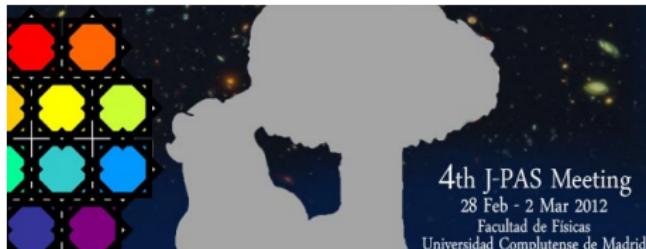


Tools to study  
**Morphological Evolution of Galaxies**  
for  $0 < z < 0.5 < 1$

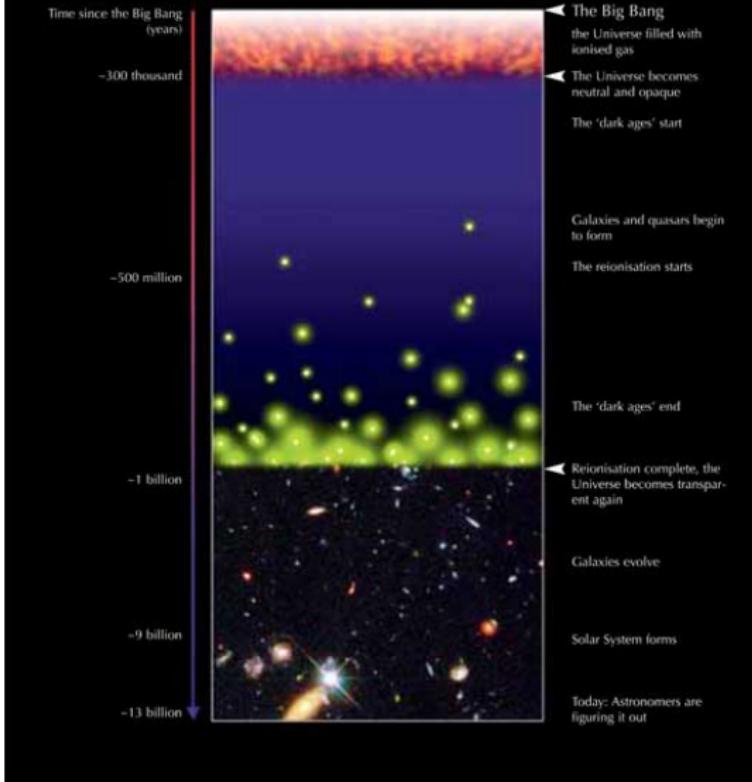
**Fabricio Ferrari**

`fabricio@ferrari.pro.br`

IMEF–FURG  
Rio Grande, Brasil



## An outline of cosmic history



Djorgovski and Digital Media Center, Caltech

# What we want

- Hint on galaxy dynamical state  $\mathbf{f}(\mathbf{r}, \mathbf{v})$

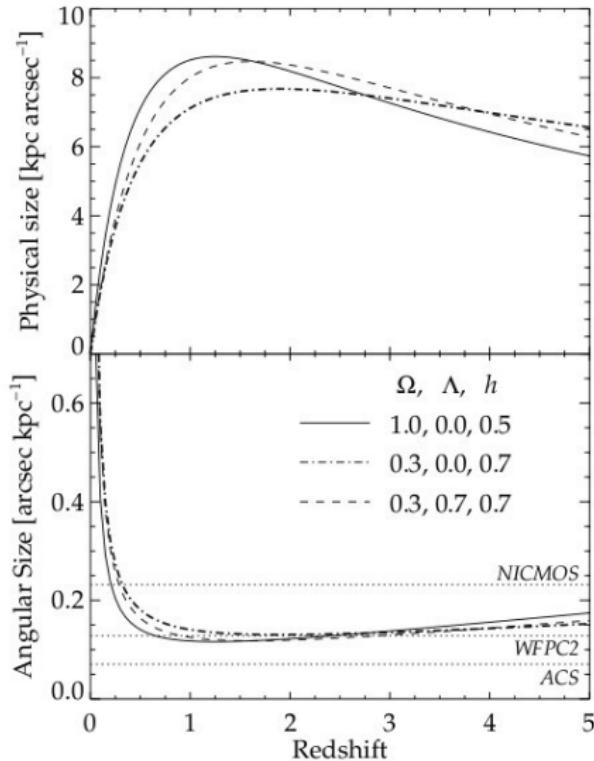
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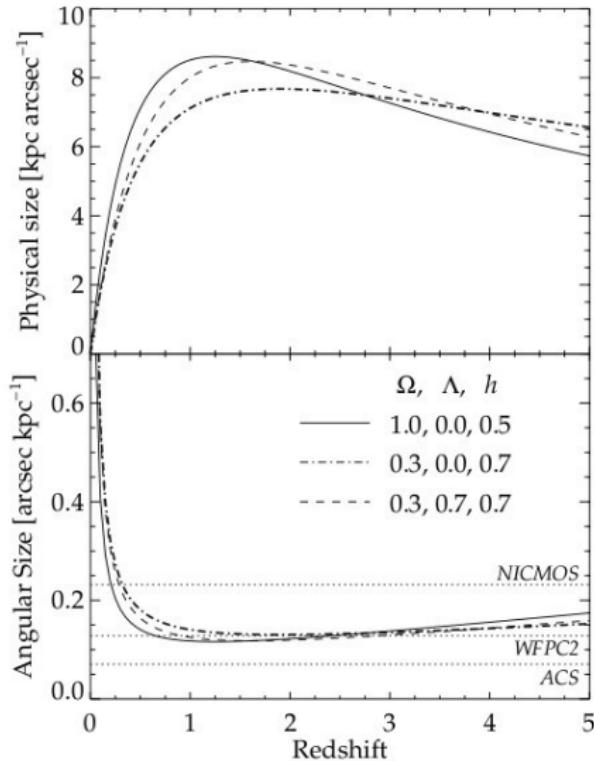
- Hint on galaxy dynamical state  $f(\mathbf{r}, \mathbf{v})$
- Galaxy distribution in the Hubble classification diagram with  $z$
- Galaxy morphology at different environments
- Two-body correlation-function, find clusters, large scale structures
- Galaxy and Universe evolution

# What we can



Papovich et al. 2003 ApJ 598 827P

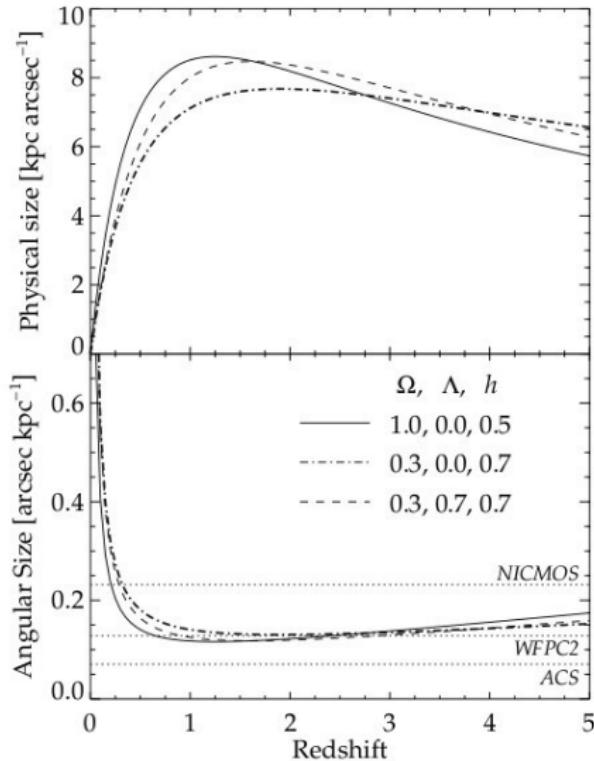
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JPAS magnitude limit

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PSF variation

$$p = p(x, y, \lambda, t) \quad t = t(T, az, alt)$$

# Deconvolution

traditionally in morphology: a sin, immoral, shameful, harmful

## Algorithms

- iterative
  - ▶ Jansson-Van Cittert
  - ▶ Richardson-Lucy (maximum likelihood)
  - ▶ Landweber
- non-iterative
  - ▶ Wiener (least squares, non-iterative)

most can be combined with **wavelet** transform to remove noise

# Deconvolution techniques

## – Wiener deconvolution

Find a filter  $g$  so that the *estimated*  $s$

$$\tilde{s} = g * o \quad \hat{\tilde{s}} = \hat{g} \cdot \hat{o}$$

The **Wiener** filter  $g$

$$\hat{g} = \frac{1}{\hat{p}} \left[ \frac{|\hat{p}|^2}{|\hat{p}|^2 + \frac{|\hat{n}|^2}{|\hat{s}|^2}} \right]$$

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## – Jansson-Van Cittert

$$s^{n+1} = s^n + \alpha(o - h * s^n)$$

term proportional do the residual is added.

similar to **Richardson Lucy** or **Landweber**

# How to measure morphology

- Standard Bulge-Disk-Halo decomposition
- Image Simulations (shapelets, multi-gaussian fitting, ...)
- Image moments
- Asymmetry indexes

## Available Tools

GIM2D – Galaxy Image 2D

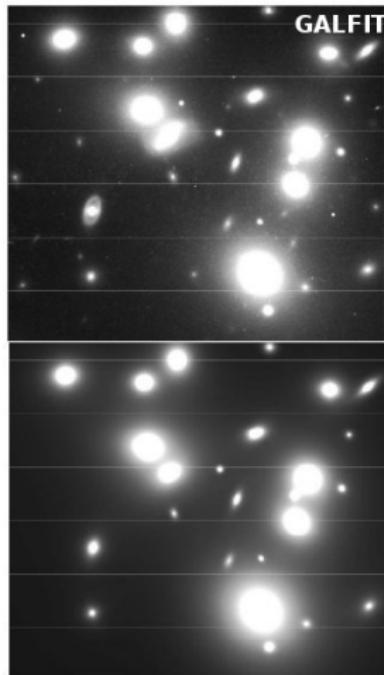
Simard et al. 2002, ApJS, **142**, 1

GALFIT

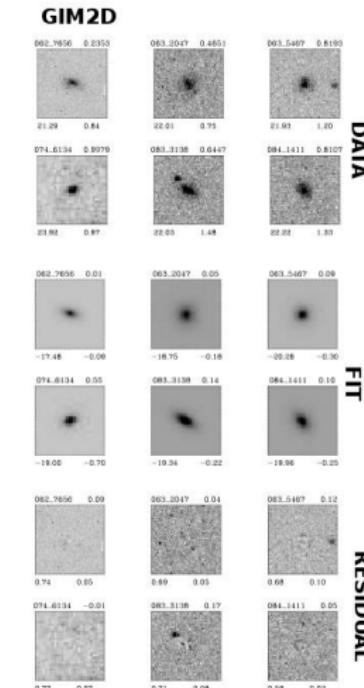
Peng et al. 2002, AJ, **124**, 266

*it would be nice to have mock images to play with*

# Examples



A1689  $z = 0.186$ , Pannella (Thesis) 2007



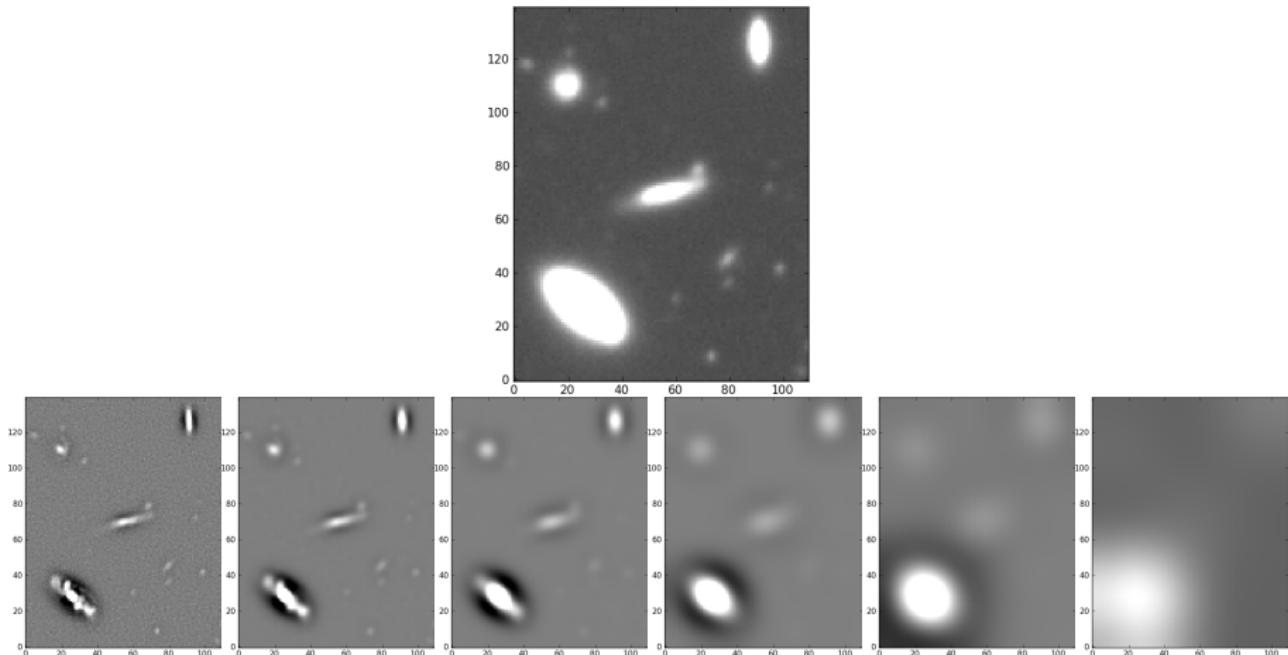
Groth Strip Survey, Simard et al 2002

# New Tools

- Discrete Wavelet Transform – DWT
- Image Invariant Moments
- Principal Component Analysis – PCA
- Waveleted Principal Component Analysis – WPCA

# Discrete Wavelet Transform

multiscale transform



# Image Moments

$$M_{pq} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x^p y^q f(x, y) dx dy \quad \rightarrow \text{discrete} \rightarrow \quad M_{ij} = \sum_x \sum_y x^i y^j I(x, y)$$

# Image Moments

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Central Normalized Moments

$$\mu_{pq} = \frac{1}{M_{00}} \sum_x \sum_y (x - \bar{x})^p (y - \bar{y})^q I(x, y)$$

Scale Invariants

$$\eta_{ij} = \frac{\mu_{ij}}{\mu_{00}^{\left(1+\frac{i+j}{2}\right)}}$$

Translation, scale and rotation invariants – Hu (1962) set

$$I_1 = \eta_{20} + \eta_{02} \tag{1}$$

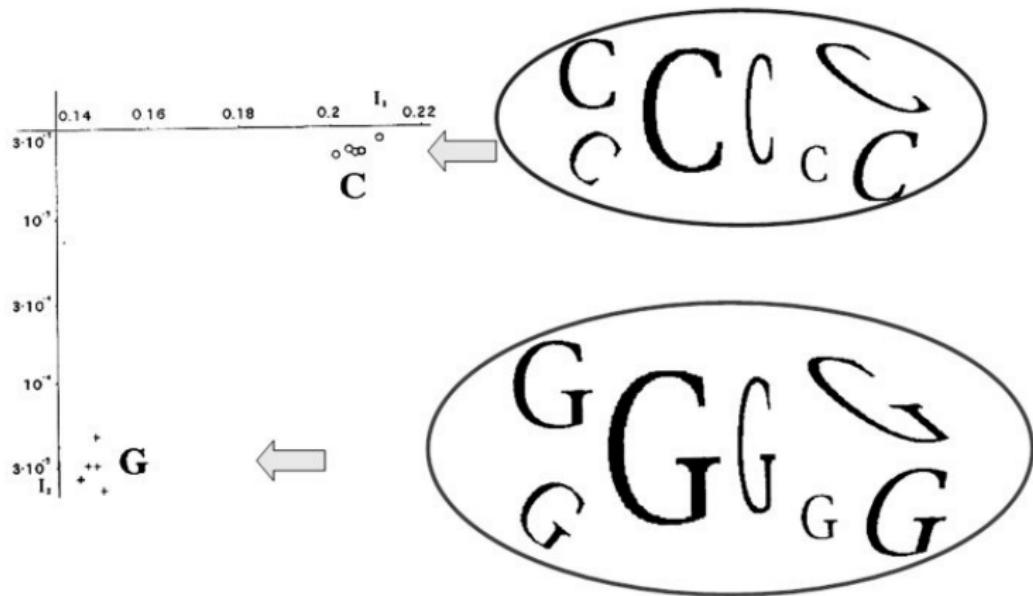
$$I_2 = (\eta_{20} - \eta_{02})^2 + (2\eta_{11})^2 \tag{2}$$

$$I_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \tag{3}$$

...

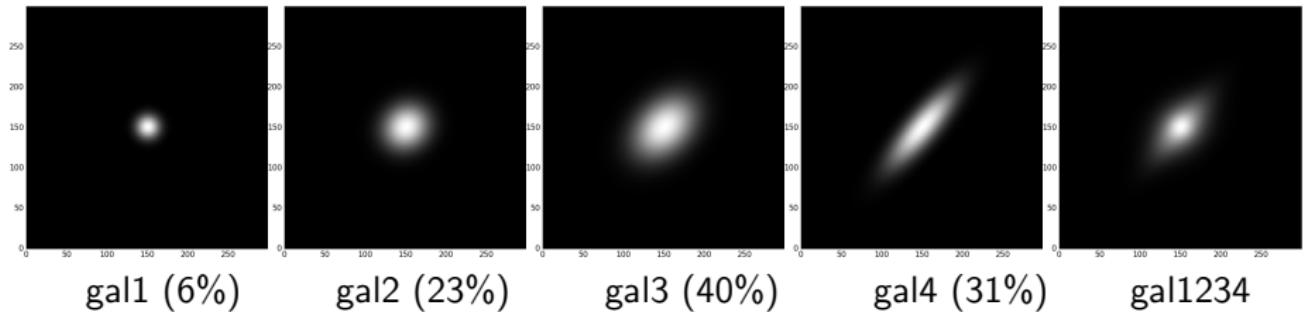
(4)

# Pattern Recognition with Moments

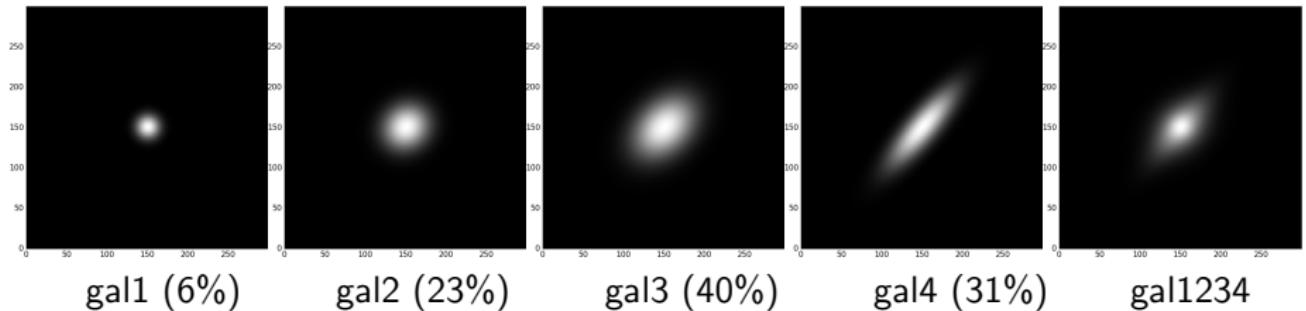


Flusser, Suk, Zitová 2009

# Synthetic example



# Synthetic example



model	$\mu_{00}$	$\mu_{01}$	$\mu_{02}$	$\mu_{10}$	$\mu_{11}$	$\mu_{12}$	$\mu_{20}$	$\mu_{21}$	$\mu_{22}$
gal1	1	0	100	0	0	0	100	0	10 000
gal2	1	0	355	0	37	0	368	0	133 800
gal3	1	0	670	0	229	-0.0011	670	-0.001124	55 4900
gal4	1	0	998	0	716	-0.3436	745	-0.2489	1 772 000
gal1234	1	0	662	0	319	-0.1133	587	-0.08201	79 5700

$\mu = 0$  means  $\mu < 10^{-10}$

# Principal Component Analysis

Write the data in a basis where all the variables are *uncorrelated*<sup>1</sup>.

Usual: PCA in spectral direction → eigenspectras

useful to compare **common spectral** features between **galaxy pixels**.

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Classification scheme

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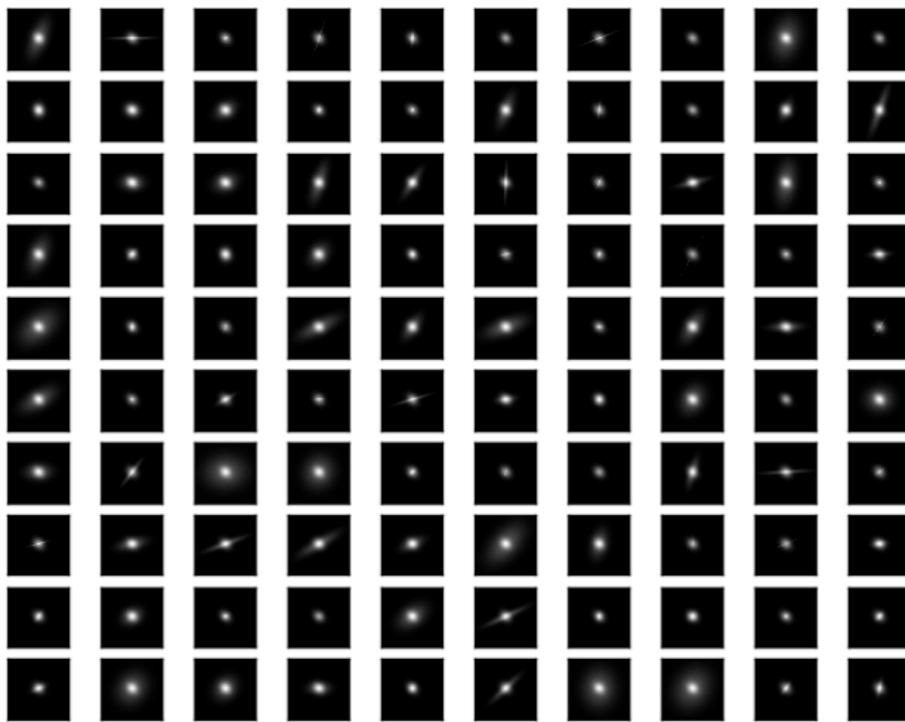
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Classification scheme

Face recognition: eigenfaces

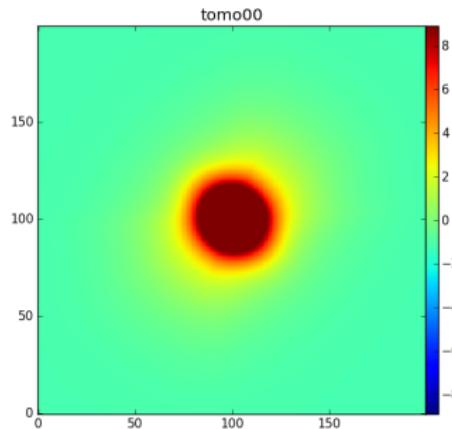


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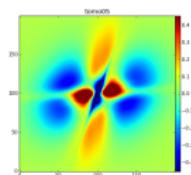
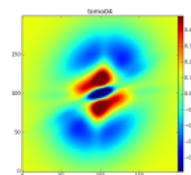
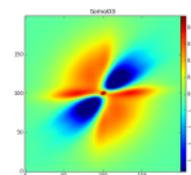
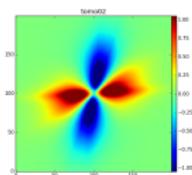
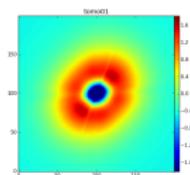
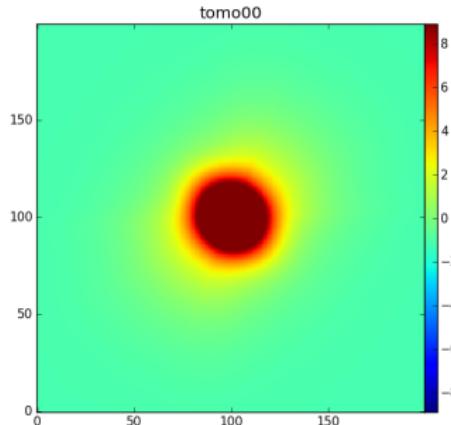
Simulated 'galaxies'.  
All have a common spherical component)



# PCA - eigengalaxies



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1st: 93%

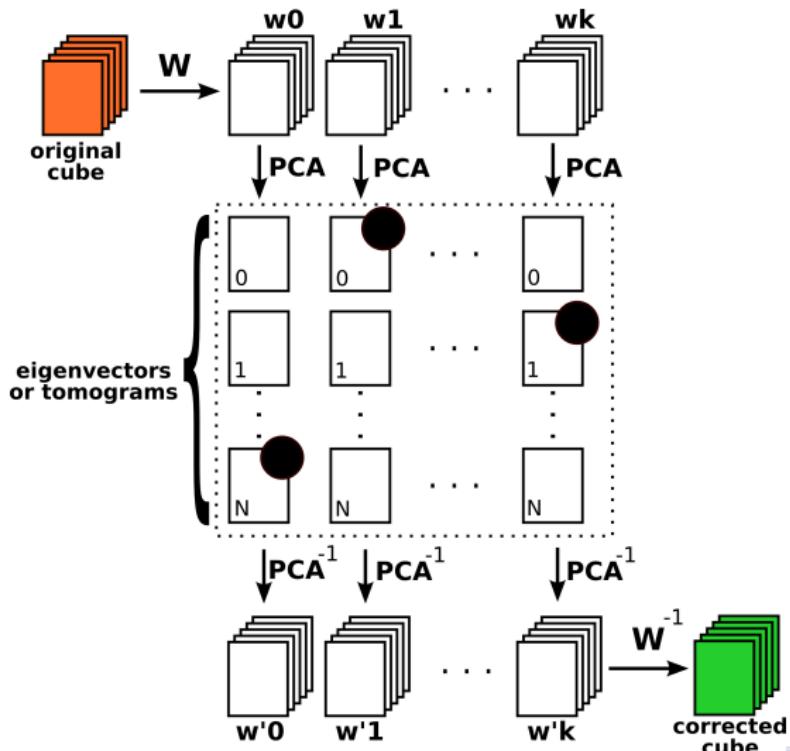
2nd: 4%

3rd: 2%

4th+5th+...:1%

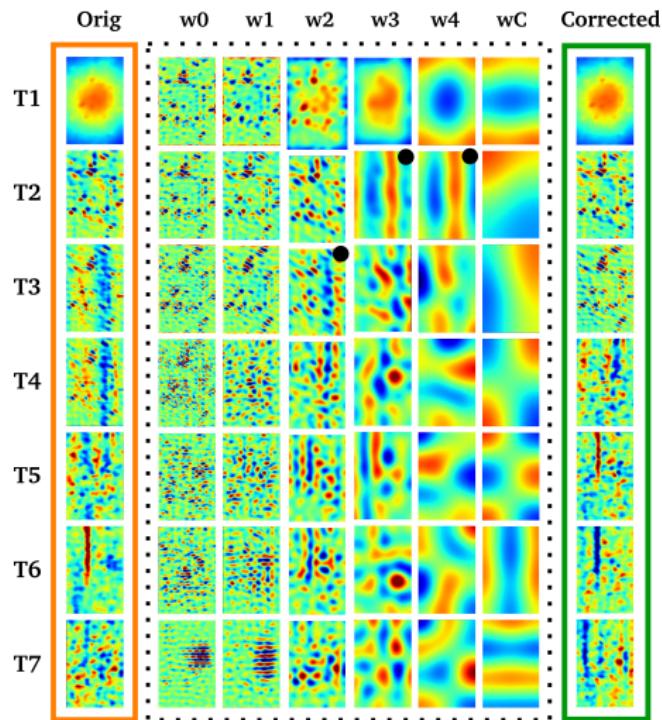
# WPCA - removal of instrumental signature

Ferrari et al 2010; Riffel, Riffel, Ferrari & Storchi-Bergmann 2011; Ferrari et al 2012 (in prep)



# WPCA NGC 1399

Steiner et al. data - Gemini GMOS



# Costs

**Linux + Python + Scipy** 200x200 pixels image

ACTION	DURATION
★ find object, retrieve data	1 s
★ deconvolution $\mathcal{F}^{-1}\{\mathcal{F}\}$	1 s
● 2D fitting	10 s
★ brightness profile with aperture photometry	1 s
★ fit brightness profile	2 s
★ moments calculation	1/10 s
● wavelet transform (6 scales)	8 s
● PCA (100 images=7s)	1 s

1 CPU	1 million objects
★ basic plan	60 days
● premium plan	1 year

300  $10^6$  objects basic plan  $\rightarrow$  50 years.

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20 GPUs 500 cores	1 million objects
★ basic plan	3 hours
● premium plan	15 hours

$300 \cdot 10^6$  objects basic plan  $\rightarrow$  36 days.

# Why

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- $n$  correlates with  $R_n$ ,  $M_B$ ,  
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- Stellar mass, size, and Sérsic index can predict the velocity dispersions in SDSS (Bezanson et al 2011 ApJ **737** 31)

## Some Similar Works

- MGC –Millennium Galaxy Catalogue
- COSMOS – Cosmic Evolution Survey
- STAGES – Space Telescope Galaxy Evolution Survey
- SAGE – Surveying the Agents of Galaxy Evolution

**Gracias**