Robust measurements of galaxy morphology with LSST

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How do galaxies evolve?

star-forming



disk-dominated

star formation

quenching mechanism = ????

morphology

quiescent



bulge-dominated

How do galaxies evolve?

star-forming



disk-dominated

gas: hydrodynamics star formation

quenching mechanism = ????

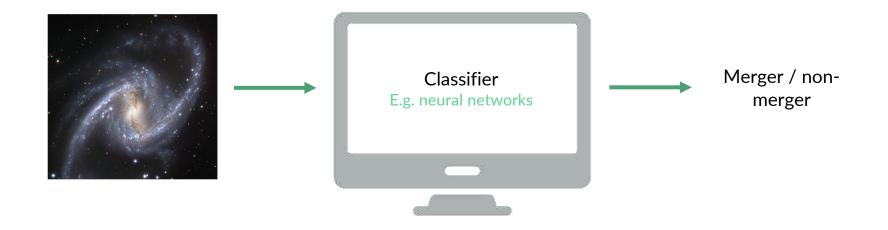
morphology stars: gravity

quiescent

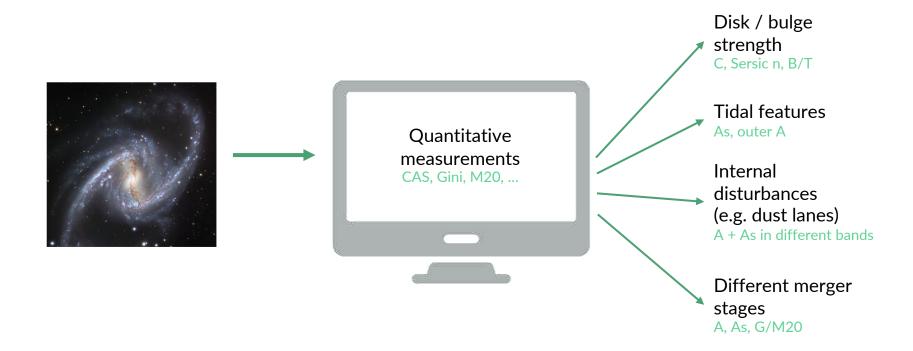


bulge-dominated

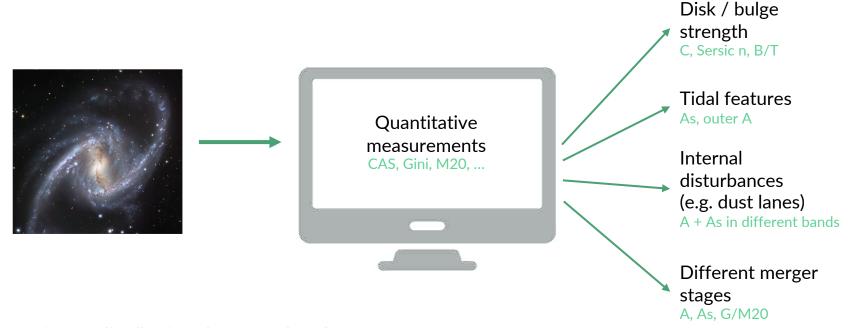
Why quantitative morphology?



Why quantitative morphology?

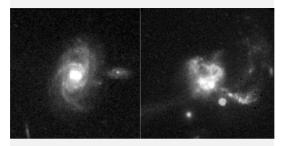


Why quantitative morphology?

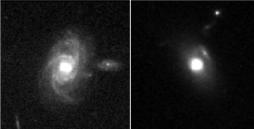


+ *Continuous* distributions let us study galaxy structure as a *function* of their environment/physical properties/etc

Disturbance



Bulge strength



Concentration G/M₂₀ bulge strength

Petrosian radius Compactness

Size

Sérsic radius

Non parametric Asymmetry

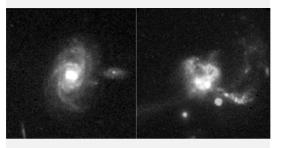
Shape asymmetry G/M_{20} disturbance Shape asymmetry

Model dependent

Residual Flux Fraction [RFF]

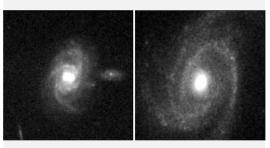
Sérsic index Bulge-to-disk ratio [B/T]

Disturbance



Bulge strength

Size



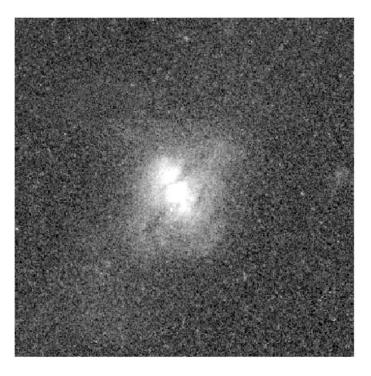
Non parametric	Asymn Shape A million definitions + implementations G/M ₂₀ Shape asymmetry		
Model dependent	Residual Flux Fraction [RFF]	Sérsic index Bulge-to-disk ratio [B/T]	Sérsic radius

Case study: asymmetry

Conselice et al. (2003)

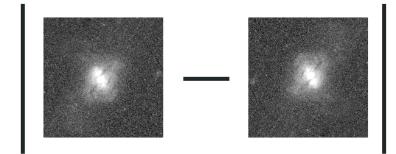
$$A = \frac{\sum |f - f^{180}| - N \langle A_{bg} \rangle}{\sum |f|} \xrightarrow{\text{background}}_{\text{asymmetry}}$$

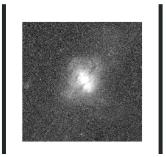
Important in detecting mergers, dust lanes, etc...



Conselice et al. (2003)

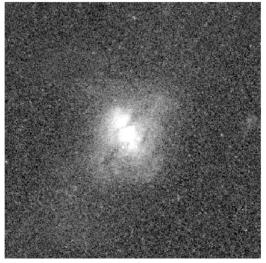
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Conselice et al. (2003)

HST R-band





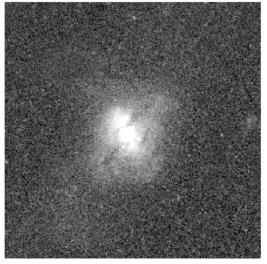
SDSS *r*-band





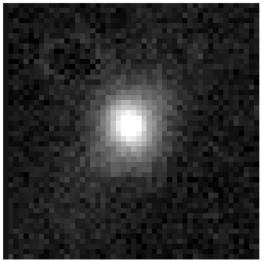
Conselice et al. (2003)

HST R-band



A = 0.35

SDSS r-band





LSST imaging will still have high seeing (~0.5 of SDSS) and a *variable* image depth across the survey lifetime!

Conselice et al. (2003)

$$A = \frac{\sum |f - f^{180}| - N \langle A_{bg} \rangle}{\sum |f|} \xrightarrow{\text{background}}_{\text{asymmetry}}$$

Only tested statistically in a few studies Lotz et al. 2004, Thorp et al. 2021

Depends strongly on noise & resolution But how much? And why?

We need to understand these measurements better before we commit to measuring them for 10⁶ galaxies

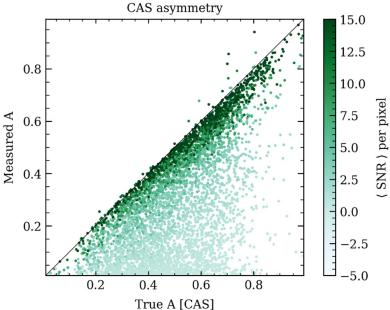


image rotated image
$$A = \frac{\sum |f - f^{180}| - N \langle A_{bg} \rangle}{\sum |f|} \xrightarrow{\text{background}}_{\text{asymmetry}}$$

$$A = \frac{\sum (f - f^{180})^2 - N \langle A_{bg}^2 \rangle}{\sum f^2 - N \langle f_{bg}^2 \rangle_{\text{background}}}$$
flux correction

Better normalization

Normalization used to include a non-zero noise contribution, making asymmetry aperture sizedependent

Better behaviour with noisy images

Gaussian noise completely decoupled from the source asymmetry

Source image

An observation is made from a source image by convolving it with a PSF and adding noise.

 $f = \lambda * f_{s} + \sigma$ PSF noise

CAS asymmetry:

$$|f - f^{180}| = |\lambda * (f_s - f_s^{180}) + (\sigma - \sigma^{180})|$$

$$\neq |\lambda * (f_s - f_s^{180})| + |\sigma - \sigma^{180}|$$

Background contribution is **not** separable

Source image

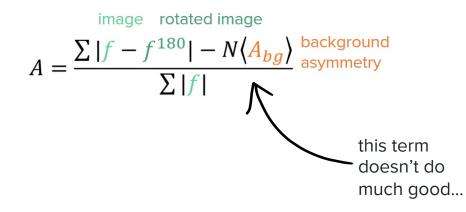
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CAS asymmetry

Absolute value calculation does not allow you to separate the noise term and recover the real asymmetry

 $f = \lambda * f_{S} + \sigma$ PSF noise

CAS asymmetry:



Source image

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CAS asymmetry

Absolute value calculation does not allow you to separate the noise term and recover the real asymmetry

 $f = \lambda * f_{s} + \sigma$ PSF noise

Squared asymmetry:

$$(f - f^{180})^2 = \lambda^2 * (f_s - f_s^{180})^2 + (\sigma - \sigma^{180})^2 + 2(\sigma - \sigma^{180}) \times \lambda * (f_s - f_s^{180})$$

This term is 0 when the image is background-subtracted!

The background term is **separable**

Source image

An observation is made from a source image by convolving it with a PSF and adding noise.

Better behaviour with noisy images

Gaussian noise completely decoupled from the source asymmetry

source $f = \lambda * f_s + \sigma_{PSF}$ noise Squared asymmetry: $A = \frac{\sum (f - f^{180})^2 - N\langle A_{bg}^2 \rangle}{\sum f^2 - N\langle f_{bg}^2 \rangle}$

Source image

An observation is made from a source image by convolving it with a PSF and adding noise.

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image rotated image
$$A = \frac{\sum |f - f^{180}| - N \langle A_{bg} \rangle}{\sum |f|} \xrightarrow{\text{background}}_{\text{asymmetry}}$$

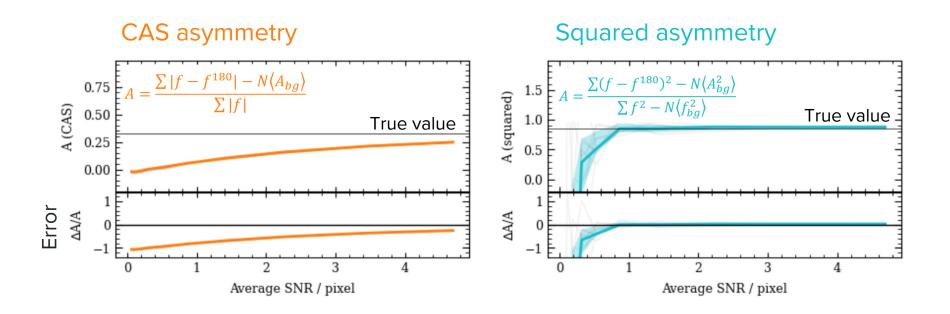
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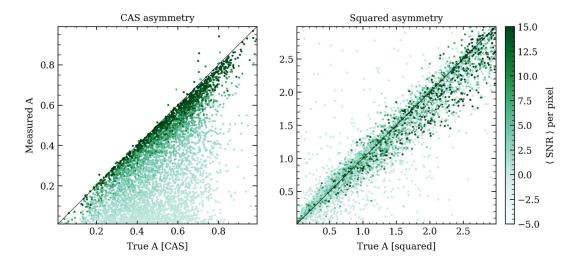
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Better normalization

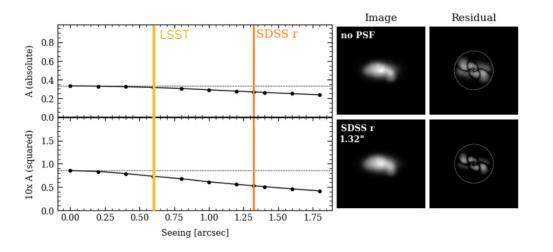
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Asymmetry squared: PSF

$$A = \frac{\sum (f - f^{180})^2 - N \langle A_{bg}^2}{\sum f^2 - N \langle f_{bg}^2 \rangle}$$



Worse at very low SNR

background flux normalization makes the denominator ~0 when background flux dominates

Worse behaviour with PSF

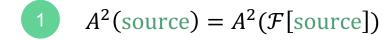
flux² responds strongly to re-distribution of flux via seeing

$f = \lambda * f_s + \sigma$ PSF noise

Fourier facts

1. Power $(\sum f^2)$ in image space and image space are the same

2. Convolution in Fourier space is multiplication \Rightarrow separable



$$f = \lambda * f_s + \sigma$$
PSF noise

Fourier facts

1. Power $(\sum f^2)$ in image space and image space are the same

2. Convolution in Fourier space is multiplication \Rightarrow separable



$$A^2$$
(source) = $A^2(\mathcal{F}[source])$



 $\mathcal{F}[\text{source}] = H \times \mathcal{F}[\text{image}]$

$$H = \frac{1 + \text{SNR}^{-2}}{\lambda^2 + \text{SNR}^{-2}}$$
PSF signal-to-noise

$$f = \lambda * f_s + \sigma$$
PSF noise

Fourier facts

1. Power $(\sum f^2)$ in image space and image space are the same

2. Convolution in Fourier space is multiplication \Rightarrow separable

1
$$A^2$$
(source) = $A^2(\mathcal{F}[source])$

2
$$\mathcal{F}[\text{source}] = H \times \mathcal{F}[\text{image}]$$

The rest of the calculation as usual, but in Fourier space!

$$A = \frac{\sum (f - f^{180})^2 - N \langle A_{bg}^2 \rangle}{\sum f^2 - N \langle f_{bg}^2 \rangle}$$

Better normalization

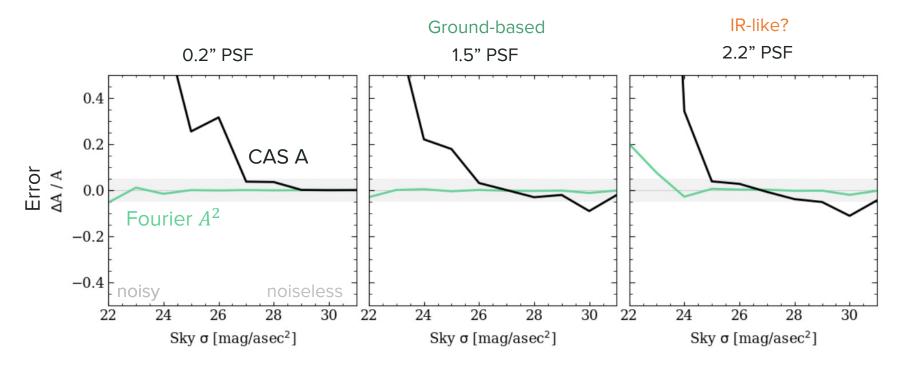
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Corrects for noise

Gaussian noise completely decoupled from the source asymmetry

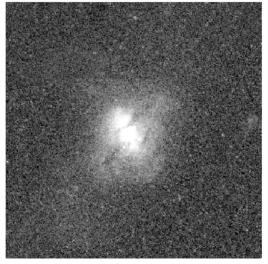
Corrects for PSF

In Fourier space, PSF can be decoupled. We calculate A in Fourier space **no deconvolution!**



Still work in progress, but...

HST R-band





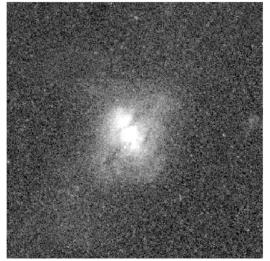
SDSS *r*-band





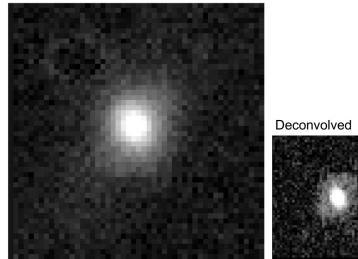
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HST R-band



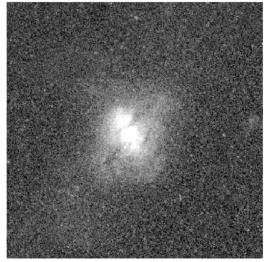
A = 0.35 $\mathcal{F}[A^2] = 1.61$

SDSS r-band



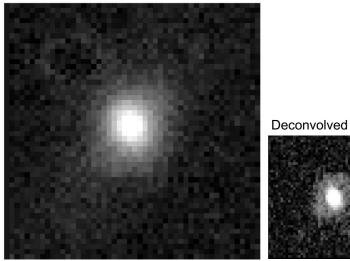
A = 0.11 $\mathcal{F}[A^2] = 1.29$ Still work in progress, but...

HST R-band



A = 0.35 $\mathcal{F}[A^2] = 1.61$

SDSS *r*-band

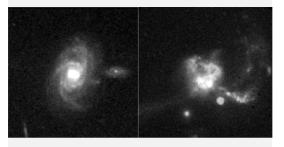


A = 0.11 $\mathcal{F}[A^2] = 1.29$ 70% error 20% error

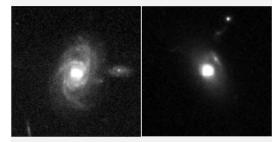


So asymmetry is great again, what next?

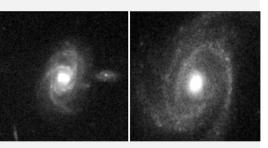
Disturbance



Bulge strength

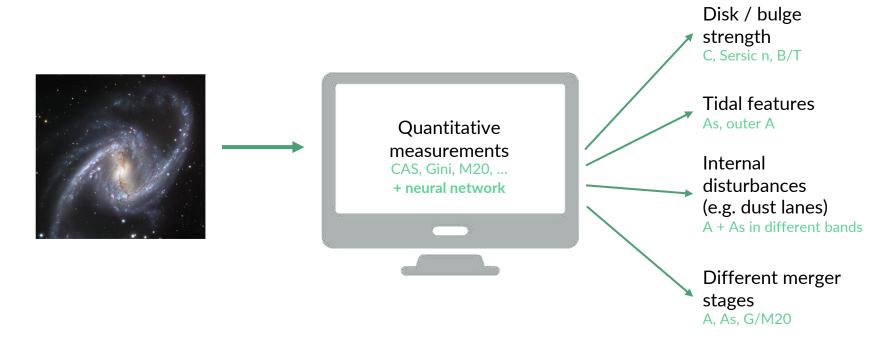


Size



Non parametric	Asymmetry	Concentration	Petrosian radius
	Shape asymmetry	G/M ₂₀ bulge strength	Compactness
	G/M ₂₀		
	Shape	Gotta test 'em all!	
		Long overdue – stay tuned ©	
Model dependent	Residual Flux Fraction [RFF]	Sérsic index	
		Bulge-to-disk ratio [B/T]	
dep			

Quantitative morphology with ML Faster and even more robust!



Work plan

- 1. Statistically test common morphology measurements. Long overdue!
 - Evaluate response to noise + seeing
 - See if improvements can be made to algorithms
 - Edit statmorph (open-source morphology code)
- 2. Train a neural network to *quickly* measure their *traditional* values Easy to use by community right away after the initial data release

3. Train a neural network to *robustly* measure *intrinsic* values These values should be consistent across all data releases

Thank you!