

Morphometry and Supervised Classification Degradation with Redshift: a case study for SDSS, DES and HST

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Outline

It is possible to perform galaxy morphology supervised classification with good reliability using only a small set of non-parametric morphometry measurements (Ferrari et al. 2015). This work aims to show how far in redshift we can go while still getting reliable results for data similar to that from SDSS, DES and HST. To estimate this limit we conducted redshift simulations (Barden et al. 2008) of the EFIGI catalog (Baillard et al. 2011) in several redshifts steps, extracted non-parametric morphology measurements using Morfometryka (Ferrari et al. 2015) and performed this supervised classification scheme for each redshift step. We show reliability limits for instruments that are similar to SDSS, DES and HST.

New Take on Usual Measurements (see Ferrari et al. 2015 for details)

Concentration (Abraham et al. 1994)

$$C = 5 \log_{10} \left(\frac{R_{\text{outer}}}{R_{\text{inner}}} \right) \quad C^* = \log_{10} \left(\frac{R_{\text{outer}}}{R_{\text{inner}}} \right)$$

Change range to match other measurements

Gini Coefficient

(Lotz et al. 2004)

Usual

How light is **distributed** over an image

New

Information Entropy H

Asymmetry and Smoothness

(Conselice et al. 2000)

Usual

New

(Lotz et al. 2004)

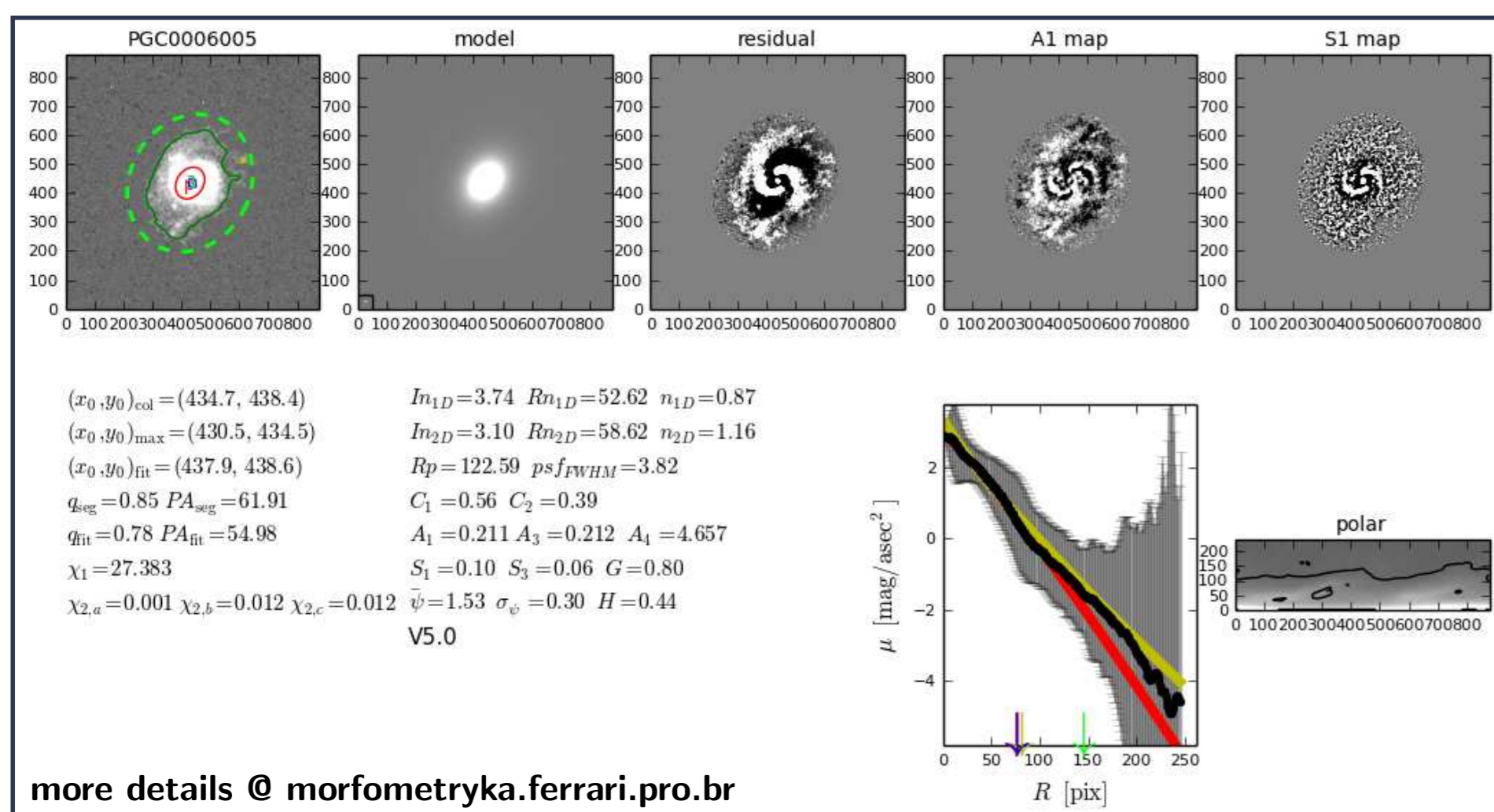
$$\left. \begin{aligned} A_1 &= | \text{img}_1 - \text{img}_2 | = \text{img}_3 \\ S_1 &= | \text{img}_1 - \text{img}_2 | = \text{img}_3 \end{aligned} \right\} \left\{ \begin{aligned} A_3 &= 1 - r_s(\text{img}_1, \text{img}_2) \\ S_3 &= 1 - r_s(\text{img}_1, \text{img}_2) \end{aligned} \right.$$

$r_s(x, y) = \text{Spearman's Rank Correlation Coefficient}$

Morfometryka

Measures morphometry reliably (Ferrari et al. 2015)

It takes each galaxy image, subtracts sky background, locates the object, measures the center, axes lengths and position angle; performs aperture photometry and fits a Sersic law to the light profile; measures Petrosian radius, concentration, asymmetry, smoothness, Gini coefficient and information entropy.



Redshifted Sample

~ 220000 redshifted images

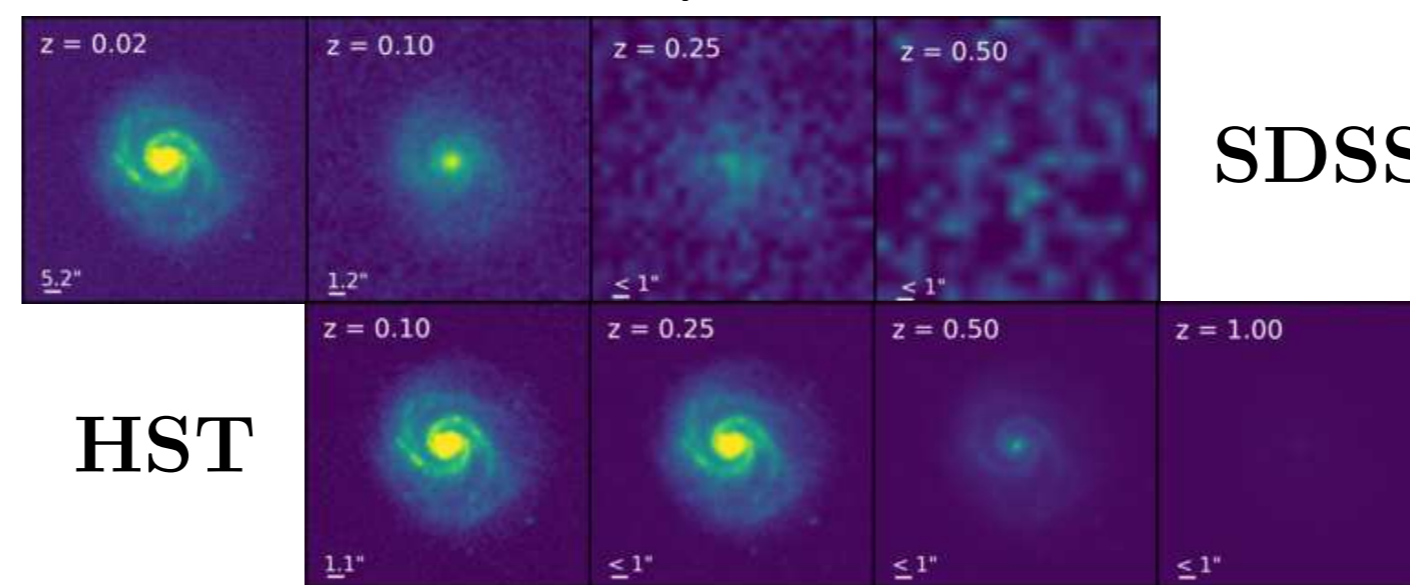
Redshift Simulations: FERENGI

Simulates the observation of an object in an instrument for given redshift (Barden et al 2008). Accounts for all effects: cosmological dimming, pixel and angular resolution degradation, bandpass shifting, noise.

Simulations Overall Configuration

	Pixel Scale	FWHM	Simulation Range	Steps
SDSS	0.4"/pixel	~ 1.2"	0.02 ≤ z ≤ 1	20
DES	0.27"/pixel	~ 0.7"	0.02 ≤ z ≤ 1	20
HST	0.05"/pixel	~ 0.15"	0.1 ≤ z ≤ 2	10

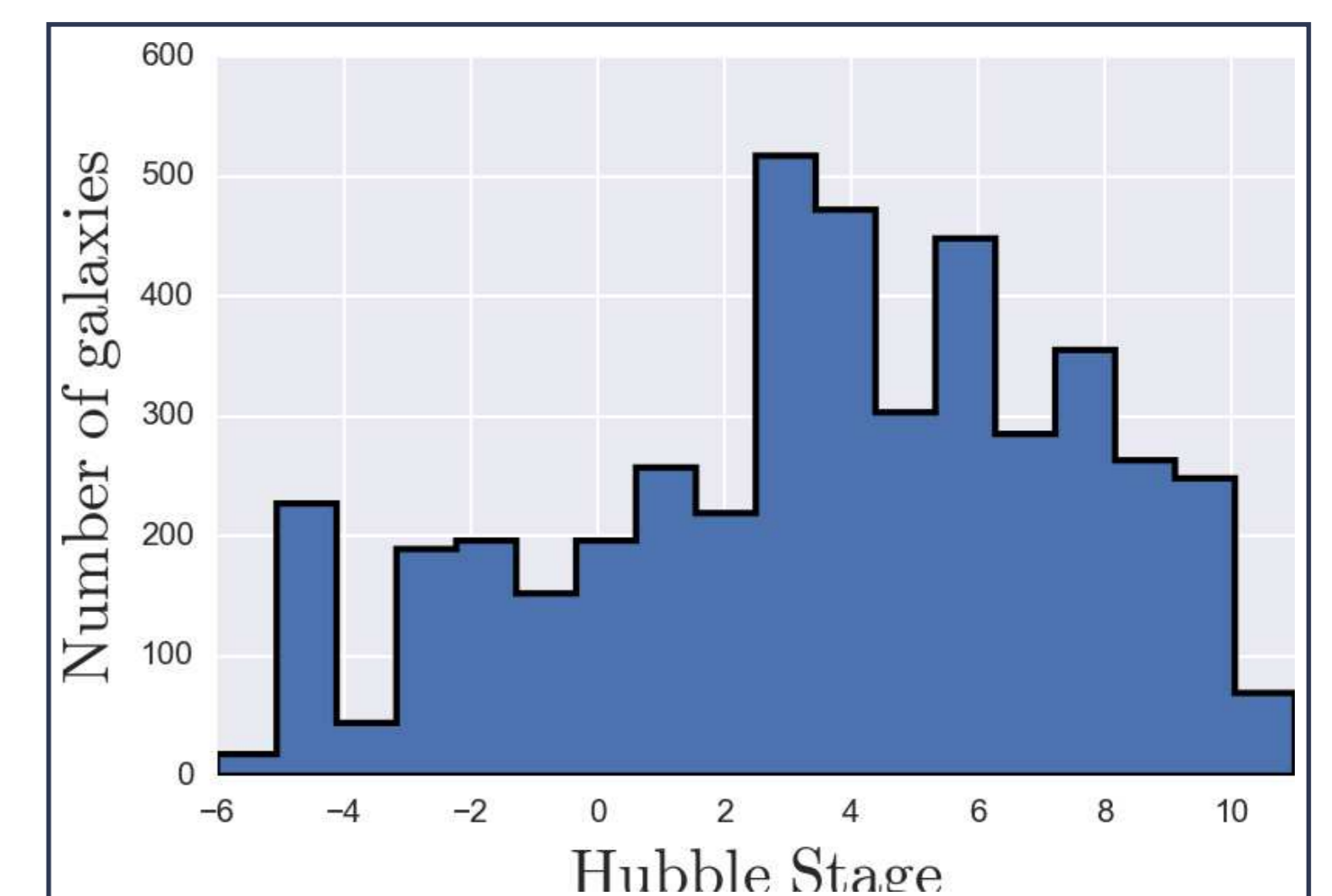
Simulation example for PGC 6855



EFIGI Catalog: Our Sample

START HERE

~ 4500 nearby galaxies from SDSS DR8 mapping the Hubble tuning-fork (Baillard et al. 2011)



DATA

Labels from Galaxy Zoo data (Lintott et al. 2011)

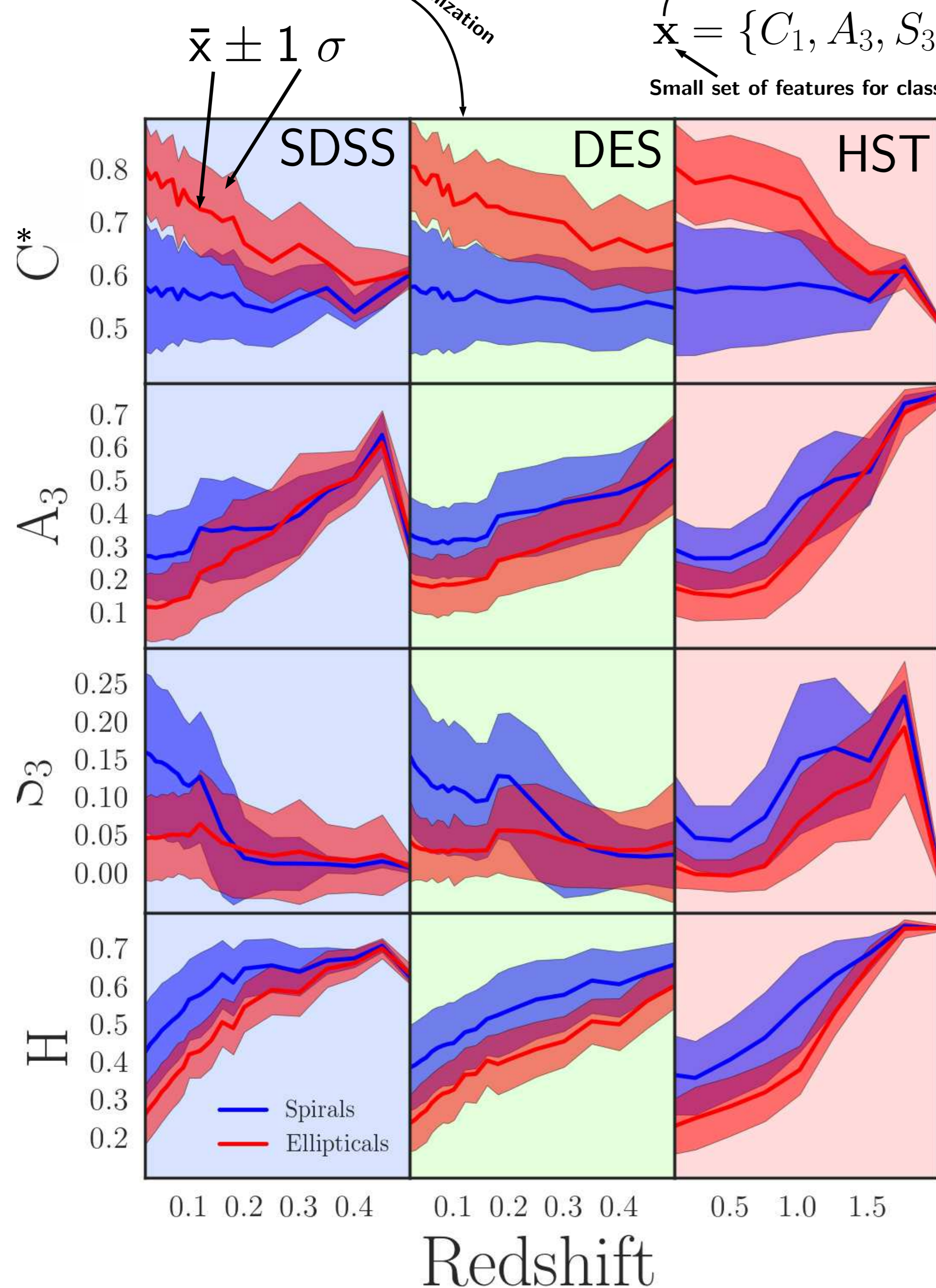
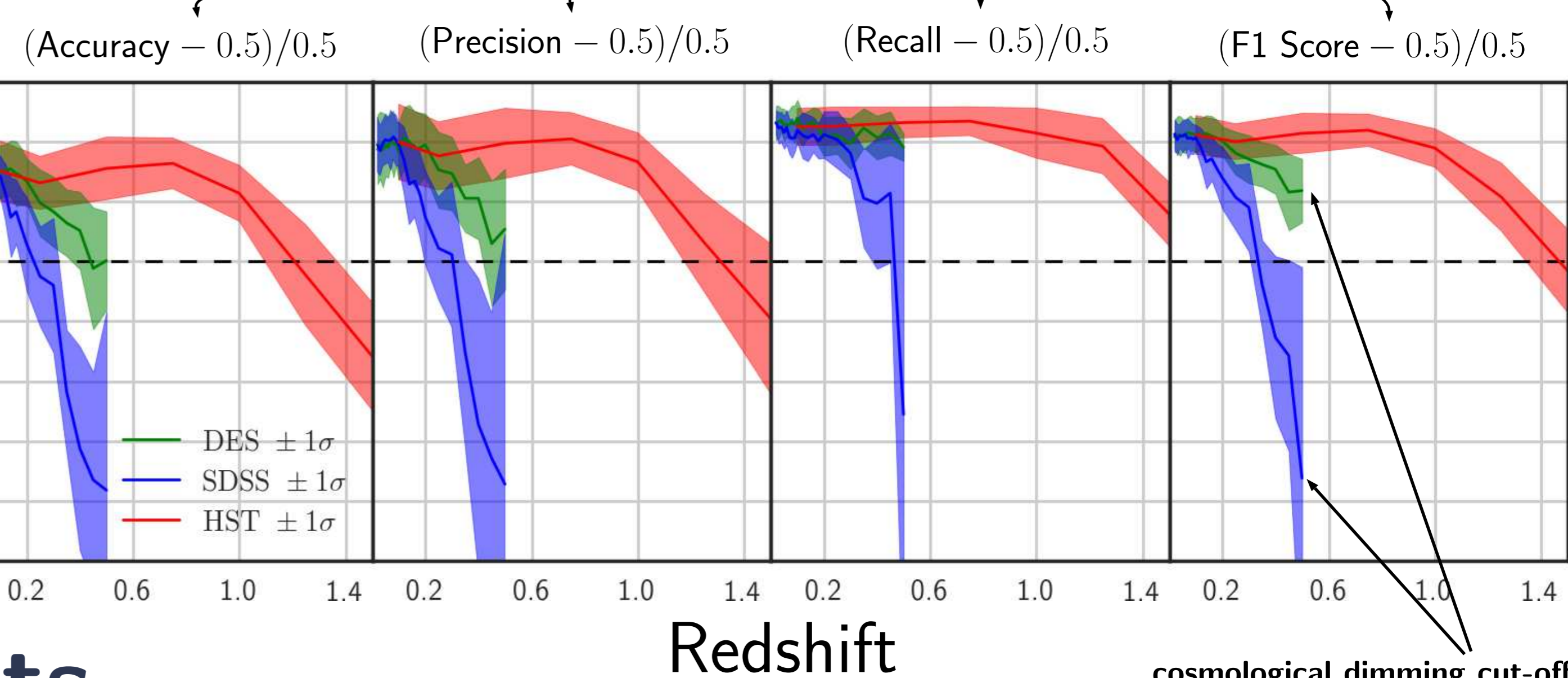
$$f(\mathbf{x}) = \mathbf{W}\mathbf{x} + w_0$$

Classification Cross-validation

$\mathbf{x} = \{C_1, A_3, S_3, H\}$
Small set of features for classification

conservative limit for reliable results

Normalized Classification Metrics, 0.5 correspond to worst cases (random classification)



Main Points

• General advice for galaxy morphometric supervised classification:

SDSS: z < 0.2 DES: z < 0.5 HST: z < 1.5

• We also suggest these limits for visual classifications

• For high-z classifications, space based telescopes are crucial

• Morphological indicators fade very rapidly (faint structures): magnitude limits and SNR are important

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