Astronomical images and OoD behaviour of generative models

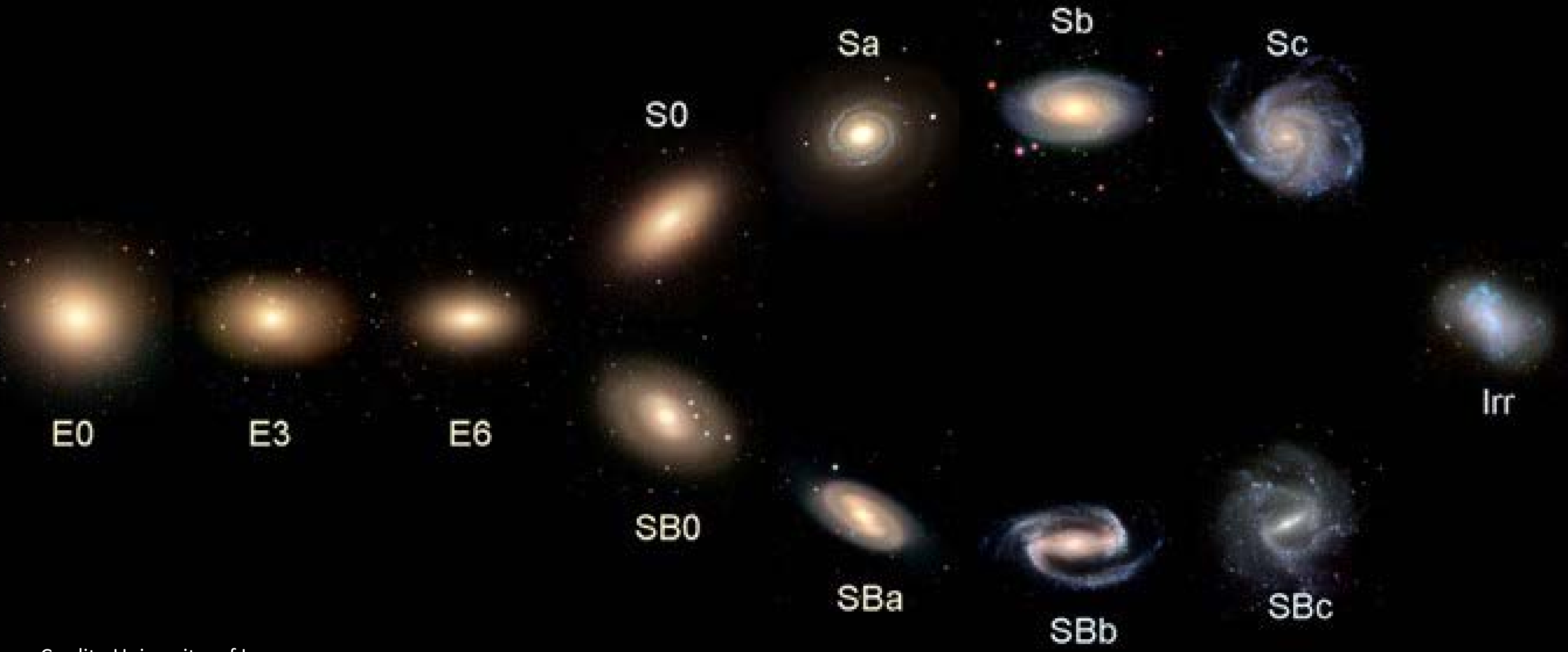
Lorenzo Zanisi, M. Huertas-Company, F. Lanusse, C. Bottrell,

A. Pillepich, D. Nelson, V. Rodriguez-Gomez

KAVLI SUMMER PROGRAM IN ASTROPHYSICS

UNIVERSITY OF Southampton

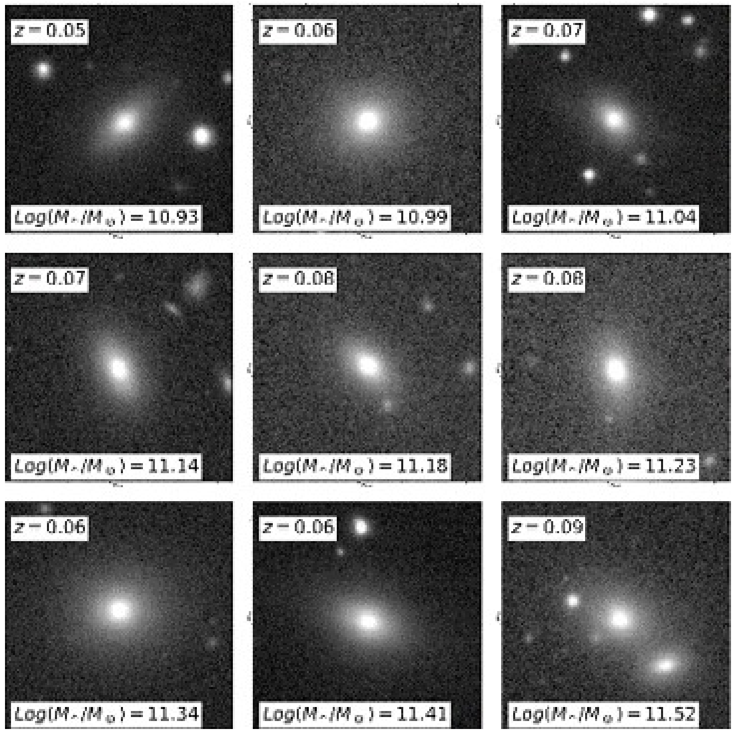
Hubble’s Galaxy Classification Scheme



Credit: University of Iowa

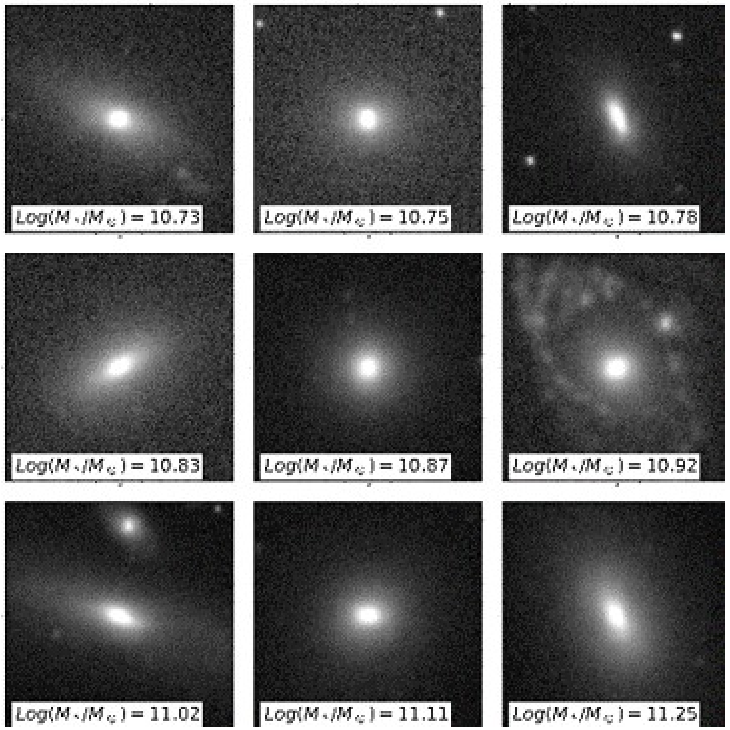
Real

Sloan Digital Sky Survey, SDSS



Simulated

Illustris TNG simulation



$$\mathbf{X} \sim p(x) \longrightarrow p \overset{?}{=} q \longleftarrow \mathbf{Y} \sim q(y)$$

Huertas-Company et al. 2019
MNRAS

Generative models for OoD detection

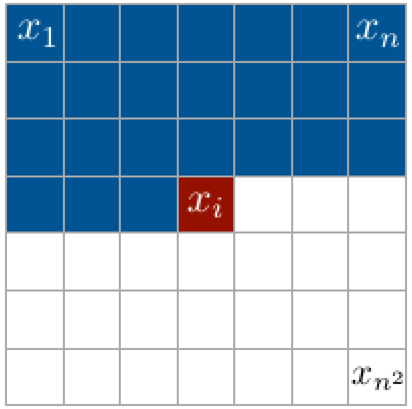
Why generative models?

- ➢ Unsupervised approach
- ➢ Distribution of data p is learned
- ➢ Use the likelihood for OoD tasks

PixelCNN

- ➢ Explicit likelihood
- ➢ Autoregressive

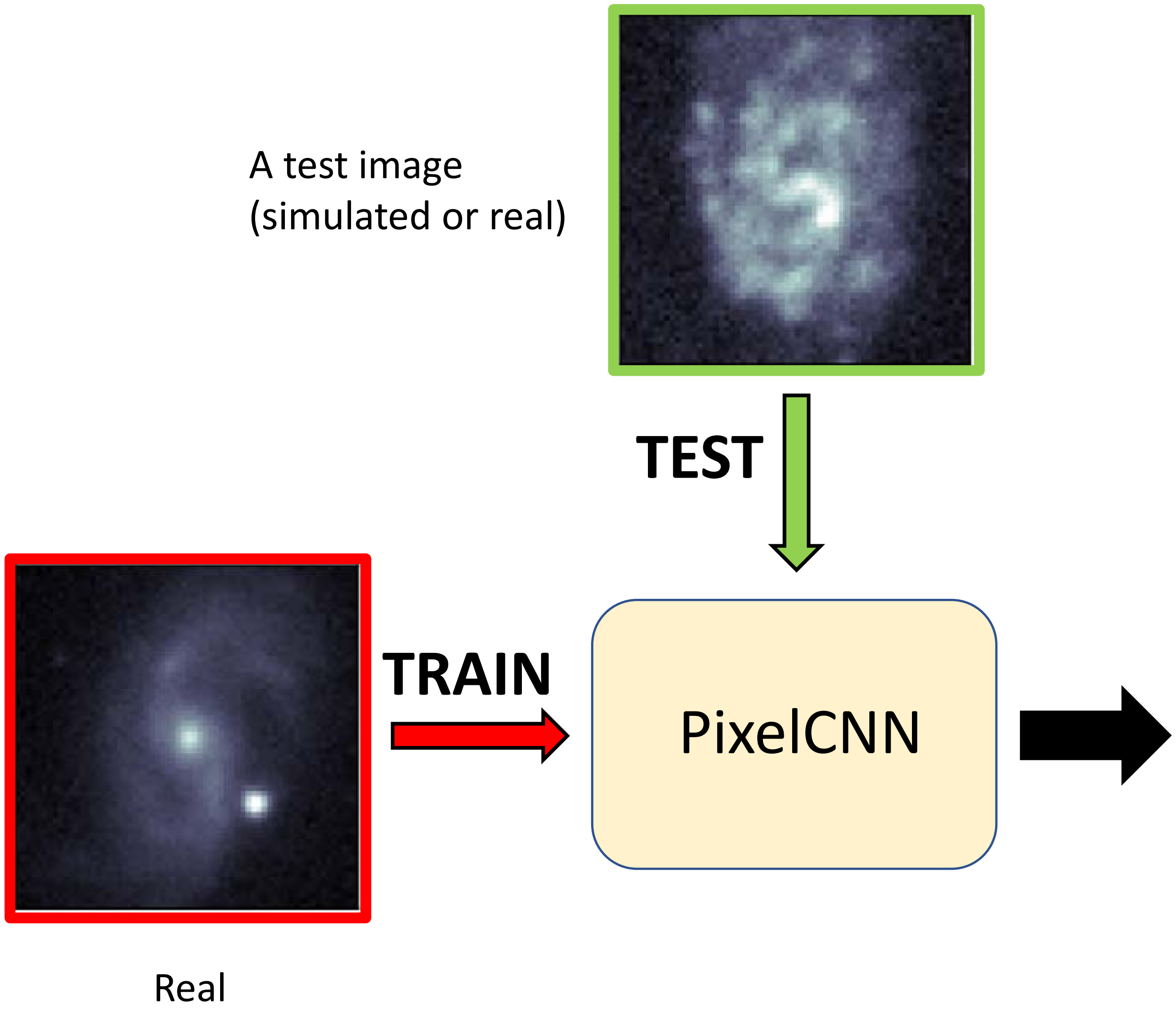
$$P(X) = \prod_{i=1}^{N^2} P(X_i | X_{1 \ldots i-1})$$

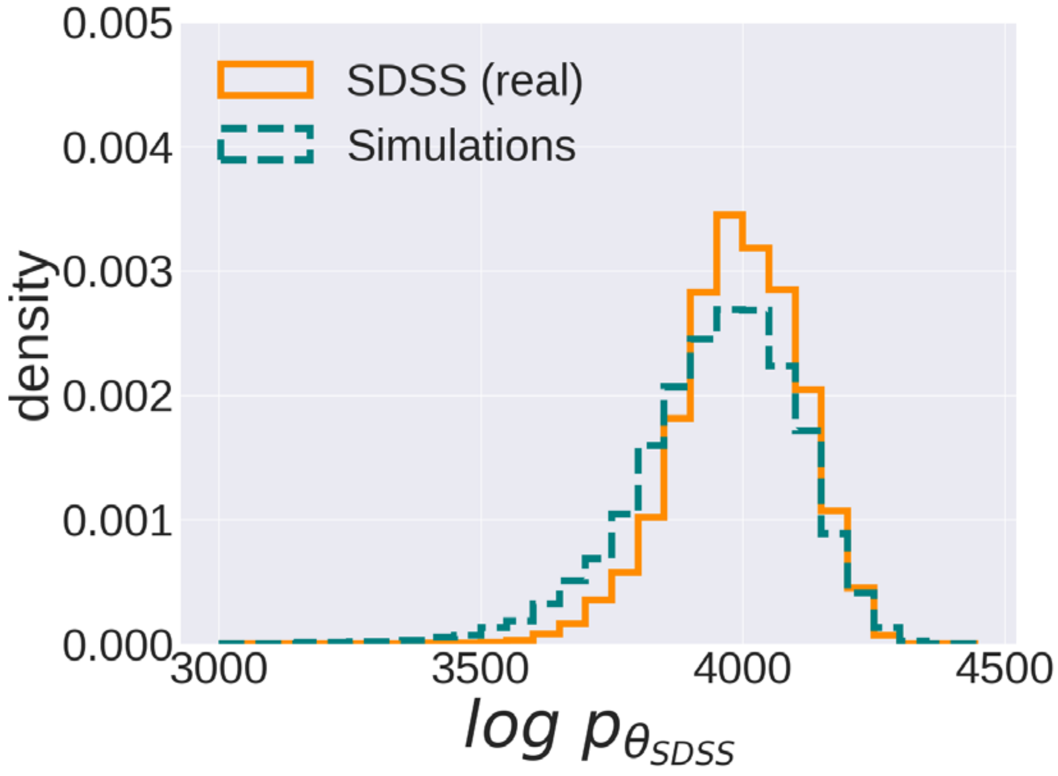


Van den Oord et al. 2016a,b ; **Salimans et al. 2017**

Likelihood-based OoD

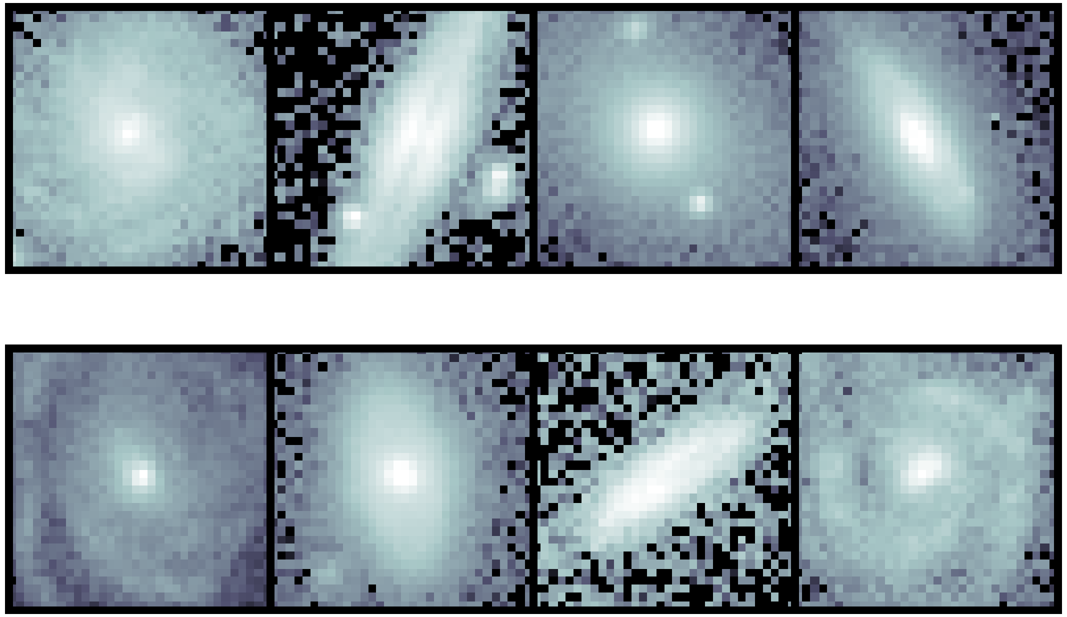
Bishop 1994





Low likelihood

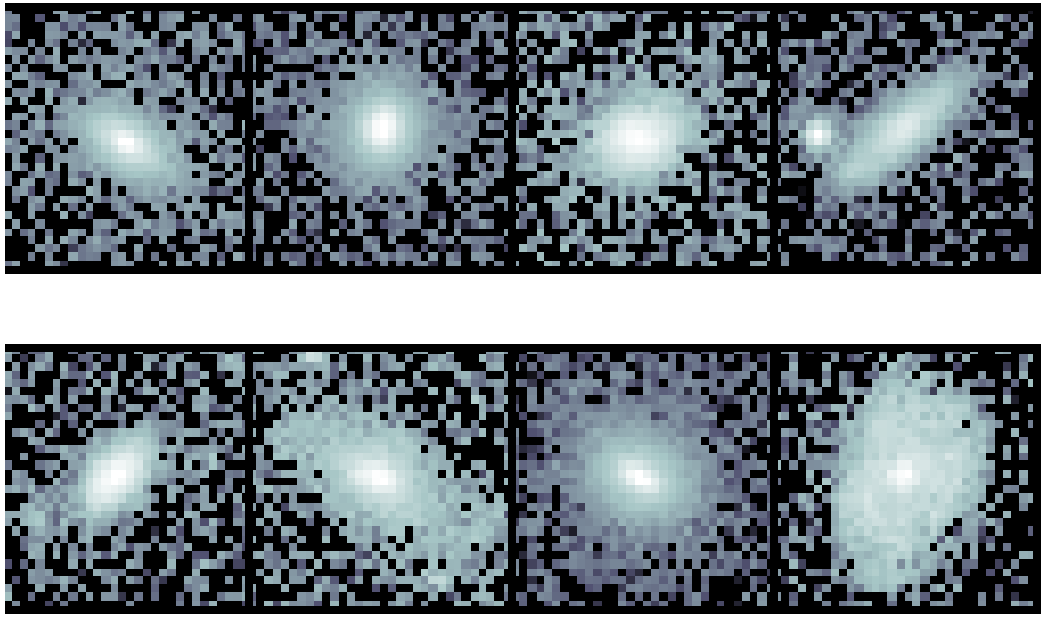
3675.0



- Larger
- More structure
- More messy background

High likelihood

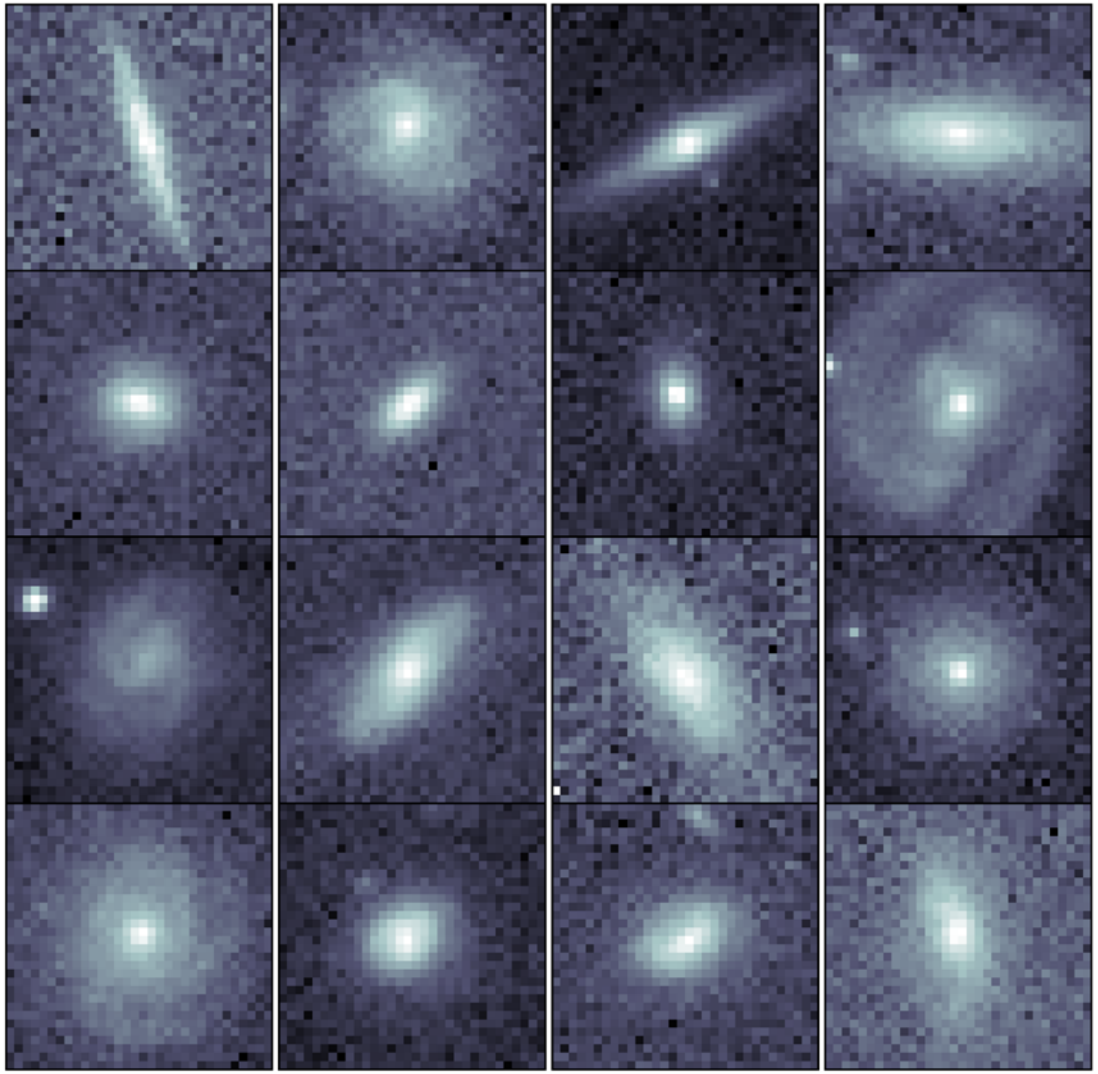
4172.0



- Smaller
- Less structure
- Less messy background

Size, background, brightness, complexity

See also:
Serrà et al. 2019
Ren et al. 2019



Complexity

- Less variance than ImageNet
- Appreciable range of shapes

Background

- Noise and interlopers
- More variance than MNIST
- Less variance than ImageNet

Our aims

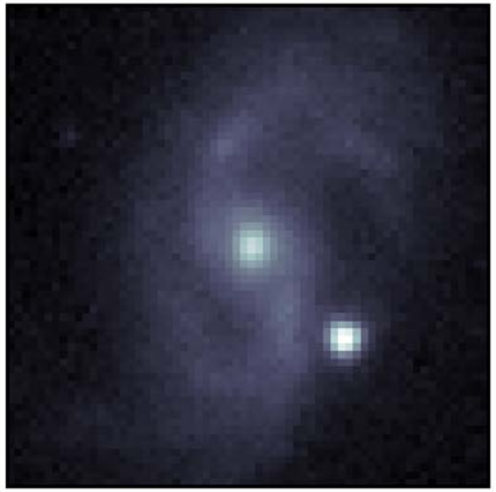
- Get rid of background
- Isolate fine shape details

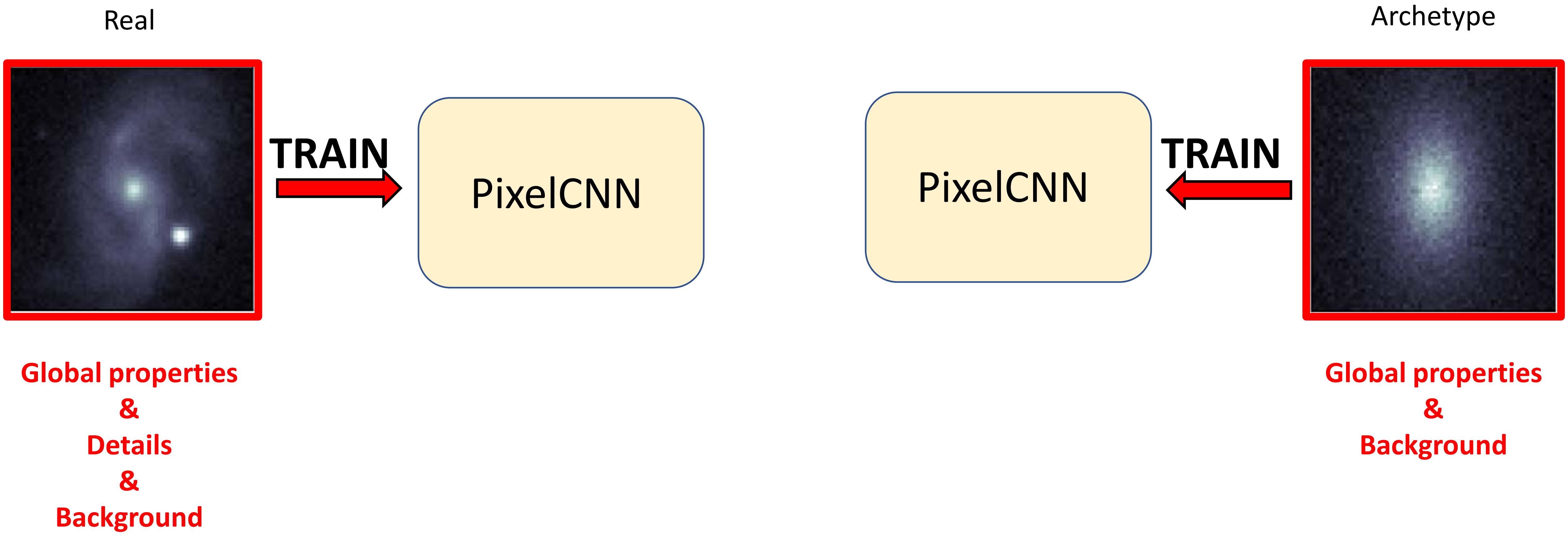
Galaxy archetypes

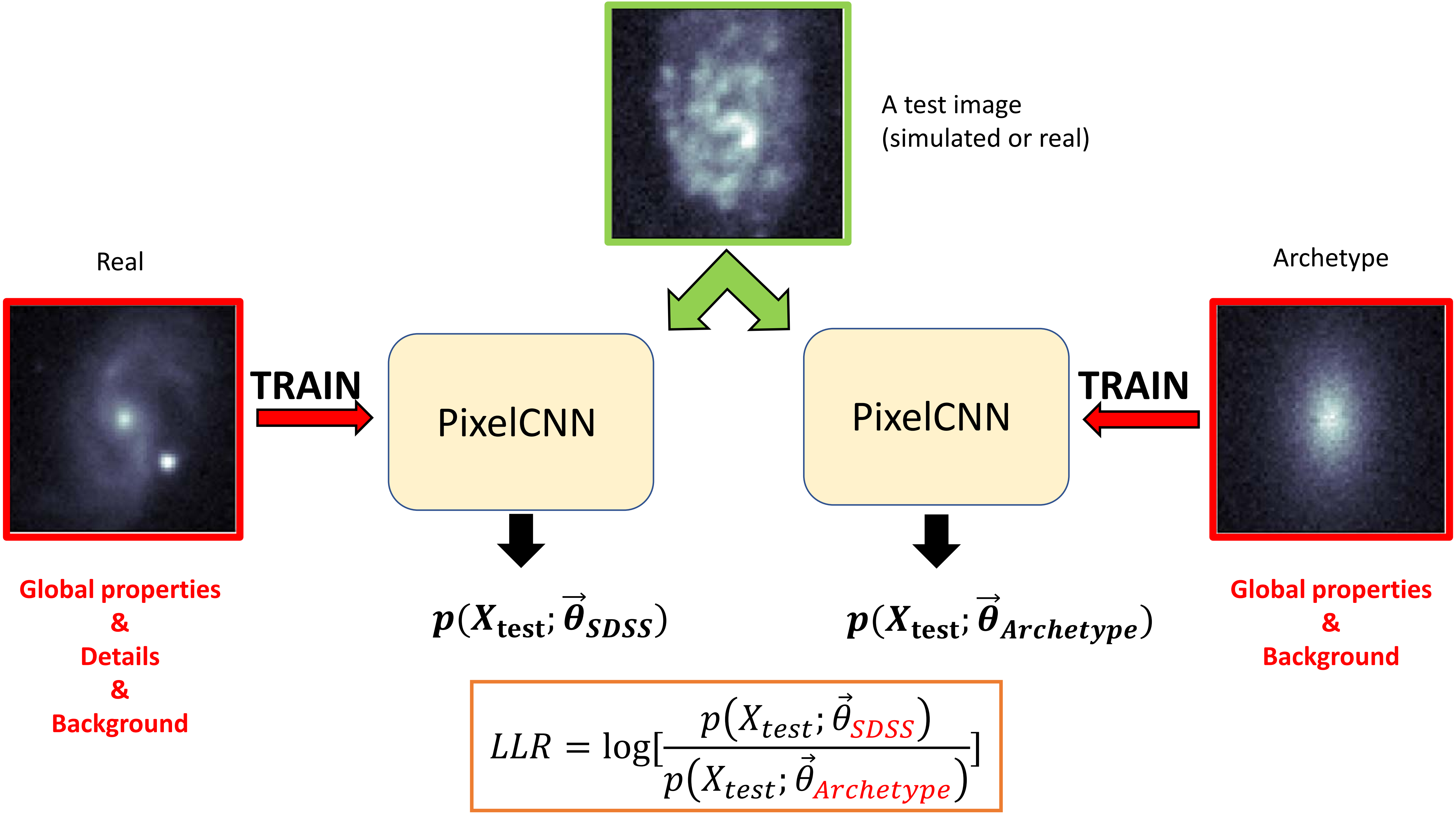
The Sèrsic Function models the light profile of a galaxy

$$I(R; n, R_e) = I_e \exp\left\{-b_n\left[\left(\frac{R}{R_e}\right)^{-1/n} - 1\right]\right\}$$

Smooth, **featureless** "blob" with ***the same global properties*** (size, luminosity, ellipticity..)




Real
TRAIN
PixelCNN
PixelCNN
TRAIN
Archetype
Global properties
&
Details
&
Background
Global properties
&
Background

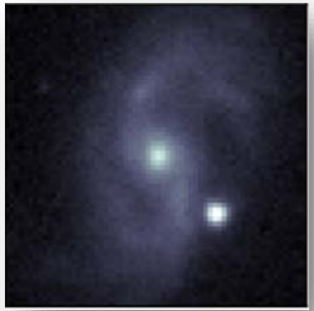

A test image
(simulated or real)
Real
Archetype
TRAIN
PixelCNN
PixelCNN
TRAIN
$p(X_{\text{test}}; \vec{\theta}_{SDSS})$
$p(X_{\text{test}}; \vec{\theta}_{Archetype})$
Global properties
&
Details
&
Background
Global properties
&
Background
$LLR = \log[\frac{p(X_{test}; \vec{\theta}_{SDSS})}{p(X_{test}; \vec{\theta}_{Archetype})}]$

$$p(X_{test};\vec{\theta}) = p(X_{subject};\vec{\theta})p(X_{bg};\vec{\theta})$$

$$LLR = \log\left\{\left[\frac{p(X_{subject};\vec{\theta}_1)}{p(X_{subject};\vec{\theta}_2)}\right]\left[\frac{p(X_{bg};\vec{\theta}_1)}{p(X_{bg};\vec{\theta}_2)}\right]\right\}$$

Background removal

Ren et al. 2019
(monochromatic bg)



$$\mathrm{p}\left(X_{test};\vec{\theta}\right) = p\left(X_{subject};\vec{\theta}\right)p\left(X_{bg};\vec{\theta}\right)$$

$$LLR = \log\left\{\left[\frac{p\left(X_{subject};\vec{\theta}_1\right)}{p\left(X_{subject};\vec{\theta}_2\right)}\right]\left[\cancel{\frac{p\left(X_{bg};\vec{\theta}_1\right)}{p\left(X_{bg};\vec{\theta}_2\right)}}\right]\right\}$$

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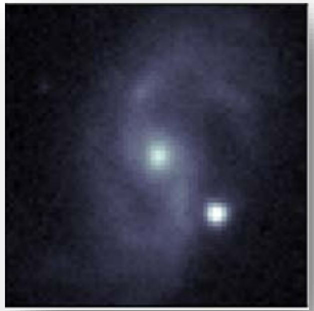

$$\mathrm{p}(X_{test};\vec{\theta}) = p(X_{subject};\vec{\theta})p(X_{bg};\vec{\theta})$$

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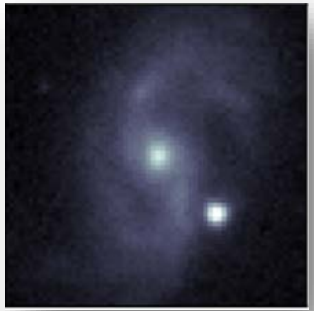


$$\boxed{\begin{gathered}\mathrm{p}(X_{subject};\vec{\theta}) = p(X_{details}|X_{global};\vec{\theta})p(X_{global};\vec{\theta}) \\ LLR = \log\left\{\left[\frac{p(X_{details}|X_{global};\vec{\theta}_1)p(X_{global};\vec{\theta}_1)}{p(X_{global};\vec{\theta}_2)}\right]\right\}\end{gathered}}$$

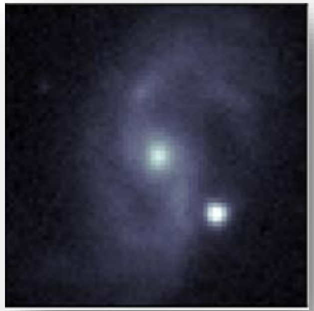
Details enhancement

$$\mathrm{p}(X_{test};\vec{\theta}) = p(X_{subject};\vec{\theta})p(X_{bg};\vec{\theta})$$

$$LLR = \log\left\{\left[\frac{p(X_{subject};\vec{\theta}_1)}{p(X_{subject};\vec{\theta}_2)}\right]\left[\cancel{\frac{p(X_{bg};\vec{\theta}_1)}{p(X_{bg};\vec{\theta}_2)}}\right]\right\}$$

Background removal

Ren et al. 2019
(monochromatic bg)

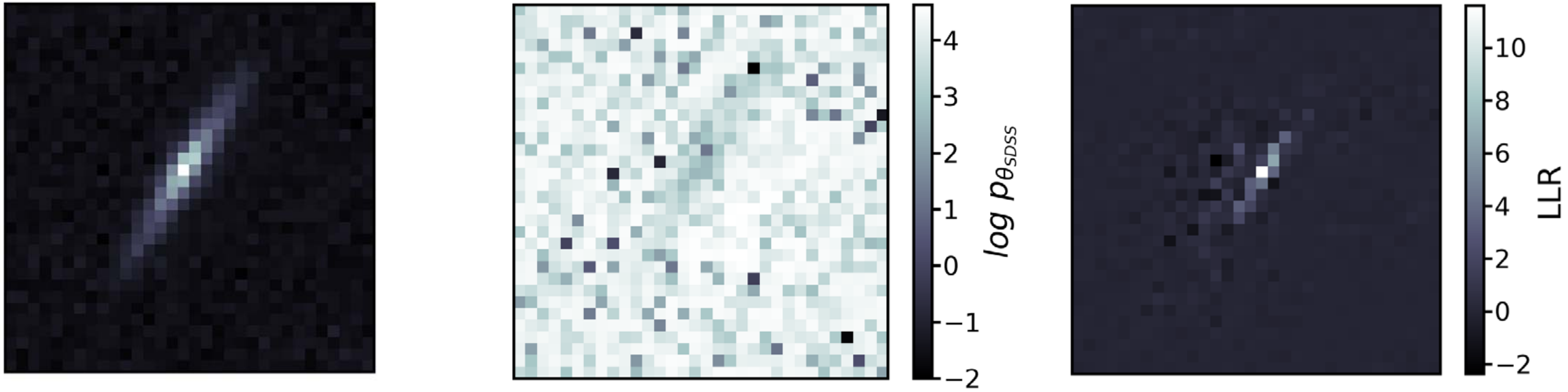


$$\mathrm{p}(X_{subject};\vec{\theta}) = p(X_{details}|X_{global};\vec{\theta})p(X_{global};\vec{\theta})$$

$$LLR = \log\left\{\left[\frac{p(X_{details}|X_{global};\vec{\theta}_1)\cancel{p(X_{global};\vec{\theta}_1)}}{\cancel{p(X_{global};\vec{\theta}_2)}}\right]\right\}$$

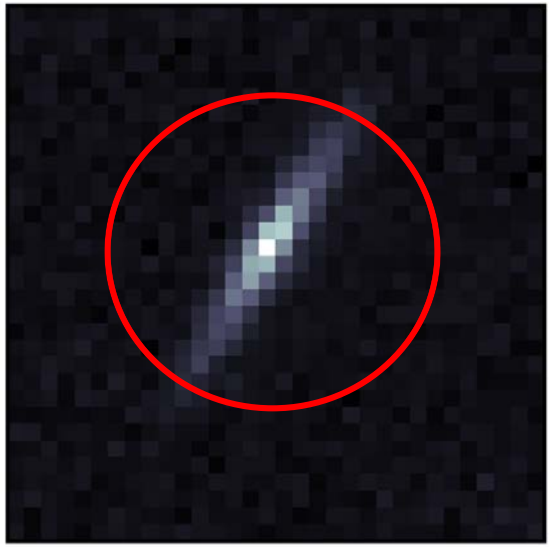
Details enhancement

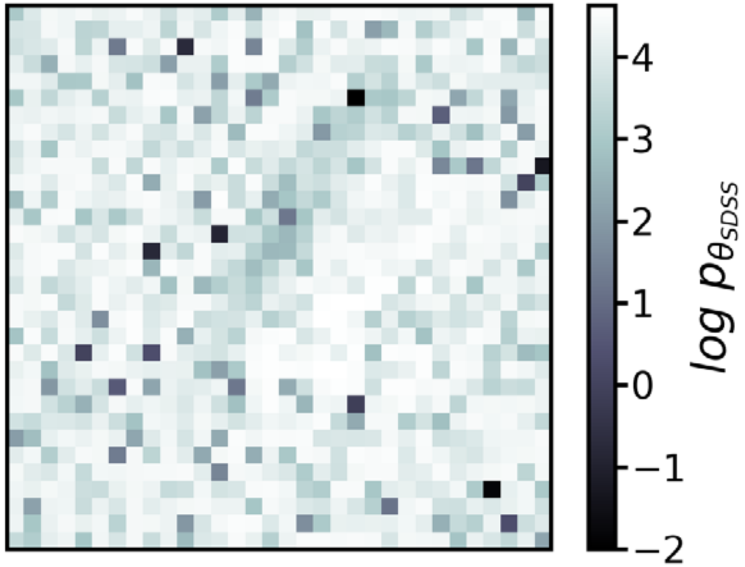
Pixel-wise contributions

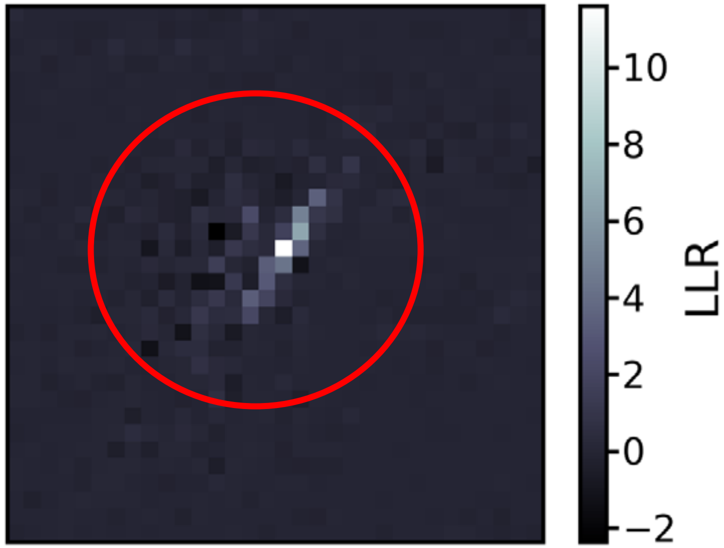


Contribution of the background is null in the LLR

Pixel-wise contributions

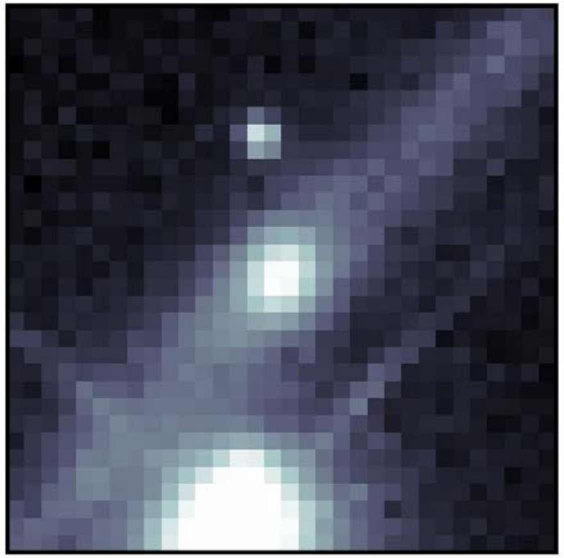


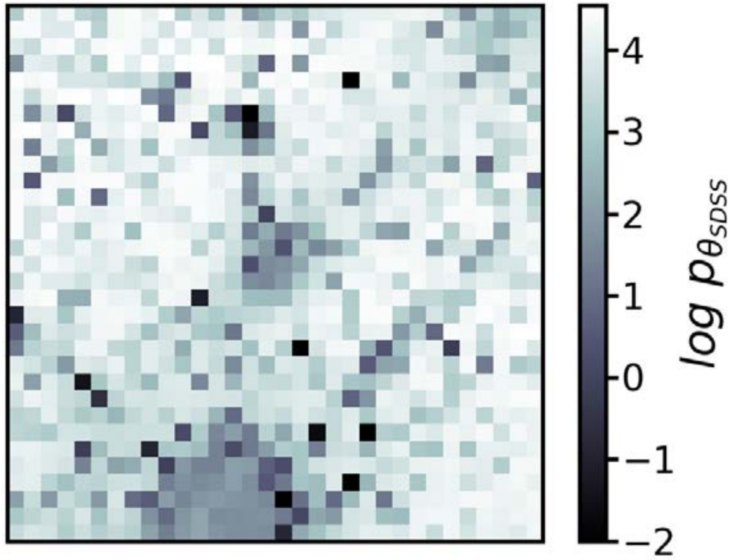


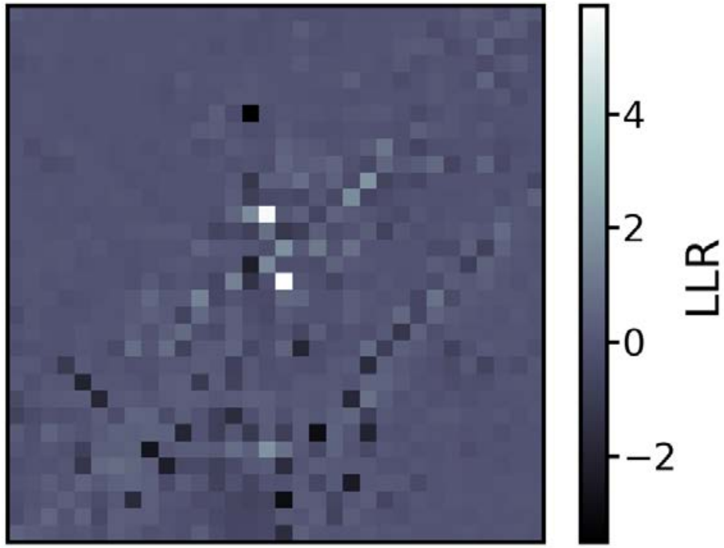


Central regions are enhanced in LLR

Pixel-wise contributions

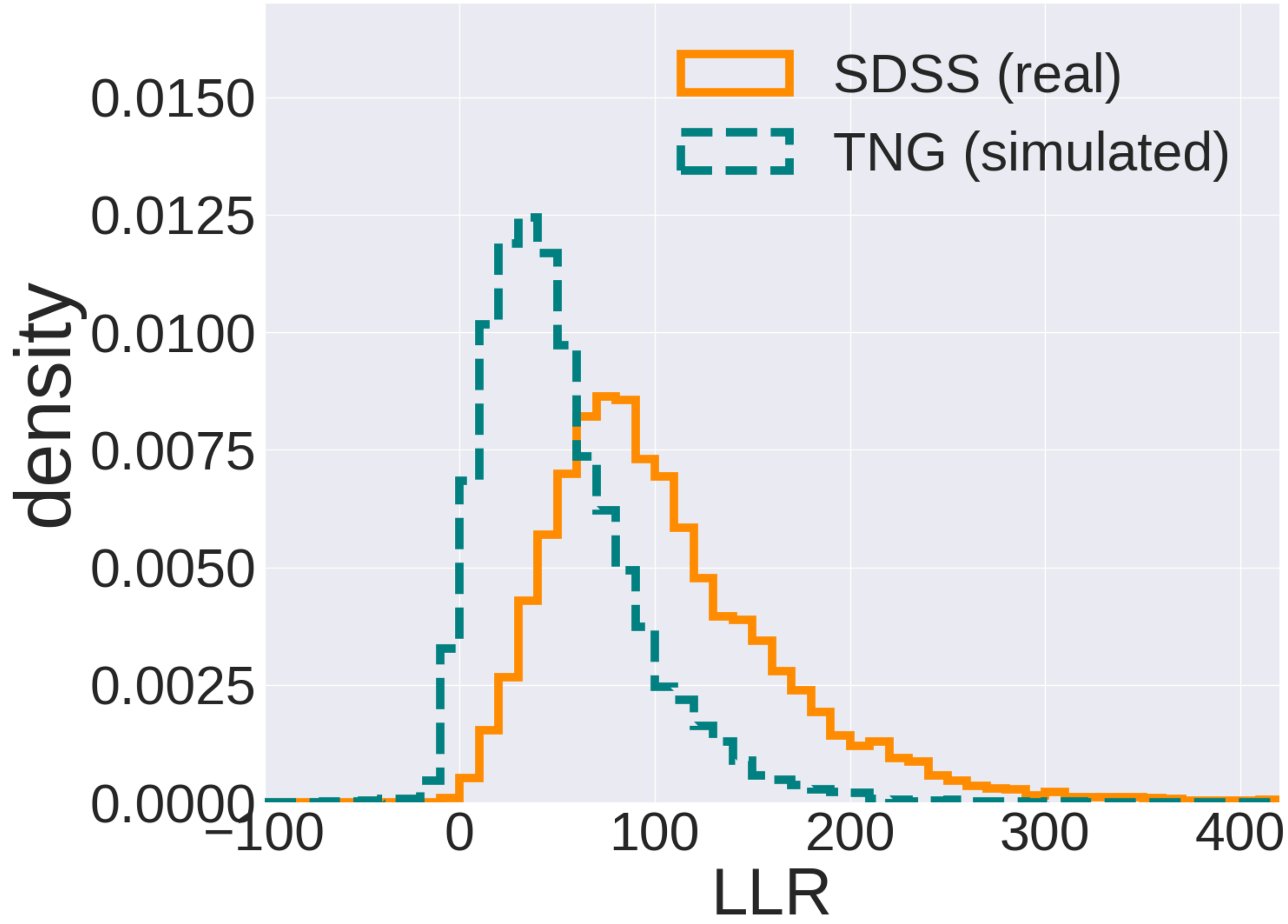




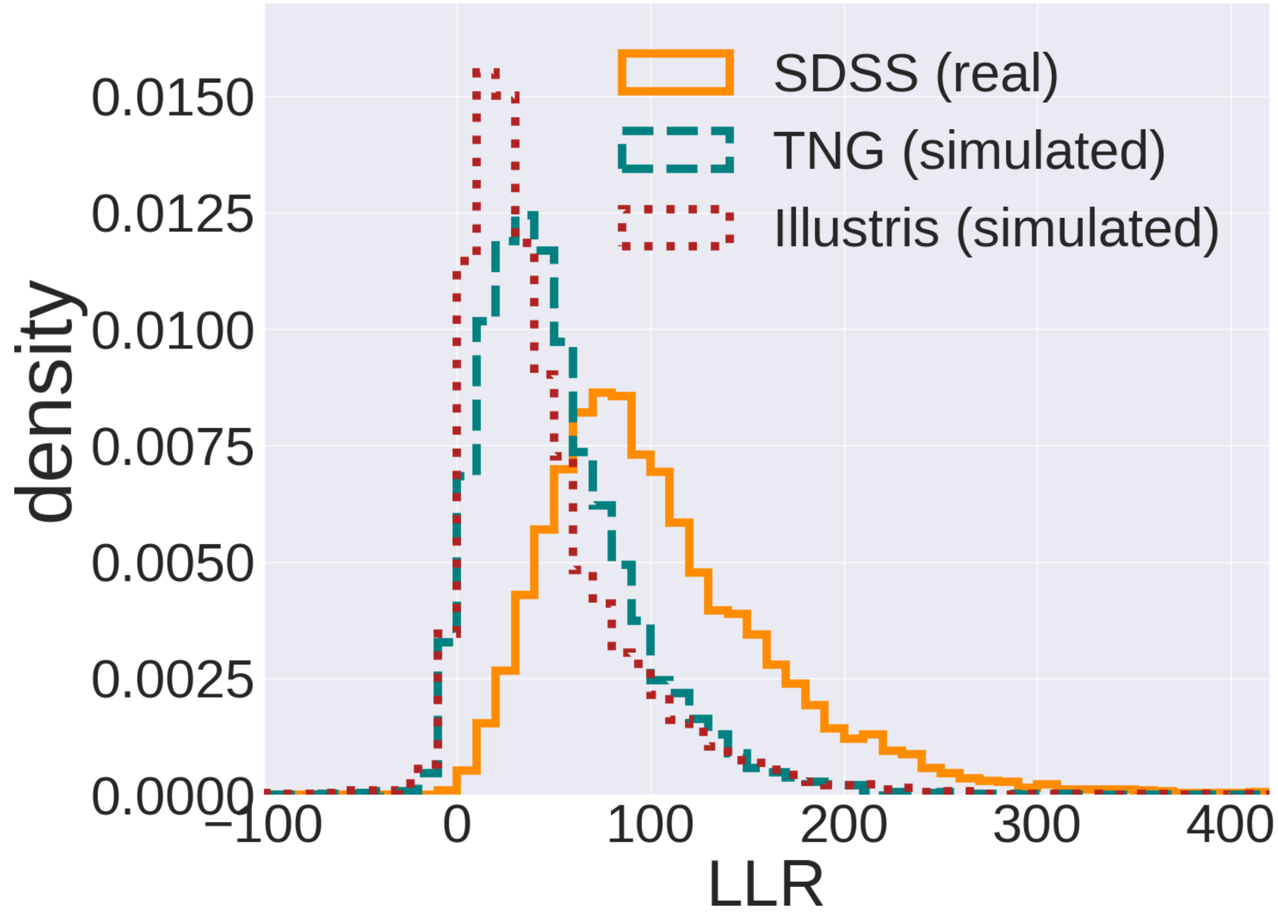


Contribution of ~~the background~~ a simple background is null in the LLR

LLR-based OoD



$$LLR \approx log[p(X_{details}|X_{global};\vec{\theta}_{SDSS})]$$



LLR-based OoD

$$LLR \approx log[p(X_{details}|X_{global}; \vec{\theta}_{SDSS})]$$

LLR-based feature enhancement and background removal:

a framework to compare datasets

Email: l.zanisi@soton.ac.uk