Galaxy Structural Analysis
clues from their formation and evolution

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Purpose

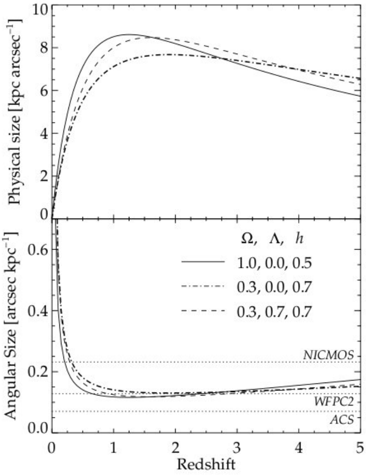
To give a general and simple overview of galaxy formation and evolution, how it affects galaxy structural parameters and how can we measure them, particularly in data from upcoming large photometric surveys

1. Galaxy Formation and Evolution
2. Structural Parameters
3. Measuring Photometric Techniques
4. (very) early results

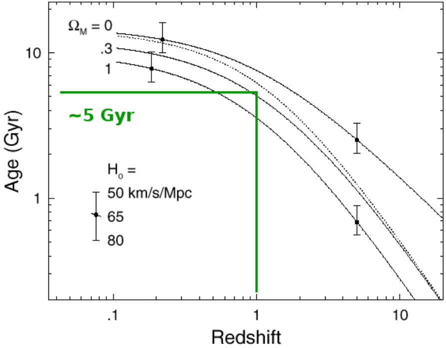
What we'd like to know

- Galaxy formation mechanisms, triggers,
- Galaxy evolutionary paths
- Galaxy morphology at different environments
- Galaxies dynamics $f(\mathbf{r}, \mathbf{v}, t)$
- Galaxy and Universe evolution
- spheroid $\times$ disc dispute over z
- Elliptical galaxies

What we can



Papovich et al. 2003 ApJ **598** 827P



Fred Hamann ASP Conf. Series, La Serena, Chile, May 18-22, 1998

JPAS $m_{\rm AB} < 25$

SDSS $r < 22$ $\overline{PSF} \sim 1.2''$

$z \sim 1$ just overall properties

Galaxy Formation Mechanisms I

Monolithic Collapse Eggen, Lynden-Bell, Sandage 1962

- observed stellar orbits with high eccentricity and high angular momentum
- forms central dense region
- deep fields revealed the opposite

Hierarchical Merging White & Rees 1978, Fall & Efstathiou 1980

- first, stable dark matter halo (80% total mass)
- luminous matter condensates in the dark halo potential well

Gas Infall Blumenthal et al. 1986

- dark matter squeeze during formation
- smaller core radius and greater central density
- halos are not isothermal spheres today
- halos are not rigid

Galaxy Formation Mechanisms II

Secular Evolution Kormendy & Kennicutt 2004 (review)

- **far past**: hierarchical clustering, merging
- **far future**: secular evolution
  slow rearrangements of energy and mass by collective phenomena
- **now**: both are important
- bulges:
  - classic: build from mergers
  - pseudo: slowly built out of disk gas

Galaxy Formation Timescales and Constrains

- Hubble time
- Dynamical time
- Cooling time
- Star formation time (rate)
- Merging time
- Dynamical friction time

cf. Mo, van den Bosch & White, Galaxy Formation and Evolution, 2009.

Some Important Facts

Morphological Evolution with z

Table 1: Summary of key ages in galaxy morphology to z=1

Redshift	**Look-back Time**	**Key Developments in Galaxy Morphology**
z<0.3	<~3.5 Gyr	Grand-design spirals exist. Hubble scheme applies in full detail.
z~0.5	~5 Gyr	Barred spirals become rare. Spiral arms are underdeveloped. The bifurcated "tines" of the Hubble tuning fork begin to evaporate.
z>0.6	>6 Gyr	Fraction of mergers and peculiar galaxies increases rapidly. By z=1 around 30% of luminous galaxies are off the Hubble sequence.

Abraham & van den Bergh 2001

Size Evolution

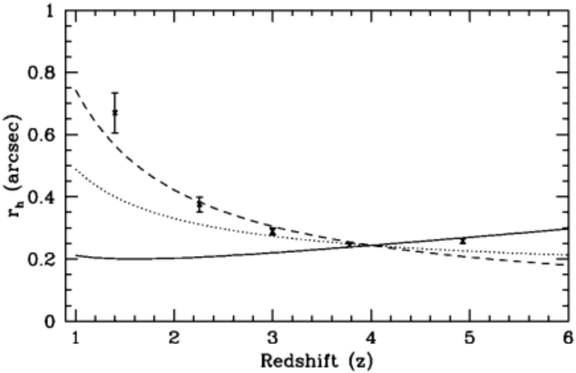
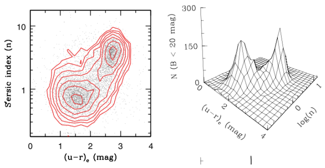


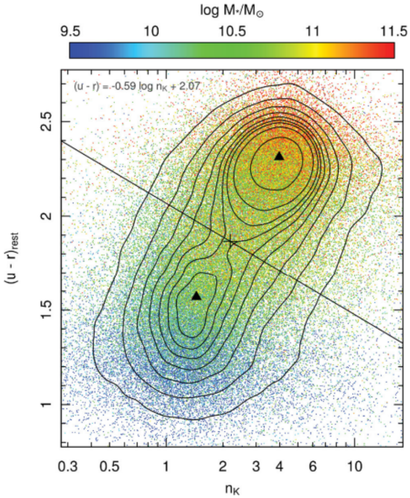
FIG. 1.—Size vs. redshift relation. Mean SExtractor half-light radii are plotted with error bars indicating the standard error of the mean (i.e., the sample standard deviation divided by the square root of the sample size). The solid blue curve shows the expected trend in the *WMAP* cosmology if physical (proper) sizes do not evolve. The dashed red curve shows the trend if sizes evolve as $H^{-1}(z)$, and the dotted green curve shows $H^{-2/3}(z)$. The curves are all normalized to the mean size at $z \approx 4$ (approximately r_h = 1.7 kpc). [*See the electronic edition of the Journal for a color version of this figure.*]

Ferguson et at 2004

Mass more important than environment



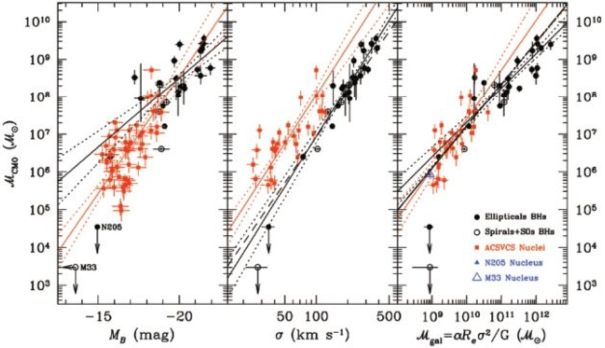
Driver et al. 2006



Kelvin, Driver et al. 2012

Relationships between nucleus and host galaxy

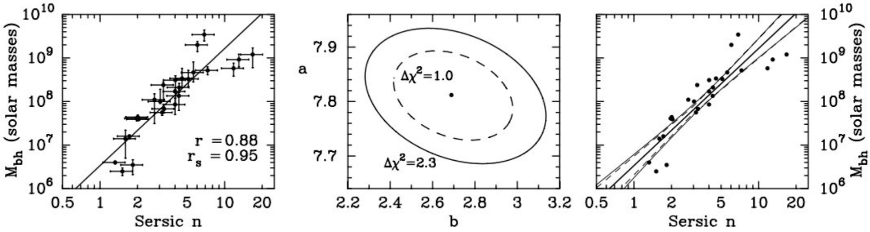
Central Massive Object   Ferrarese et al. 2006 ApJ **644**, L21



- Most galaxies contain a central massive object (CMO)
- byproduct of galaxy formation
- CMO: either *supermassive black hole* or *compact stellar nucleus*
- if $M_{\rm gal} \gtrsim 10^{10}\ M_\odot$ CMO → SBH

Relationships between nucleus and host galaxy

BH Mass and Sérsic index



Graham & Driver 2007 ApJ **655**, 77

Classification and Understanding

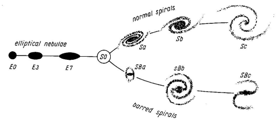
Classification is related to understanding

How classify galaxies? i.e. Which types are there?

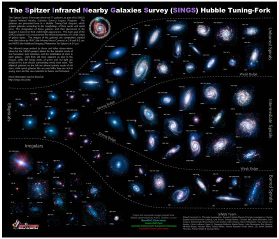
How classes vary with wavelength, mass, SFR, redshift, ...

Which are the physical fundamental parameter's?

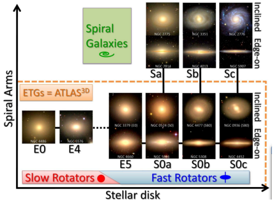
Hubble fork I



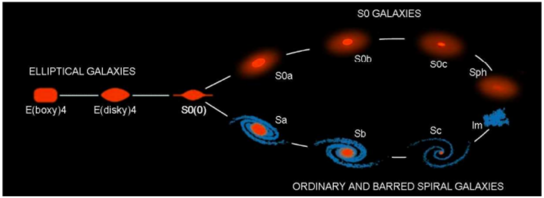
Hubble 1936



Spitzer Science Center



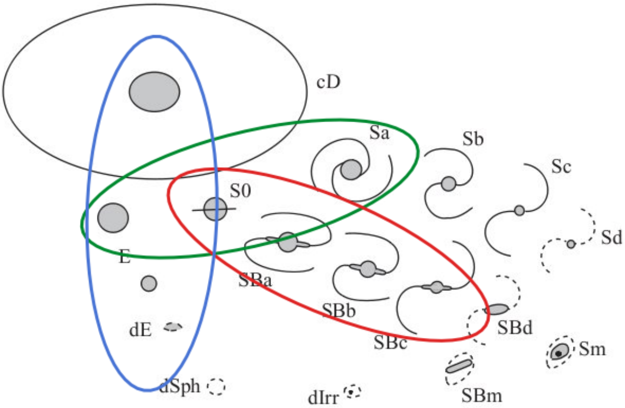
Cappellari et al 2011, ATLAS^{3D}



Kormendy & Bender 2012

"Most elliptical galaxies are like spirals" **?**

Hubble fork II



adapted from Sparke & Gallagher 2007

Hubble fork III

Hubble and modified Hubble schemes

- only apply to local universe.
- no evolution implied by the fork
- strong wavelength based
- there is **no eye classification** for ETG

How they look like

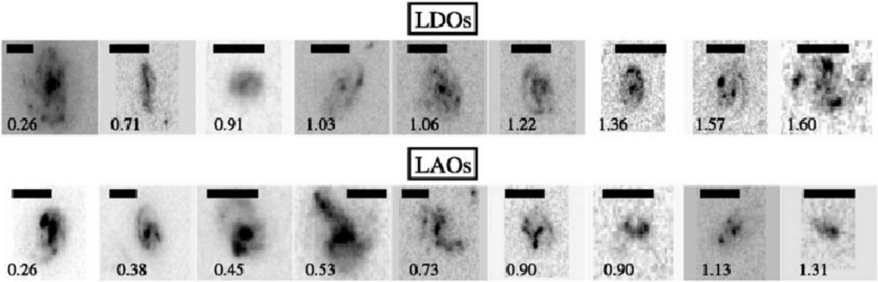


FIGURE 7: Various images of LDOs (luminous and diffuse) and LAOs (luminous and asymmetric) galaxies. Bar shows approximately $0''.5$. Redshifts, mainly photo-zs, are given by the numbers in the lower left corner of images. These redshifts are thought to be reliable at the moderate distances in question here. The figure is from Conselice et al. (2004).

Some Structural Parameters

Structural Parameters

1. Colors and Magnitudes
2. Sersic Parameters
   1. Surface brightness (central extrapolated or effective)
   2. Effective radius
   3. Sérsic index
3. CASGM – Concentration, Asymmetry, Clumpiness, Gini coefficient, M20
   1. Concentration C28, C59
   2. A = (I-I180)/I (problems: center, noise, ETG)
   3. S = S -Ss
   4. G (related to C and n)
   5. M20 related to n
4. **New parameters**
   1. skewness and kurtosis along major and minor axis
   2. wavelet power spectra $\rightarrow$ meansize, info.entropy

Colors and Magnitudes

1. global and core colors
2. star formation
3. mass-to-light ratio → total mass estimate (Bell & de Jong 2001)
4. total mass

$$
\begin{aligned}
\log\left(\frac{\mathcal{M}_*}{L_B}\right) &= -1.224 + 1.251(B-R) \\
\frac{\mathcal{M}_*}{L_B} &= 10^{1.93(g-r)-0.79} \\
M - M_\odot &= -2.5\log(L/L_\odot) \\
z \approx \frac{v}{c} &= \frac{d}{D_H} = \frac{dc}{H_0} \qquad 0 < z \ll 1 \\
&\text{otherwise} \quad z = z(H_0, \Omega_m, \Omega_k, \Omega_\Lambda)
\end{aligned}
$$

Sersic Parameters I

Effective Radius and Surface Brightness

I_n independent of distance in local Universe

I_n gives a scale of density

R_n gives a scale of size

both correlates with many other structural parameters

Sersic Parameters II

Sérsic index

- **Most important** morphological parameter for ETGs
- **Very difficult** to measure (1950-1990: $n = 4$)
- There is **no global** Sérsic index (Ferrari et al 2004)
- Related to formation and structure (merger history)
- discriminates bulge versus disk dominated
- fundamental plane $(Rn, In, \sigma) \cup (n, L)$
- $\log(n)$ makes more sense

  $n = 1 \rightarrow 2$ compares to $n = 4 \rightarrow 8$

  physical sequence $n = \frac{1}{2}, 1, 2, 4, 8, 16$

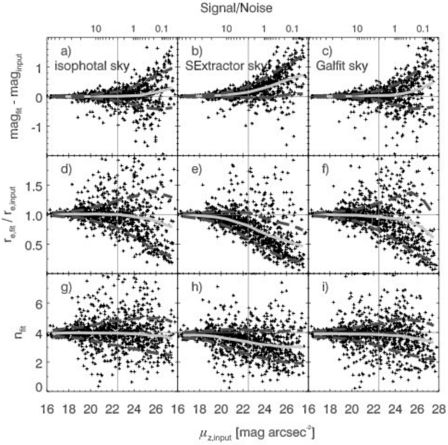
Why n is so important?

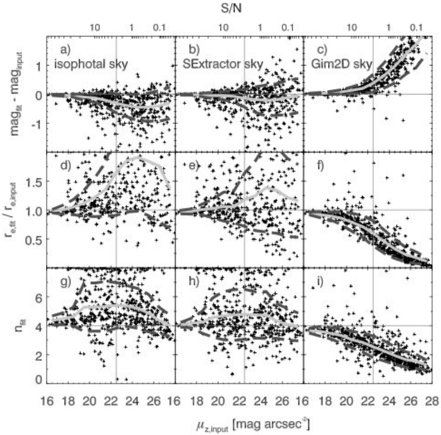
- n correlates with R_n, M_B,
  (Caon et al 1993,..., Kormendy et al 2009)
- Merger remnants have higher Sérsic index $n > 2$
  (e.g., F. Bournaud astro-ph/1106.1793)
- Sérsic index increases with number merger events (Kormendy et al 2009)
- Sérsic index correspond to different PDF $f(\mathbf{r}, \mathbf{v})$ (Ciotti 1991)
- E – Sph dichotomy (Kormendy et al 2009)
- Stellar mass, size, and Sérsic index can predict the velocity dispersions
  (SDSS data, Bezanson et al 2011 ApJ **737** 31)

Measuring Sersic Parameters I

$n_{\rm input} = 4$

Häussler et al 2007, ApJS **172** 615
GEMS HST survey (Rix et al 2004)





GALFIT

GIM2D

Measuring Sersic Parameters II

Synthetic galaxies:

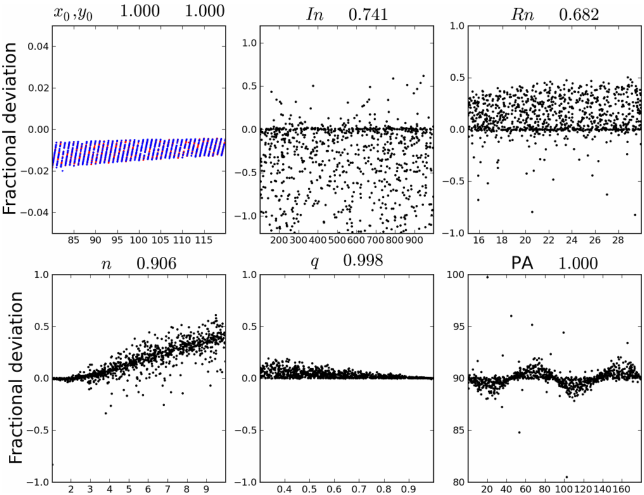
pure Sersic profiles 1000 images 255x255 no seeing SNR=5

$$10 < I_n < 1000$$
$$5 < R_n < 15$$
$$1 < n < 10$$
$$0 < PA < 180$$
$$0.3 < q < 1.0$$

$$\text{fractional deviation} \quad \varepsilon = \frac{P_{\rm in} - P_{\rm out}}{P_{in}}$$

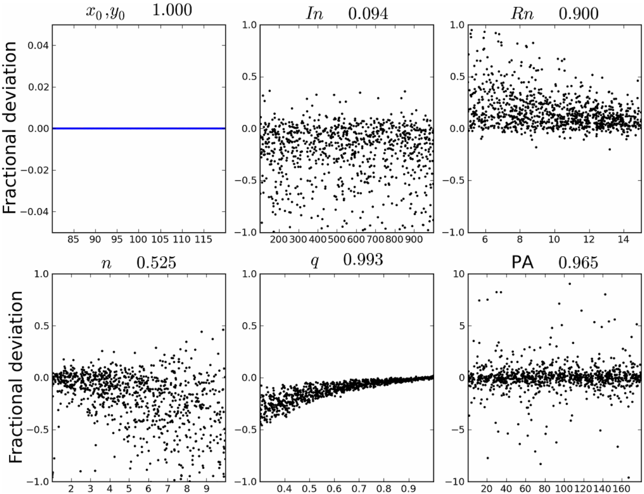
Measuring Sersic Parameters III

Galfit Peng et al. 2010, AJ **139** 2097



Measuring Sersic Parameters IV

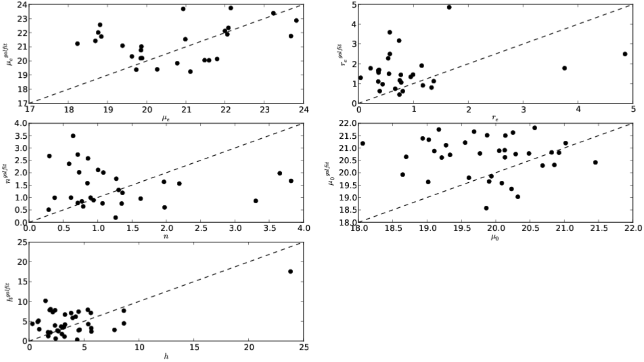
our results – aperFFot Ferrari 2012



Measuring Sersic Parameters V

GHASP Survey (OAM Marseille)   Carlos Eduardo Barbosa, IAG-USP

Galfit   vs   Homo Sapiens+IRAF+STSDAS+Ellipse



Measuring Sersic Parameters VI

I_n, R_n, n are very **difficult to measure** reliably

Measurements of I_n, R_n, n must be taken with **great care**

GALFIT (Peng 2010) and GIM2D (Simard 2002) are **alarming**.

CASGM system

Concentration C Abraham et al. 1996

$$C_{28} = 5 \log \left(\frac{R_{80}}{R_{20}} \right) \qquad C_{\rm disk} = 2.7 \quad C_{\rm deVauc} = 5.2$$

separate morphological type, correlates with mean stellar age

Asymmetry A   Abraham et al. 1996

$$A = \frac{\sum_{i,j} |I_{i,j} - I_{ij}^{180}|}{\sum_{ij} |I_{ij}|} - B_{180}$$

Smoothness S   Conselice 2003

$$S = \frac{\sum_{i,j} |I_{i,j} - I_{ij}^{S}|}{\sum_{ij} |I_{ij}|} - B_s$$

Gini coefficient G social index – depart from equal distribution
$\mathbf{M_{20}}$ second order moment of 20% brightest pixels on image

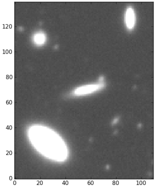
Lotz et al 2004

Wavelet Transform I

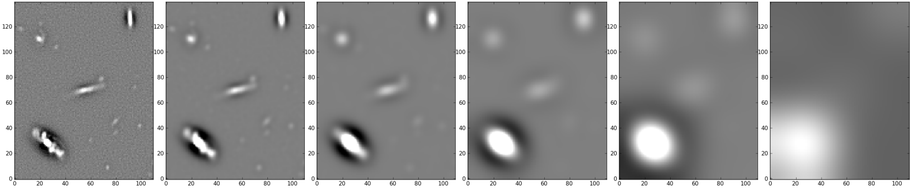
multiscale transform

$$S \equiv C_0 = C_J + \sum_{i}^{J} w_j \qquad w_{j+1} = c_j - c_{j+1}$$

c_j lowpass filtered signal at scale 2^j



original



wavelet transform

Wavelet Transform II

multiscale transform

wavelet spectral density (power spectra) at scale $\lambda_j = 2^j$

$$\Gamma(\lambda_j) = \sum_{pixels} w^2_{\lambda_j}$$

Mean size

$$\overline{\lambda} = \sum_j \lambda_j \; \Gamma(\lambda_j)$$

Information entropy

$$\Theta = -\sum_j \Gamma(\lambda) \; \log(\Gamma(\lambda))$$

Wavelet Transform III

multiscale transform

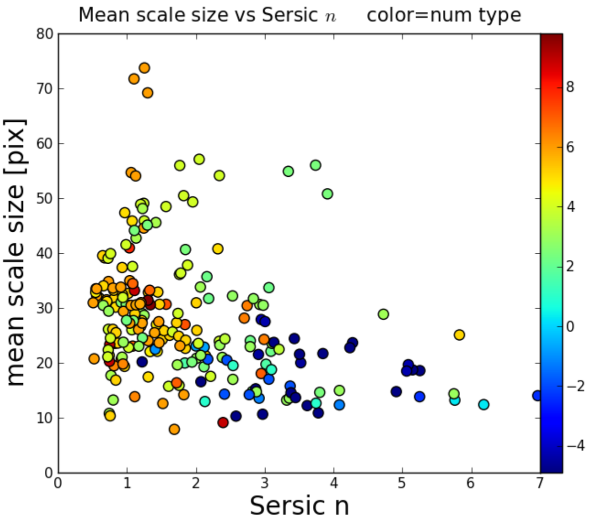


Image Moments

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

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

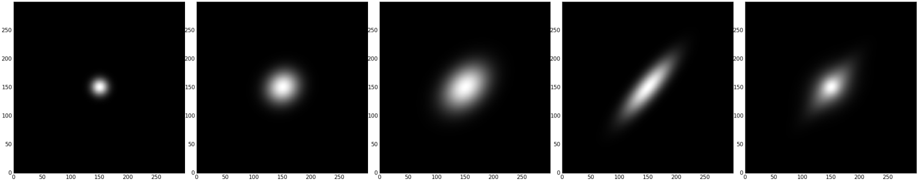
$$\eta_{ij} = \frac{\mu_{ij}}{\mu_{00}^{\left(1+\frac{i+j}{2}\right)}}$$

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

$$I_1 = \eta_{20} + \eta_{02} \qquad I_2 = (\eta_{20} - \eta_{02})^2 + (2\eta_{11})^2 \qquad I_3 = \ldots$$

Convolution invariants Flusser, Suk, Zitová 2009

Synthetic example



gal1 (6%) gal2 (23%) gal3 (40%) gal4 (31%) gal 1+2+3+4

not normalized

model	μ_{02}	μ_{11}	μ_{20}	μ_{22}
gal1	100	0	100	10 000
gal2	355	37	368	133 800
gal3	670	229	670	554 900
gal4	998	716	745	1 772 000
gal1234	662	319	587	795 700

In parameter distance space gal3 is the closest to gal1234

Our approach

Develop a **fully automatic** algorithm to **measure structural parameteres**, correct and robust at low SNR and low spatial resolution, suited to process large photometric surveys.

next decade dominated by photometric data

few reliable tools to automatically perform photometry

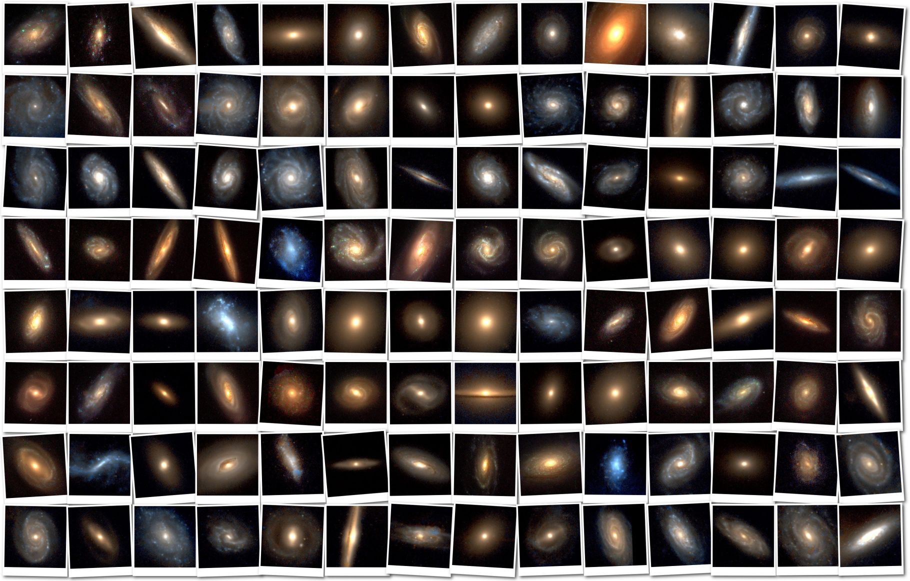
photometry is a complicated task

must to be done without human intervention

Databases

- Frei 113 galaxies – simple clean known database (test)
  Frei 1996 AJ **111** 174
- EFIGI 5k SDSS eye-classified galaxies (test)
  A.Baillard, E.Bertin, et al. 2011
- **SPIDER** (SDSS/UKIDSS) $\sim$50k ETGs
  F. La Barbera, R.R. de Carvalho et al 2010 MNRAS 408 1313
  39 993 Bright ($^{0.1}M_r < -20$) ETG *griz* SDSS-DR6 bands
  many measured physical parameters (magnitudes, Starlight$^{\mathrm{TM}}$, ...)
  $0.05 < z < 0.095$
- JPAS-Pau Brasil collaboration
  10^8 galaxies in 40 filters (2014)
  analysis in the same rest frame λ_0 for some
  $z \lesssim 1$
- DES database

Frei database overview



Created by Zsolt Frei and James E. Gunn

Why 1D photometry? I

- does not assume any functional form for $I(\mathbf{R})$
- there is no global Sérsic index, 1D can recover n_a and n_b
- faster and more robust than 2D

Why 1D photometry? II

The relationship between the Sérsic law profiles measured along the major and minor axes of elliptical galaxies*

F. Ferrari[1]†, H. Dottori[1], N. Caon[2], A. Nobrega[1,3], D. B. Pavani[1]‡

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$$\mu(R) = A + B\ R^{\frac{1}{n}} \qquad \frac{d\mu(b)}{db} = \frac{1}{\mathcal{F}(a)} \frac{d\mu(a)}{da}$$

constant eccentricity

$$\mu(b) = A_{\rm a} + \frac{B_{\rm a}}{e_{\rm c}}\ b^{1/n_{\rm a}}$$

variable eccentricity

$$e(a) = e_0 + (e_1 - e_0)\left(\frac{a}{a_{\rm M}}\right)^l,$$

$$\mu_{\rm L}(b) = A_{\rm a} + \frac{B_{\rm a}}{e_0\ n_{\rm a}\ l}\ \ a^{1/n_{\rm a}}\ \ \Phi\left(1 - \frac{\mathcal{F}(a)}{e_0}\ ;\ 1\ ;\ \frac{1}{n_{\rm a}\ l}\right)$$

Background, segmentation, resampling, star masking I

Background

median of corner values

Segmentation

- lowpass filter galaxy (filter width $\simeq$ image_size/10)
- threshold at $\overline{I} + \kappa\,\sigma_I \qquad (\kappa \sim 0.2)$
- connect component label regions

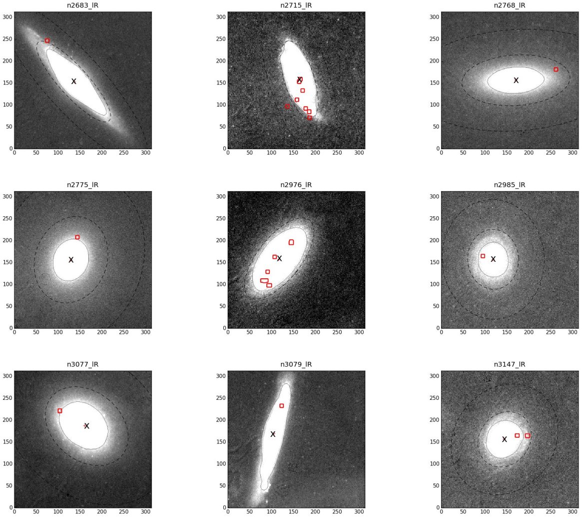
Resample

- to subpixel precision

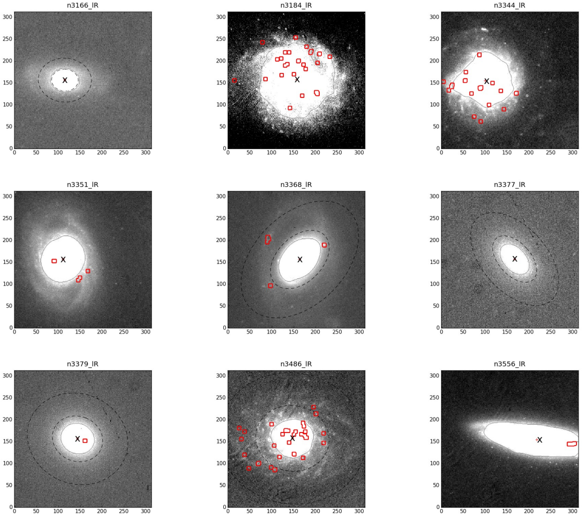
Geometric parameters

- $x_{\rm peak}, y_{\rm peak}, a, b, PA$ to measure profile

Background, segmentation, resampling, star masking II



Background, segmentation, resampling, star masking III



Geometrical Moments

center of mass, standard deviation, skewness, kurtosis

peak of lowpass filtered image $x_{\rm peak}, y_{\rm peak}$

center of mass $x_0 = \frac{m_{10}}{m_{00}}$ $\qquad y_0 = \frac{m_{01}}{m_{00}}$

semiaxes are eigenvalues from

$$\mathbb{J} = \begin{pmatrix} \mu_{20} & \mu_{11} \\ \mu_{11} & \mu_{02} \end{pmatrix}$$

Axis ratio $q = b/a$

Position Angle

$$PA = \frac{1}{2}\arctan(2\mu_{11}, \mu_{20} - \mu_{02})$$

skewness $\zeta_3^x = \frac{\mu_{30}}{\sqrt{\mu_{20}^3}}$

kurtosis $\zeta_4^x = \frac{\mu_{40}}{\mu_{20}^2}$

Luminosity profile I

1. $sma \in [R_{min}, R_{max}, dR]$
2. ellipse e_i centered at $(x, y)_{\mathrm{peak}}$, width dR
3. size sma, axis ratio q
4. mask stars:
   substitute pixels with $I_* > \langle I \rangle + k\,\sigma_I \qquad k = 5$
   by the mean of isophote.
5. measure $I(\text{over } e_i)$, $\overline{I(\text{inside } e_i)}$, $L_T(\text{inside } e_i)$
6. cut the profile at $2\,R_p$

Petrosian Radius

$$\eta(R_p) = 5 \qquad \eta(R) = \frac{\langle I \rangle(R)}{I(R)}$$

Single Sérsic fit I

Optimization

Penalised least square fit

$$\chi = \sum_i \frac{\mu_i^{\mathrm{obs}} - \mu_i^{\mathrm{mod}}}{\sigma_\mu}$$

points with large errors σ_i weight less

Goodness of fit

Fractional deviation

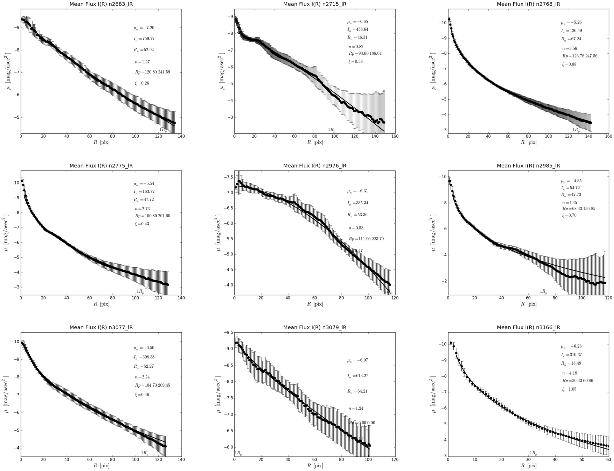
$$\xi = \sum_i \frac{\mu_i^{\mathrm{obs}} - \mu_i^{\mathrm{mod}}}{\mu_i^{\mathrm{mod}}}$$

Error weighted fractional deviation

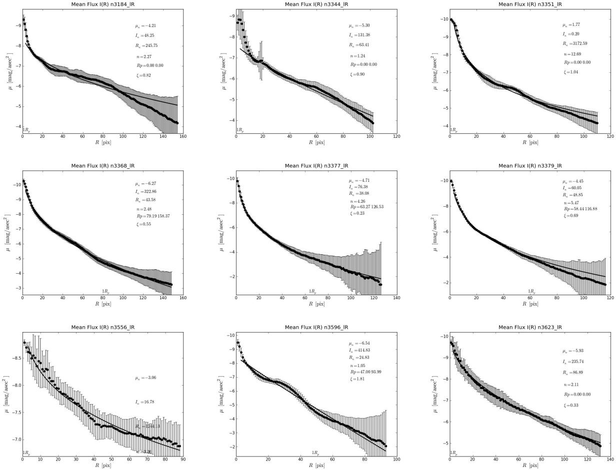
$$\xi = \sum_i w_i \, \frac{\mu_i^{\mathrm{obs}} - \mu_i^{\mathrm{mod}}}{\mu_i^{\mathrm{mod}}} \qquad w_i = \frac{\sigma_\mu}{\langle \sigma_\mu \rangle}$$

Single Sérsic fit II

Frei data



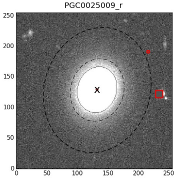
Frei data

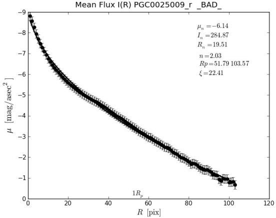


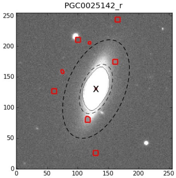
Mean Flux I(R) n3184_IR
μn =−4.21
In =48.25
Rn =245.75
n =2.27
Rp =0.00 0.00
ξ =0.82
Mean Flux I(R) n3344_IR
μn =−5.30
In =131.38
Rn =63.41
n =1.24
Rp =0.00 0.00
ξ =0.90
Mean Flux I(R) n3351_IR
μn =1.77
In =0.20
Rn =3172.59
n =12.69
Rp =0.00 0.00
ξ =1.04
Mean Flux I(R) n3368_IR
μn =−6.27
In =322.86
Rn =43.58
n =2.48
Rp =79.19 158.37
ξ =0.55
Mean Flux I(R) n3377_IR
μn =−4.71
In =76.38
Rn =38.08
n =4.26
Rp =63.27 126.53
ξ =0.23
Mean Flux I(R) n3379_IR
μn =−4.45
In =60.05
Rn =48.85
n =5.47
Rp =58.44 116.88
ξ =0.69
Mean Flux I(R) n3556_IR
μn =−3.06
In =16.78
Mean Flux I(R) n3596_IR
μn =−6.54
In =414.83
Rn =24.83
n =1.05
Rp =47.00 93.99
ξ =1.81
Mean Flux I(R) n3623_IR
μn =−5.93
In =235.74
Rn =86.89
n =2.11
Rp =0.00 0.00
ξ =0.33
μ [mag/asec²]
R [pix]
1Rp

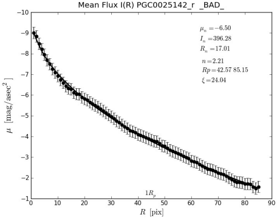
Single Sérsic fit IV

EFIGI data

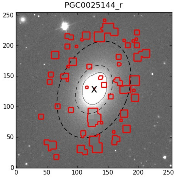


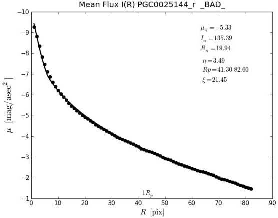


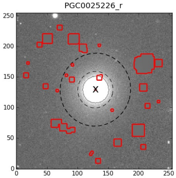


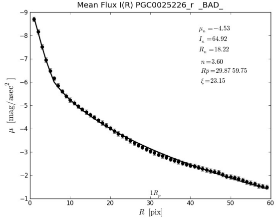


EFIGI data

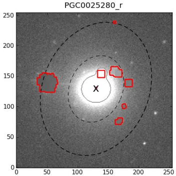

PGC0025144_r

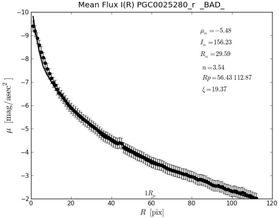

Mean Flux I(R) PGC0025144_r _BAD_
$\mu_n = -5.33$
$I_n = 135.39$
$R_n = 19.94$
$n = 3.49$
$Rp = 41.30$ 82.60
$\xi = 21.45$
$1R_p$
μ [mag/asec^2]
R [pix]

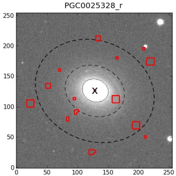

PGC0025226_r

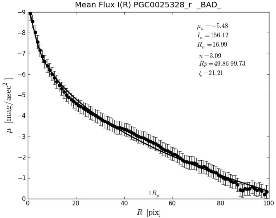

Mean Flux I(R) PGC0025226_r _BAD_
$\mu_n = -4.53$
$I_n = 64.92$
$R_n = 18.22$
$n = 3.60$
$Rp = 29.87$ 59.75
$\xi = 23.15$
$1R_p$
μ [mag/asec^2]
R [pix]

EFIGI data

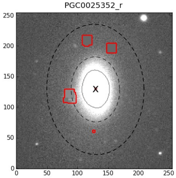

PGC0025280_r
X

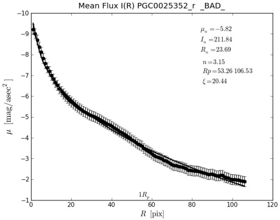

Mean Flux I(R) PGC0025280_r _BAD_
$\mu_n = -5.48$
$I_n = 156.23$
$R_n = 29.59$
$n = 3.54$
$Rp = 56.43$ 112.87
$\xi = 19.37$
μ [mag/asec^2]
$1R_p$
R [pix]

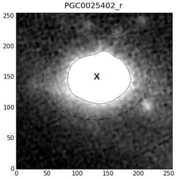

PGC0025328_r
X

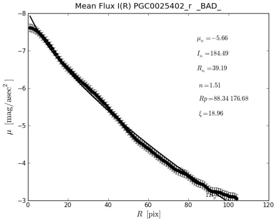

Mean Flux I(R) PGC0025328_r _BAD_
$\mu_n = -5.48$
$I_n = 156.12$
$R_n = 16.99$
$n = 3.09$
$Rp = 49.86$ 99.73
$\xi = 21.21$
μ [mag/asec^2]
$1R_p$
R [pix]

EFIGI data


PGC0025352_r


Mean Flux I(R) PGC0025352_r _BAD_
$\mu_n = -5.82$
$I_n = 211.84$
$R_n = 23.69$
$n = 3.15$
$Rp = 53.26\ 106.53$
$\xi = 20.44$
μ [mag/asec^2]
R [pix]


PGC0025402_r


Mean Flux I(R) PGC0025402_r _BAD_
$\mu_n = -5.66$
$I_n = 184.49$
$R_n = 39.19$
$n = 1.51$
$Rp = 88.34\ 176.68$
$\xi = 18.96$
μ [mag/asec^2]
R [pix]

Next Steps

- Seeing effects
- Ellipse fitting (superellipse, Fourier coefs)
- Standard data (axis ratio=1, PA=0, same $\overline{I}$, σ_I)
- Apply dynamically motivated luminosity profiles
  (G.Brum & F.Ferrari, **poster 48**, this conference)
- Multivariate data analysis with measured parameters
  (PCA, ICA, Factor, Discriminant)
- Alternative techniques :
  - Cladistics/Taxonomy
  - Nearest neighbor tree
  - Cluster finding

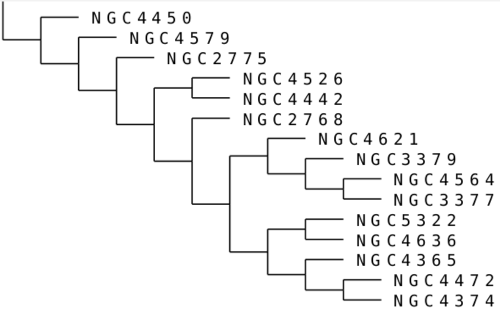
Cladistics

parameters

$t \quad lc \quad (b-v)_t \quad V_{\max}^{\text{gas}} \quad \sigma \quad B_{\text{mag}} \, C_r \quad A_r \quad S_r \quad G_r \quad M20r \quad In \quad Rn \quad n \quad q \quad PA \quad Rp \quad C$

parsimony: least evolutionary change to explain the data

"ellipticals" clade (branch)

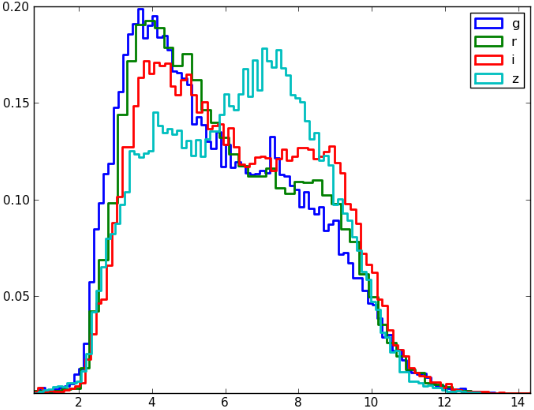


analysis courtesy **Augusto Ferrari**, Zoology Dept., Bioscience Institute, UFRGS.

Bimodality in concentration between ETG

SPIDER database
Early-type galaxies

Sersic index n



Costs I

Linux + Python + Scipy
300x300 pixels image

ACTION	DURATION
⋆ find object, retrieve data	.3 s
⋆ brightness profile with aberture photometry	1 s
⋆ fit brightness profile	0.5 s
⋆ moments calculation	0.1 s
• wavelet transform (6 scales)	3 s
total	5 s

Costs II

laptop @ home, using a single core
10^4 obj: 13h
10^5 obj: 5 days
10^6 obj: 2 months

laptop @ home, using 4 cores
10^4 obj: 3.5h
10^5 obj: 1.5 day
10^6 obj: 14 days

optimizing OpenMP: (L.Ferreira & F. Ferrari, **poster 50**, this conference)
10^6 obj: 1 day

Conclusions

- Hubble fork apply to local Universe
  - galaxies grow, merge, evolve
- two component in galaxies:
  - red, pressure dominated, concentrated component
  - blue, rotationi dominated, extended component
  - mass is determinant
- nuclear and global properties correlate → evolve together
- Sérsic parameters are **very important**
  they are **very difficult** to measure
- we need to classify (understand) galaxies with new parameters
  - CASGM system
  - Wavelet, moments, inform. entropy, ...
- new techniques
  - multivariate data analysis
  - cladistics, taxonomy, cluster

thanx