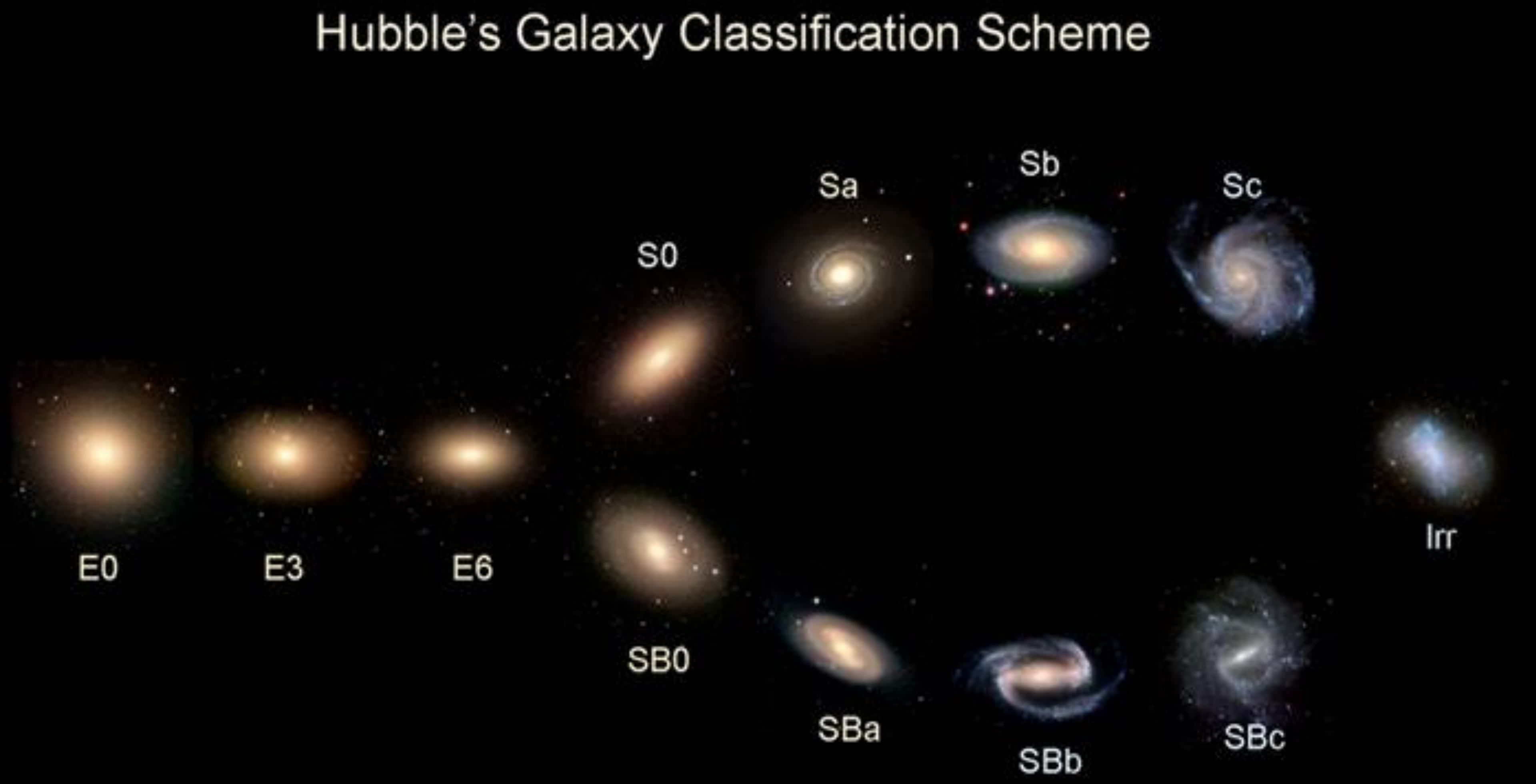
UNIVERSITY OF Southampton

KAVLI SUMMER PROGRAM IN ASTROPHYSICS

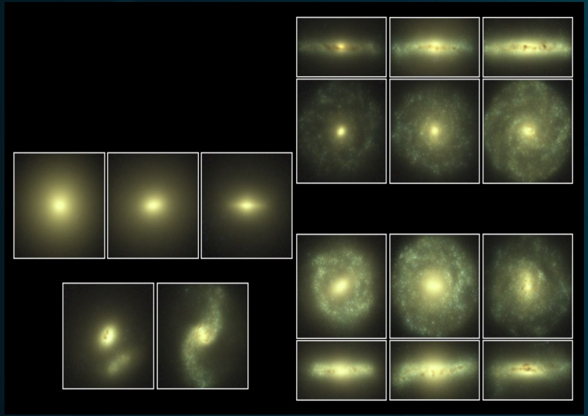
Testing the small-scale properties of galaxies in hydrodynamical simulations with deep learning

arXiv:2007.00039

Lorenzo Zanisi & M. Huertas-Company, F. Lanusse, C. Bottrell, A. Pillepich, D. Nelson, V. Rodriguez-Gomez, F. Shankar, L. Hernquist, A. Dekel, B. Margalef-Bentabol, M. Vogelsberger, J. Primack



Credits: U. Iowa

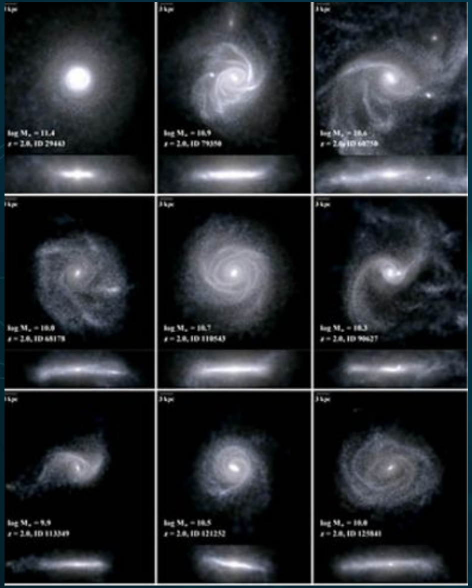


EAGLE

Schaye+15, Crain+15

ILLUSTRIS

Vogelsberger+14ab, Genel+14, Sijacki+15



ILLUSTRIS TNG

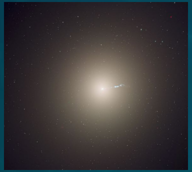
Pillepich+18, Nelson+18,Naiman+18,Springel +18, Marinacci+18

The science questions

1. How realistic is the morphology of simulated galaxies?
2. Can we accurately quantify this?

Strategy

Training: learning the distribution of real galaxies



Neural Network

Minimize likelihood **P(X)**

Outlier detection: evaluating the PDF

Simulated galaxies & test set of observations

Neural Network

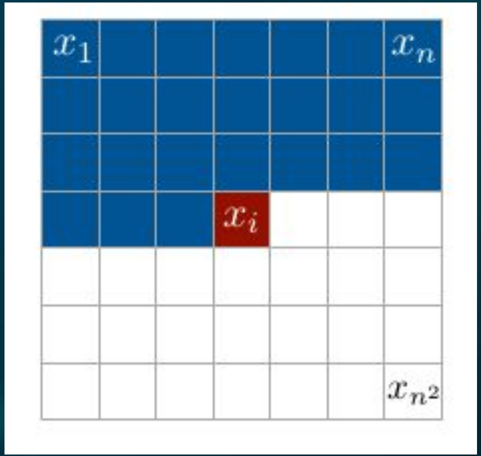
"How close to the average **<u>real</u> galaxy**?"

P(X)

PixelCNN

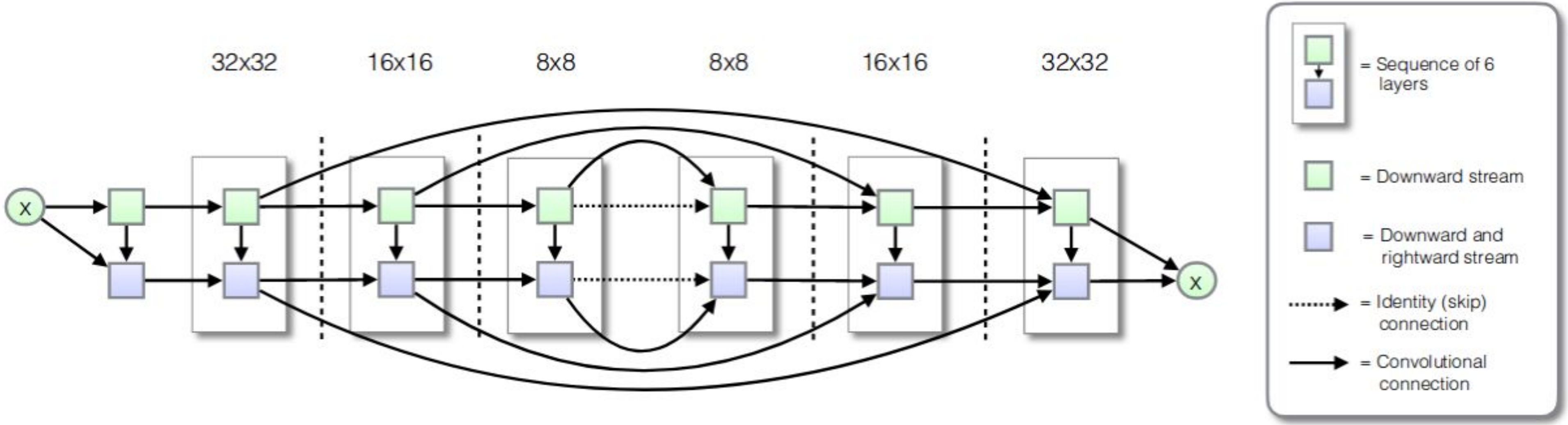
The probability distribution is explicitly modelled pixel by pixel

$$p(\mathbf{x}) = \prod_{i=1}^{n^2} p(x_i | x_1, ..., x_{i-1})$$



Van der Oord+16ab

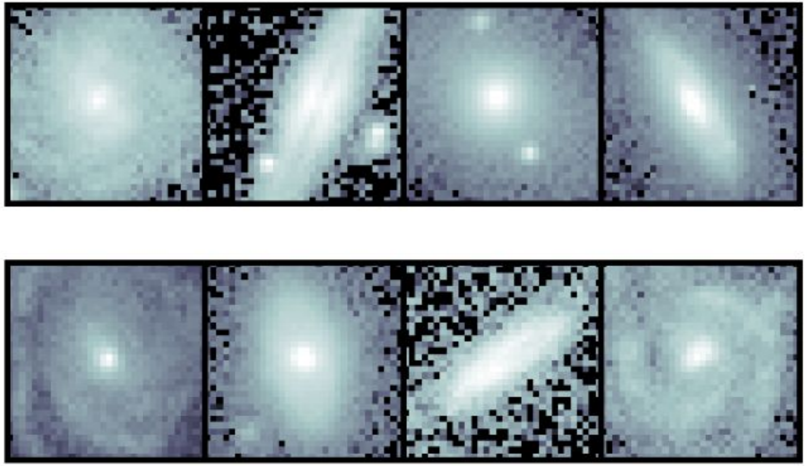
PixelCNN++



Salimans+17

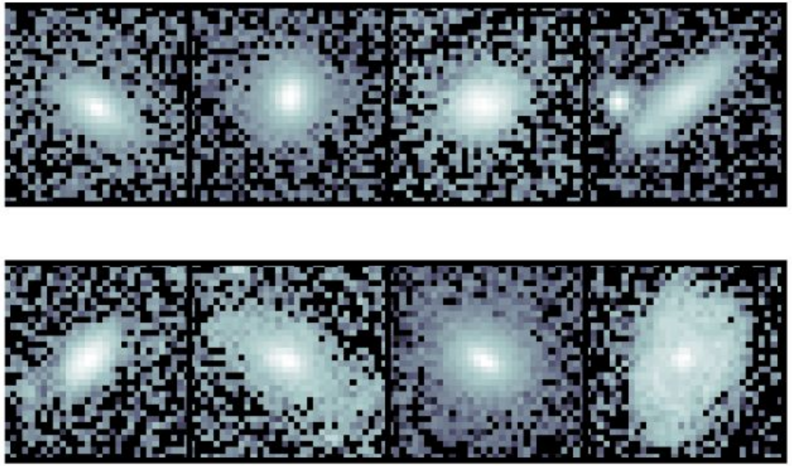
Low likelihood

3675.0



High likelihood

4172.0



$$p(\mathbf{x}) = \prod_{i=1}^{n^2} p(x_i | x_1, ..., x_{i-1})$$

The likelihood “knows too much” about the sky.

What can we do?

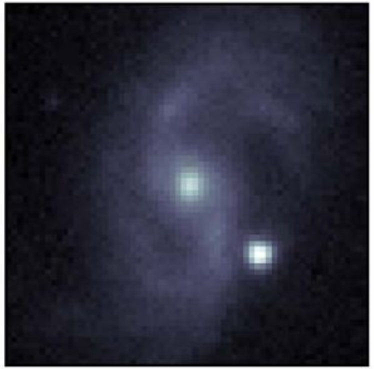
See also:
Serrà et al. 2019
Ren et al. 2019

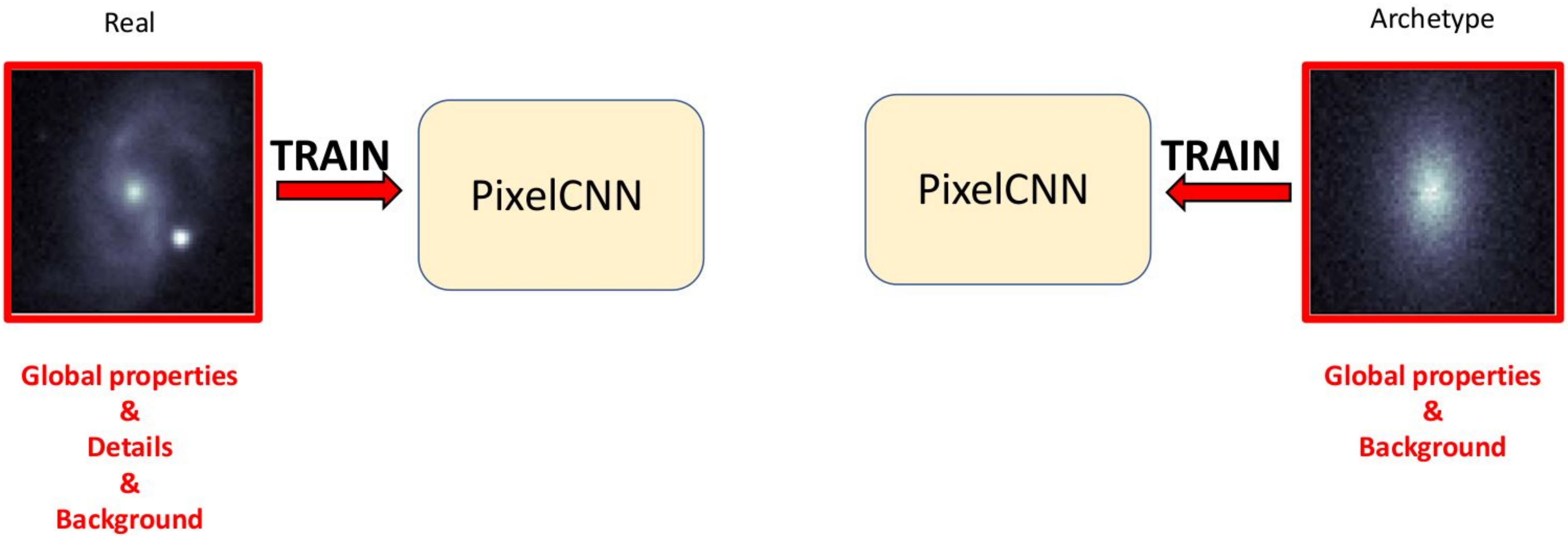
Galaxy archetypes

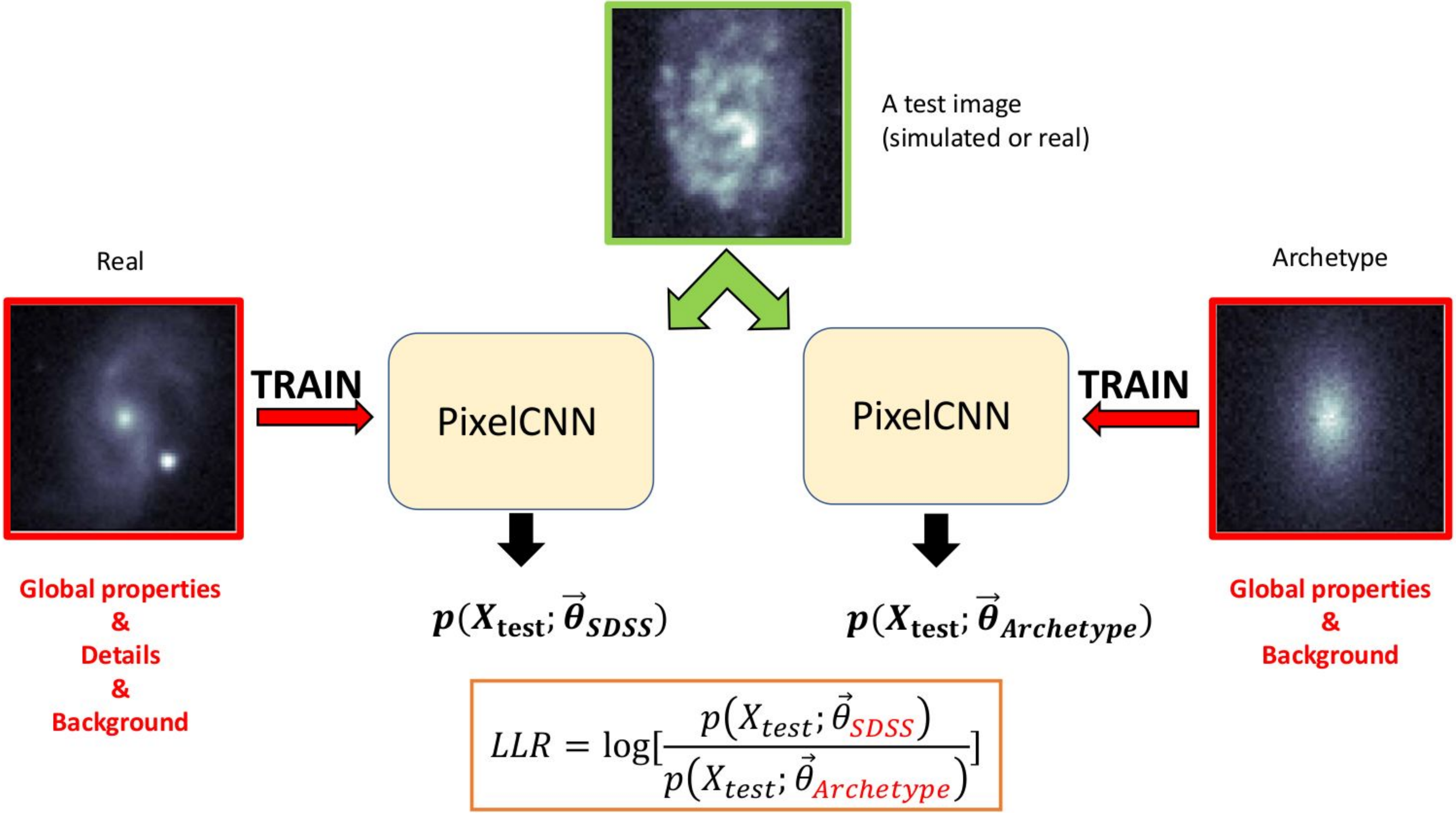
The Sèrsic Function models the light profile of a galaxy

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

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




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



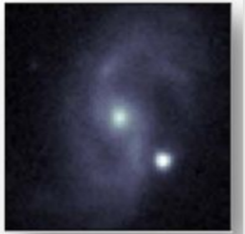
A test image
(simulated or real)
Real
Archetype
TRAIN
PixelCNN
PixelCNN
TRAIN
$p(X_{\text{test}}; \vec{\theta}_{SDSS})$
$p(X_{\text{test}}; \vec{\theta}_{Archetype})$
Global properties
&
Details
&
Background
Global properties
&
Background
$LLR = \log[\frac{p(X_{test}; \vec{\theta}_{SDSS})}{p(X_{test};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

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

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

Background removal

Ren et al. 2019
(monochromatic bg)



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

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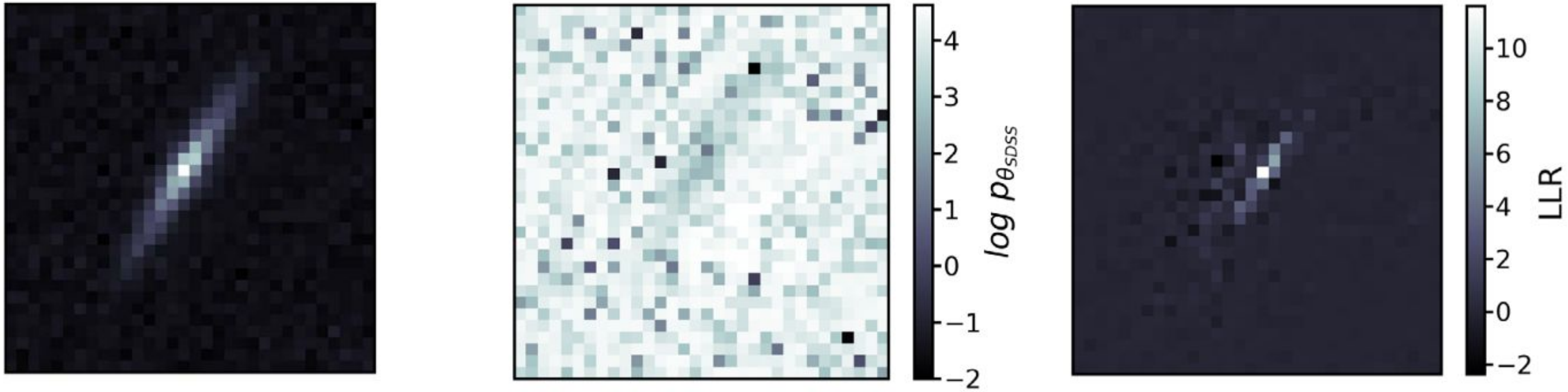
Background removal

Ren et al. 2019
(monochromatic bg)

Pixel-wise contributions



Contribution of the background is null in the LLR

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

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

Background removal

Ren et al. 2019
(monochromatic bg)

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

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

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

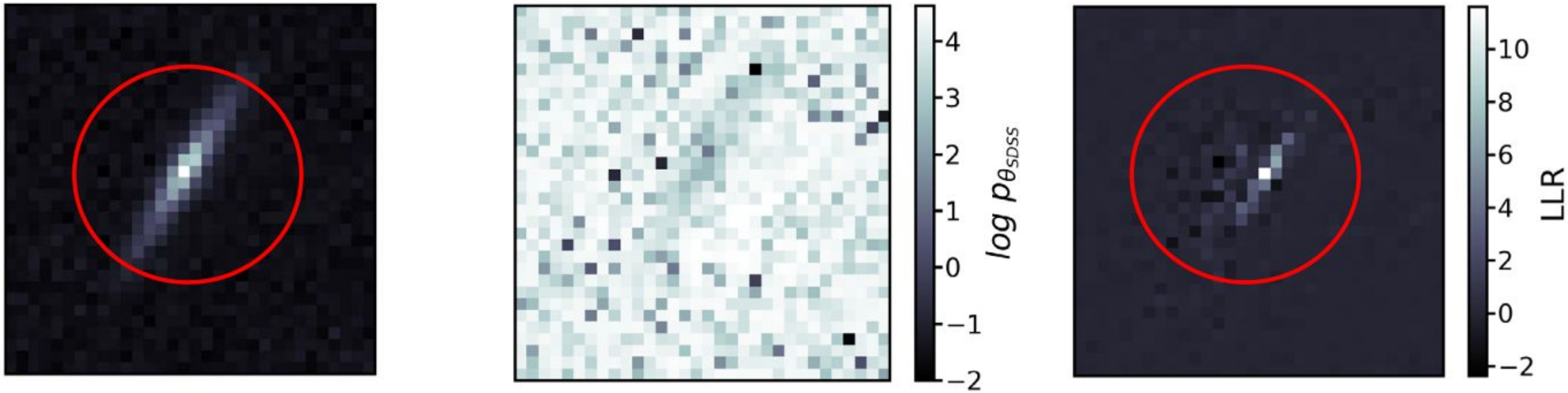
Ren et al. 2019
(monochromatic bg)

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

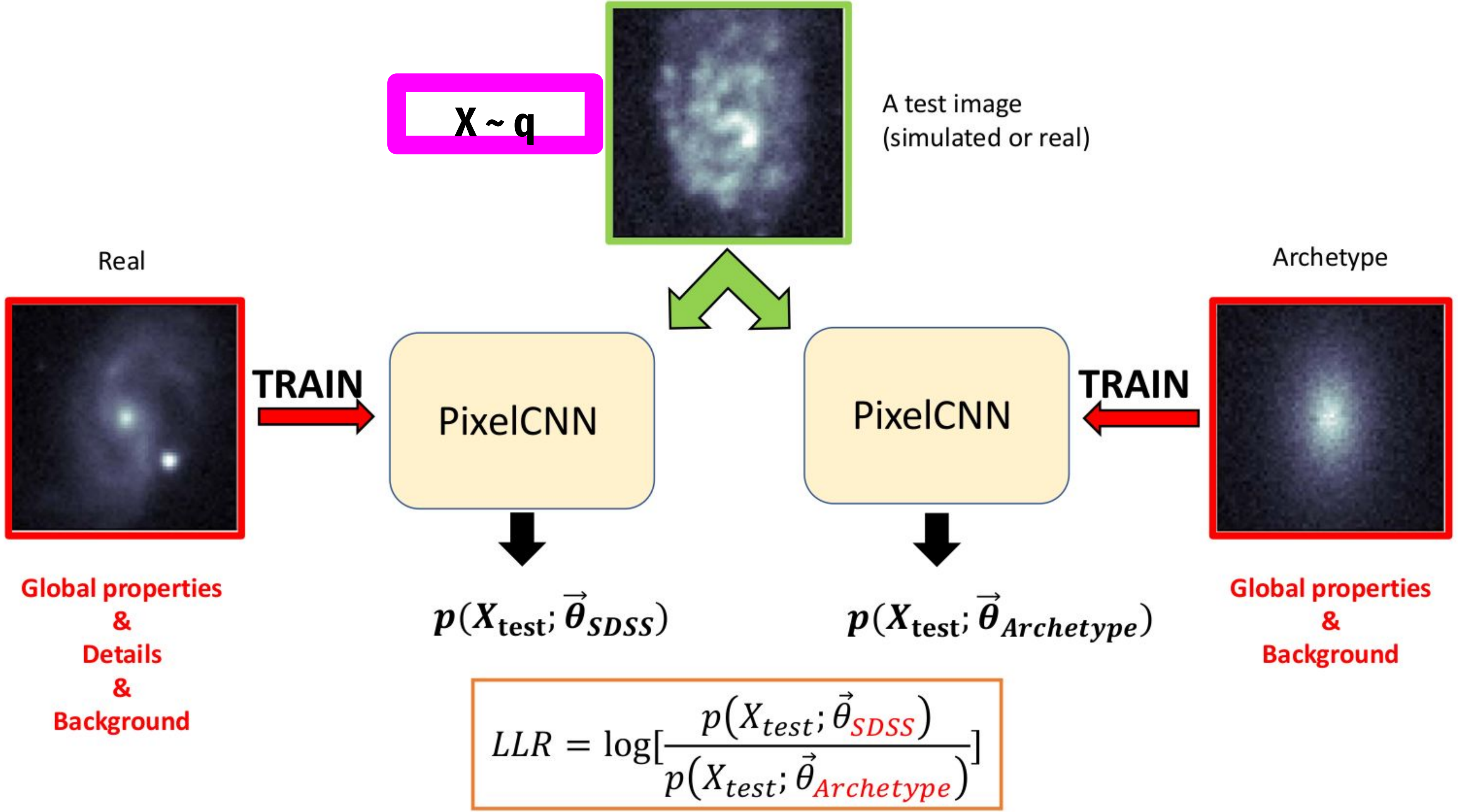
$$LLR = \log\left\{\left[\frac{p(X_{details}|X_{global};\vec{\theta}_1)\cancel{p(X_{global};\vec{\theta}_1)}}{\cancel{p(X_{global};\vec{\theta}_2)}}\right]\right\}$$

Details enhancement

Pixel-wise contributions



Central regions are enhanced in LLR


X ~ q
A test image
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Real
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Global properties
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$p(X_{\text{test}}; \vec{\theta}_{SDSS})$
$p(X_{\text{test}}; \vec{\theta}_{Archetype})$
Global properties
&
Background
$LLR = \log[\frac{p(X_{test}; \vec{\theta}_{SDSS})}{p(X_{test}; \vec{\theta}_{Archetype})}]$

A key property

$$\mathbb{E}_{x\sim q}[LLR] = \int log\left\{\frac{p_{\theta_{\text{obs}}}(X)}{p_{\theta_{\text{sersic}}}(X)}\right\}q(X)dX =$$
$$= D_{KL}(q||p_{\theta_{\text{sersic}}}) - D_{KL}(q||p_{\theta_{\text{obs}}})$$

D_{KL} : Kullback-Leibler divergence.
"distance between two distributions"

A key property

$$\mathbb{E}_{x\sim q}[LLR] = \int log\left\{\frac{p_{\theta_{\text{obs}}}(X)}{p_{\theta_{\text{sersic}}}(X)}\right\}q(X)dX =$$
$$= D_{KL}(q||p_{\theta_{\text{sersic}}}) - D_{KL}(q||p_{\theta_{\text{obs}}})$$

>0: q is closer to observations

<0: q is closer to Sérsic

Highest LLR for observations

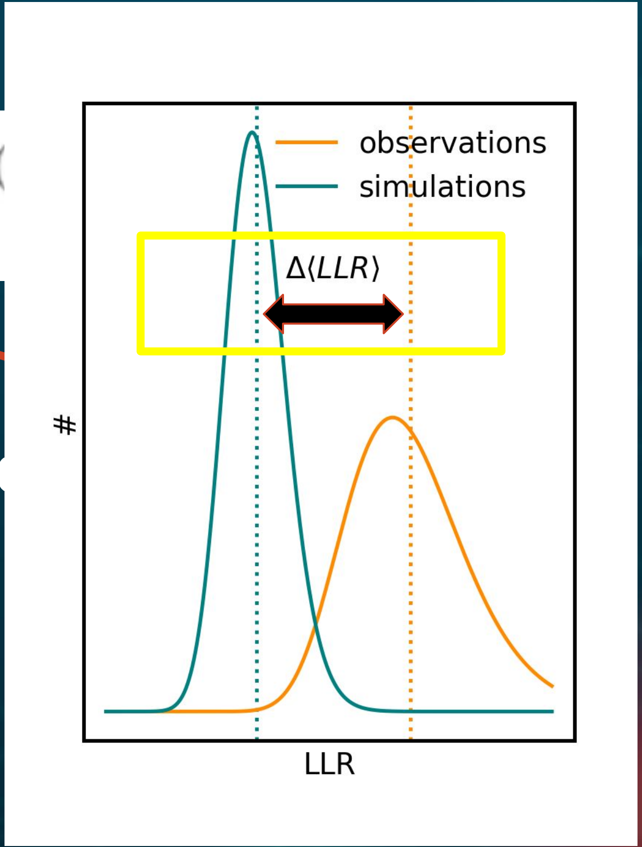
A high LLR is a sign of good agreement with observations

A key property

$$\mathbb{E}_{x\sim q}[LLR] = \int log\left\{\frac{p_{\theta_{\mathrm{obs}}}(X)}{p_{\theta_{\mathrm{sersic}}}(X)}\right\}q($$
$$= D_{KL}(q||p_{\theta_{\mathrm{sersic}}}) - D_{KL}(q||p_{\theta_{\mathrm{obs}}})$$

>0: closer to observations

<



Low delta: good agreement

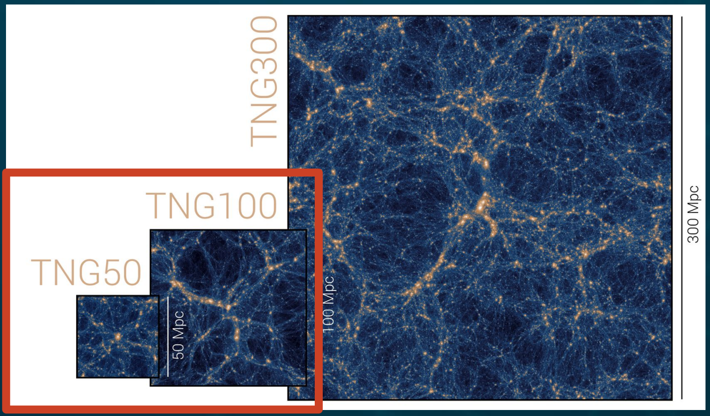
Datasets

Training

~40,000 r-band images from Sloan Digital Sky Survey

Best Sérsic fit parameters from Meert+15

Inference



Pillepich+18, Nelson+18,Naiman+18,Springel+18, Marinacci+18

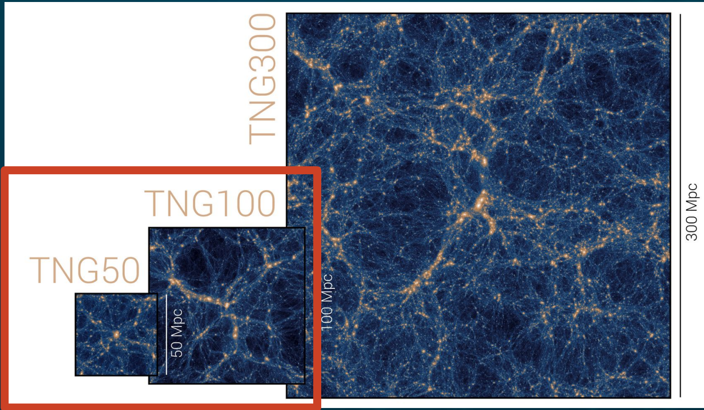
ILLUSTRIS

Vogelsberger+14ab, Genel+14, Sijacki+15

Datasets

		TNG50	TNG100
Volume	$[\mathrm{Mpc}^3]$	51.7^3	110.7^3
L_{box}	$[\mathrm{Mpc}/h]$	35	75
N_{GAS}	-	2160^3	1820^3
N_{DM}	-	2160^3	1820^3
N_{TR}	-	2160^3	2×1820^3
m_{baryon}	$[\mathrm{M}_\odot]$	8.5×10^4	1.4×10^6
m_{DM}	$[\mathrm{M}_\odot]$	4.5×10^5	7.5×10^6
$\epsilon_{\mathrm{gas,min}}$	[pc]	74	185
$\epsilon_{\mathrm{DM},\star}$	[pc]	288	740

Inference



Pillepich+18, Nelson+18, Naiman+18, Springel+18, Marinacci+18

ILLUSTRIS

name	volume $[(\mathrm{Mpc})^3]$	DM particles / hydro cells / MC tracers	$\epsilon_{\mathrm{baryon}}/\epsilon_{\mathrm{DM}}$ [pc]	$m_{\mathrm{baryon}}/m_{\mathrm{DM}}$ $[10^5\ \mathrm{M}_\odot]$	$r_{\mathrm{cell}}^{\mathrm{min}}$ [pc]
Illustris-1	106.5^3	$3 \times 1,820^3 \simeq 18.1 \times 10^9$	$710/1,420$	$12.6/62.6$	48

Vogelsberger+14ab, Genel+14, Sijacki+15

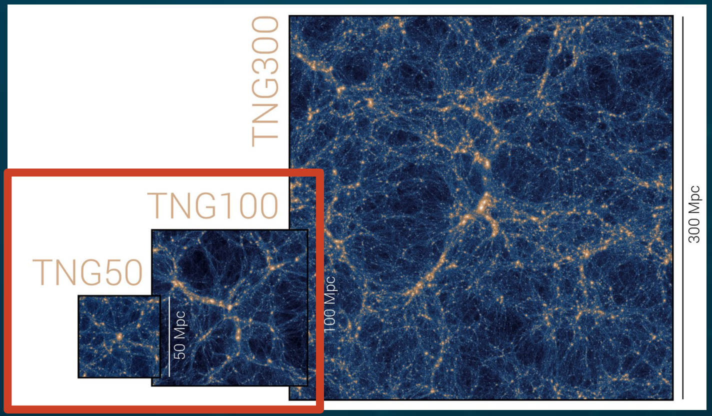
Datasets

Fully realistic mock observations

1. **Dust-inclusive radiative transfer**
2. **SDSS r-band mock images**
3. **Realistic PSF & sky background**

Rodriguez-Gomez+19, Bottrell+19

Inference



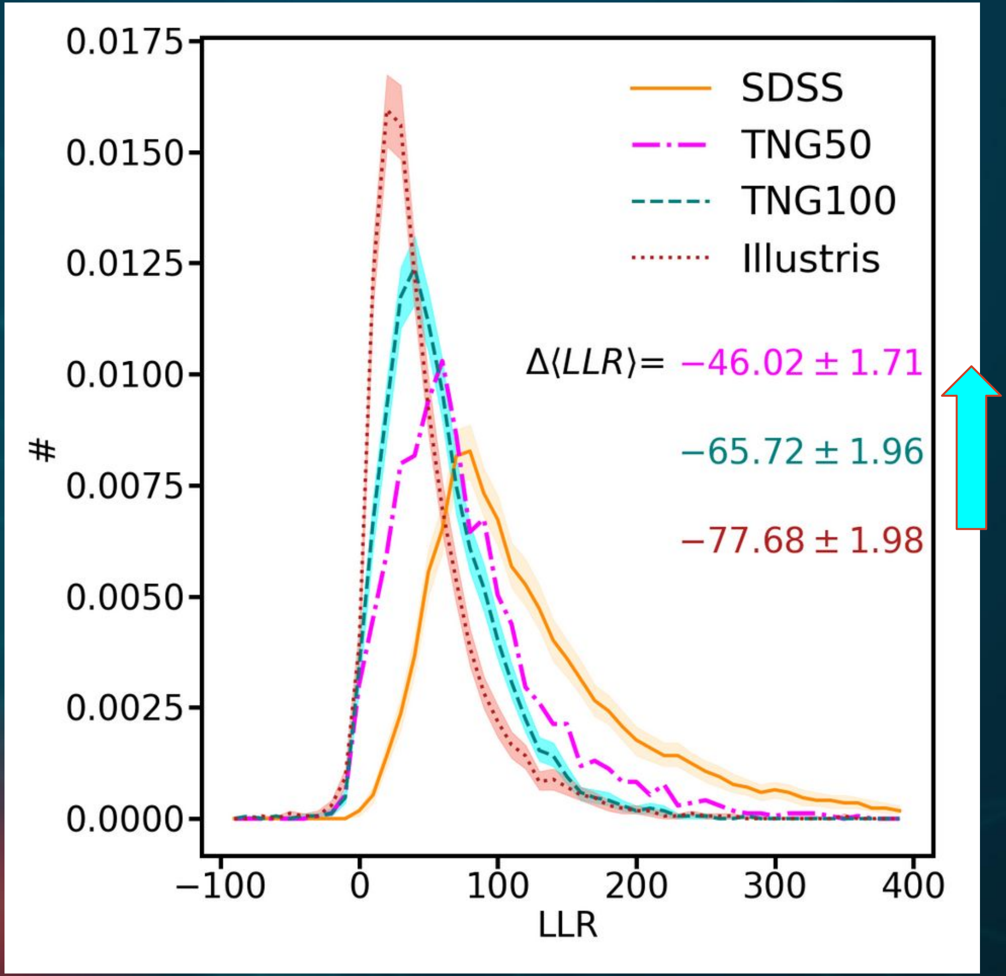
Pillepich+18, Nelson+18,Naiman+18,Springel +18, Marinacci+18

ILLUSTRIS

Vogelsberger+14ab, Genel+14, Sijacki+15

The **small**-scale morphology
of TNG and Illustris galaxies

Results



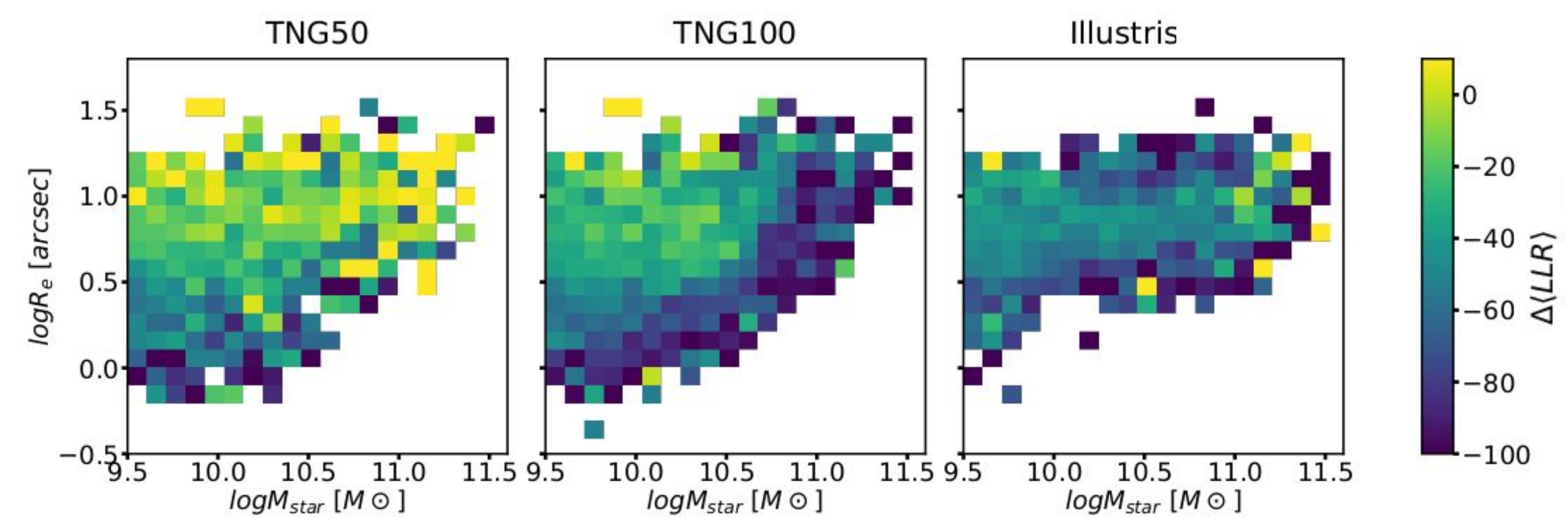
Higher is better

1. Illustris TNG improves over Illustris: better physics
2. TNG50 (higher res) improves on TNG100 (lower res)

Quantifying galaxy morphology with just one number!

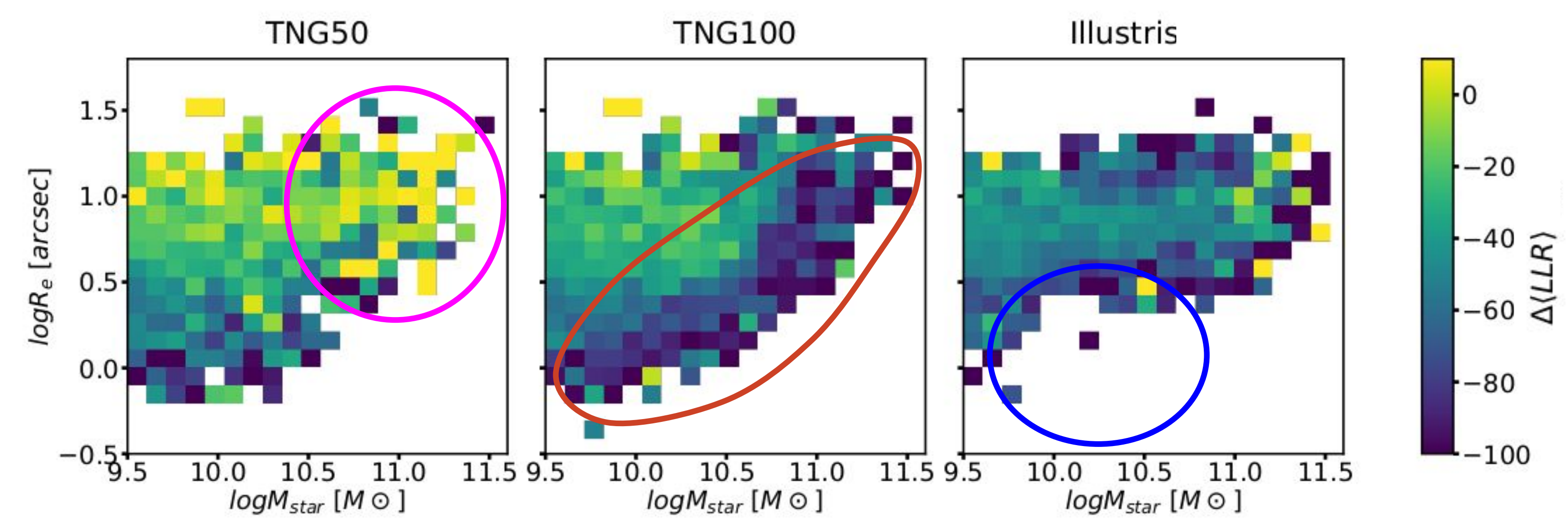
Size-mass relation

Brighter is better



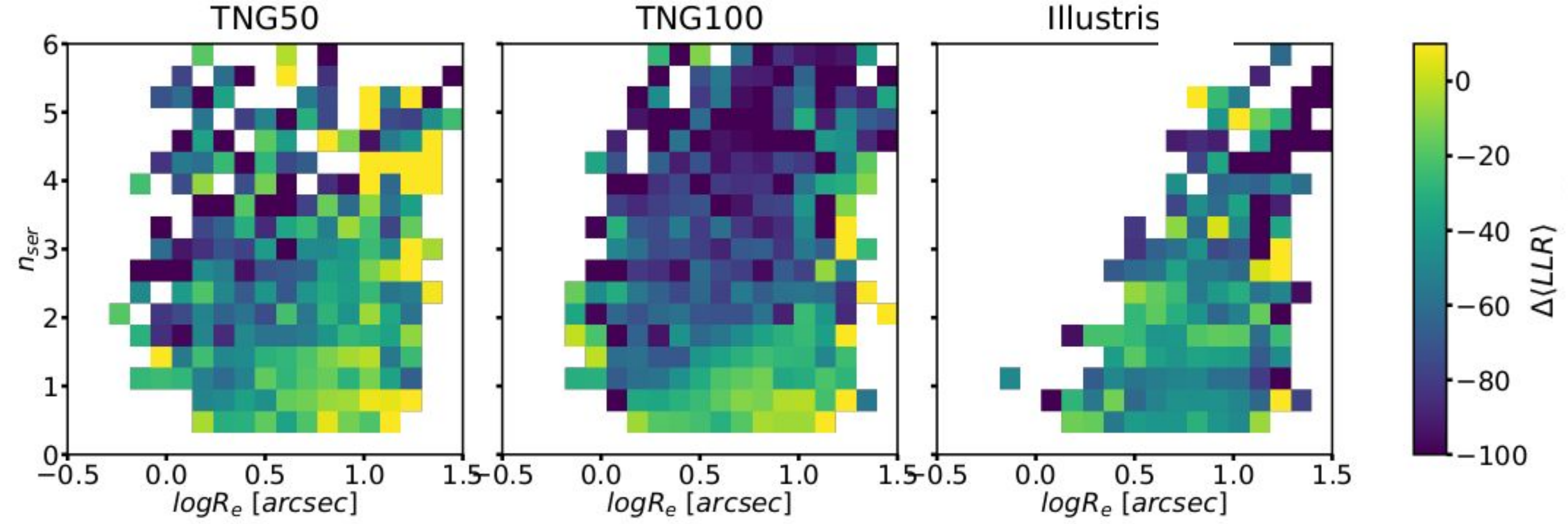
Size-mass relation

Brighter is better



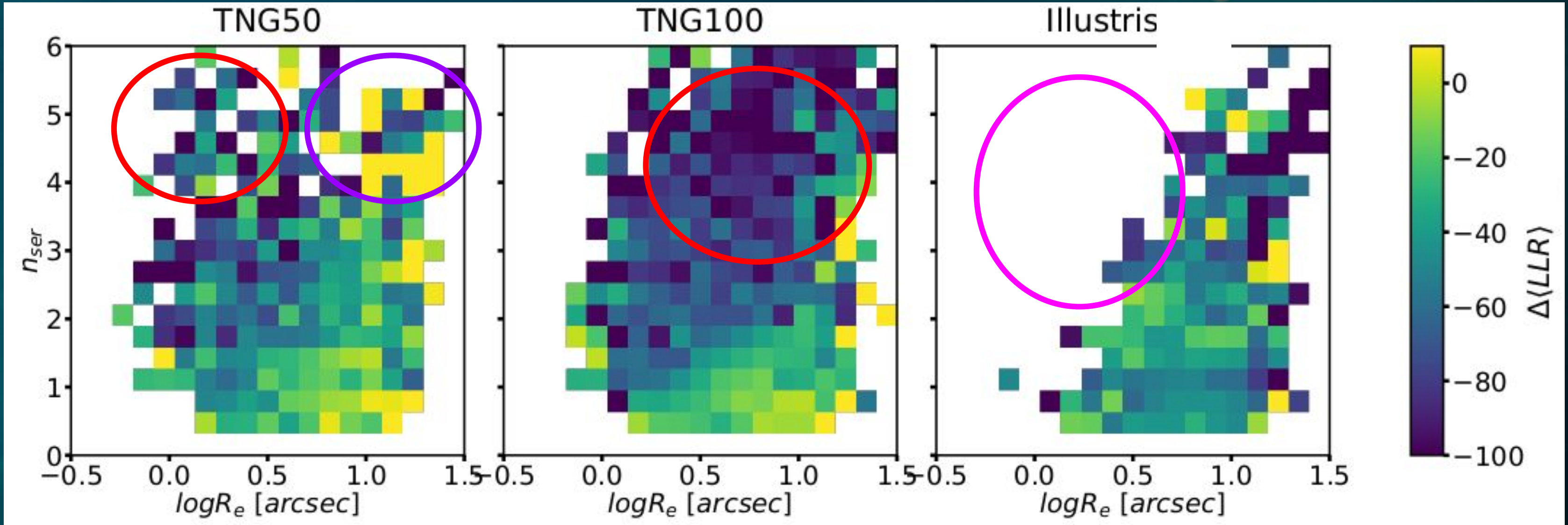
Sérsic index-size relation

Brighter is better



Sérsic index-size relation

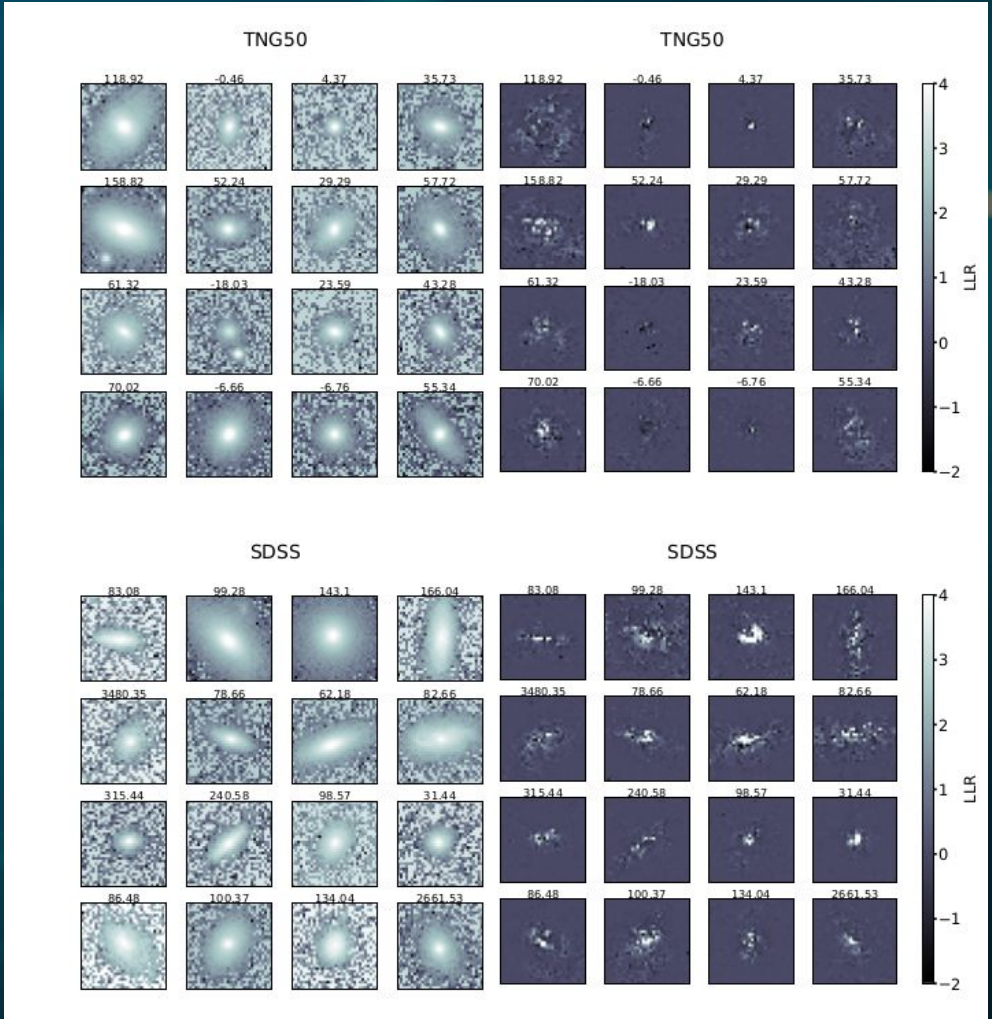
Brighter is better



See also Bottrell+17

Mock TNG50 and SDSS observations:

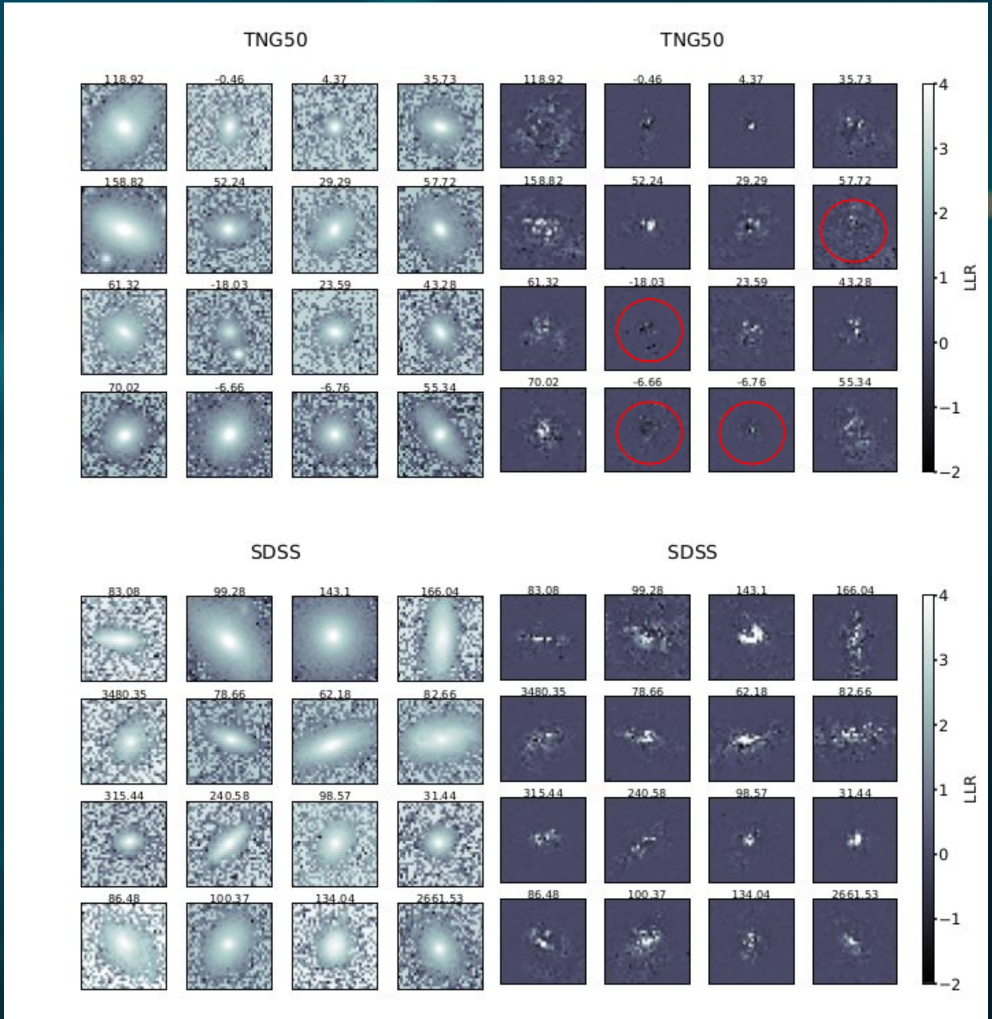
Very similar to human eye!



Pixel-wise contribution to LLR

Mock TNG50 and SDSS observations:

Very similar to human eye!



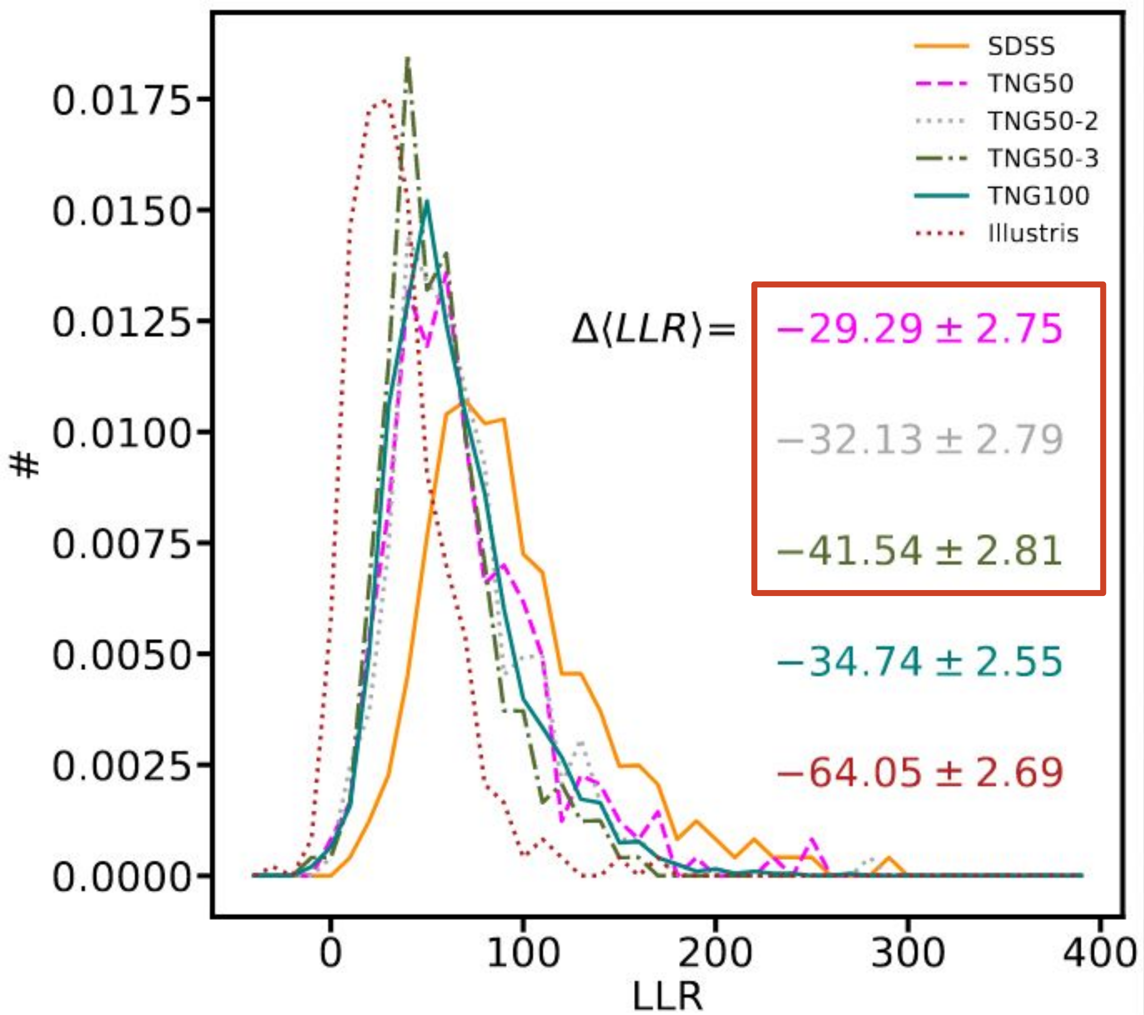
Pixel-wise contribution to LLR:

Lack of strong signal in inner regions for TNG50

Why?

A possible answer: resolution

1. TNG50 (high res) achieves best performance
2. Small & concentrated: tightly packed orbits, softening length becomes important
3. Central regions not well reproduced



TNG50-2 and TNG50-3: lower resolution runs of TNG50

Lower resolution: worse performance

Summary

- ➔ Deep learning framework to compare sets of images (N.B. can be used in other applications!): two generative models
- ➔ Based on a metric (LLR) which quantifies the difference between distributions
- ➔ Quantitative test of very high level features in simulated galaxies
- ➔ Simulated compact, concentrated galaxies are in tension with observations
- ➔ Resolution might be the culprit

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