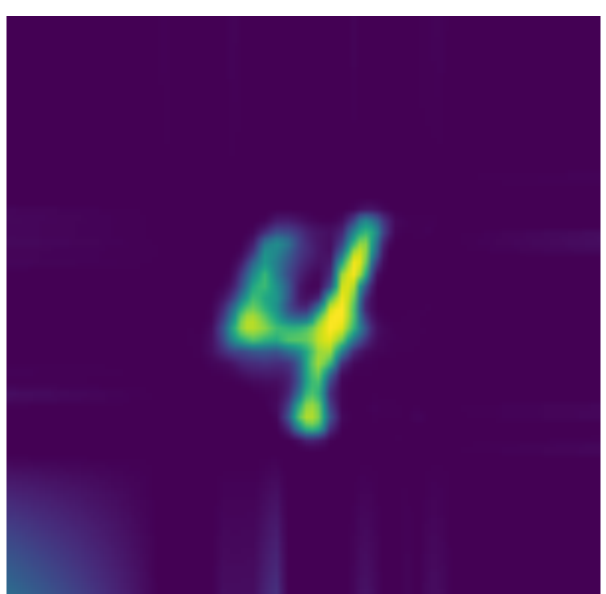
Poissonian observation noise

Observation

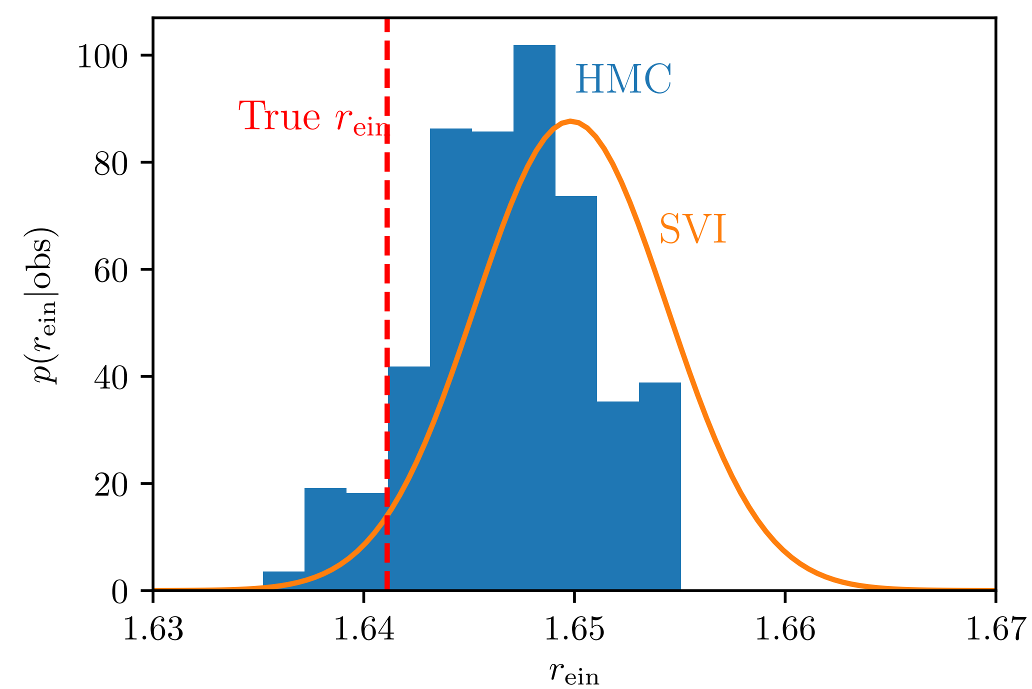


Outputs from simplified analysis

Best-fit source from VAE



Lens parameter inference



Training VAEs

- Maximize a lower bound on $p(x^{(i)})$:

$$\mathrm{ELBO}(x^{(i)}) = \mathbb{E}_{e(z|x^{(i)})}\left[\log d(x^{(i)}\,|\,z)\right] - \mathrm{KL}\left[e(z\,|\,x^{(i)})\,||\,m(z)\right]$$

Encoded means
for MNIST

Source

Training VAEs

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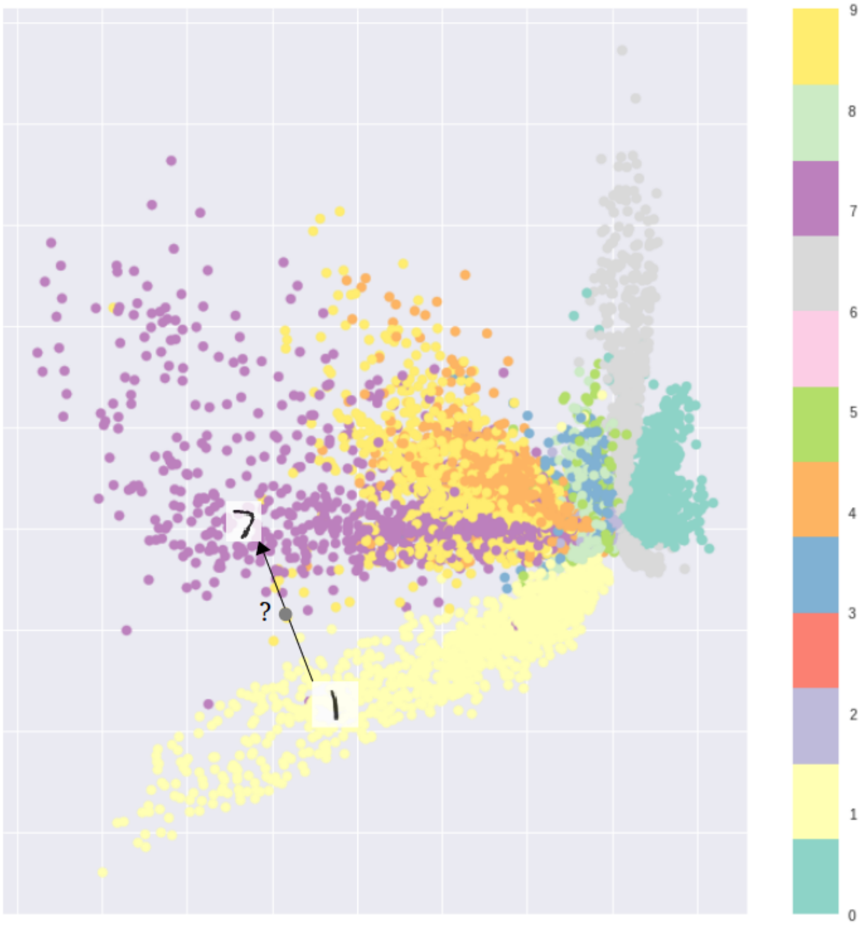
Encoded means for MNIST



Source

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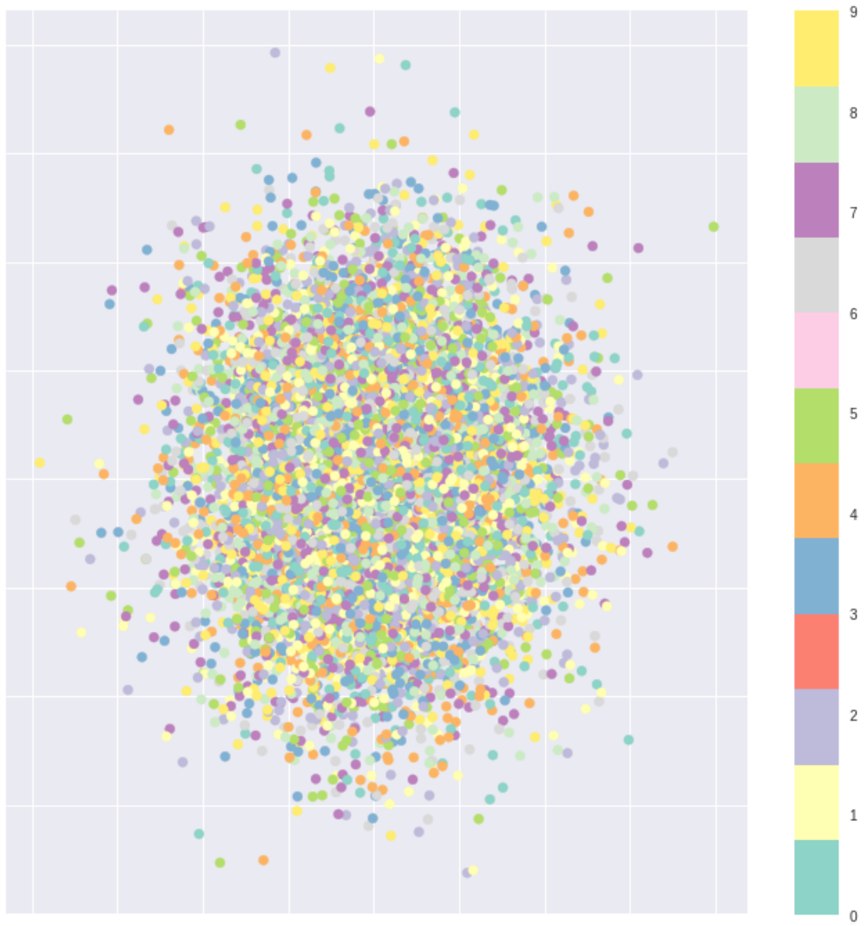
Encoded means for MNIST



Source

Training VAEs

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Encoded means for MNIST

Source