Automated Detection of Objects Based on Sérsic Profiles

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Introduction

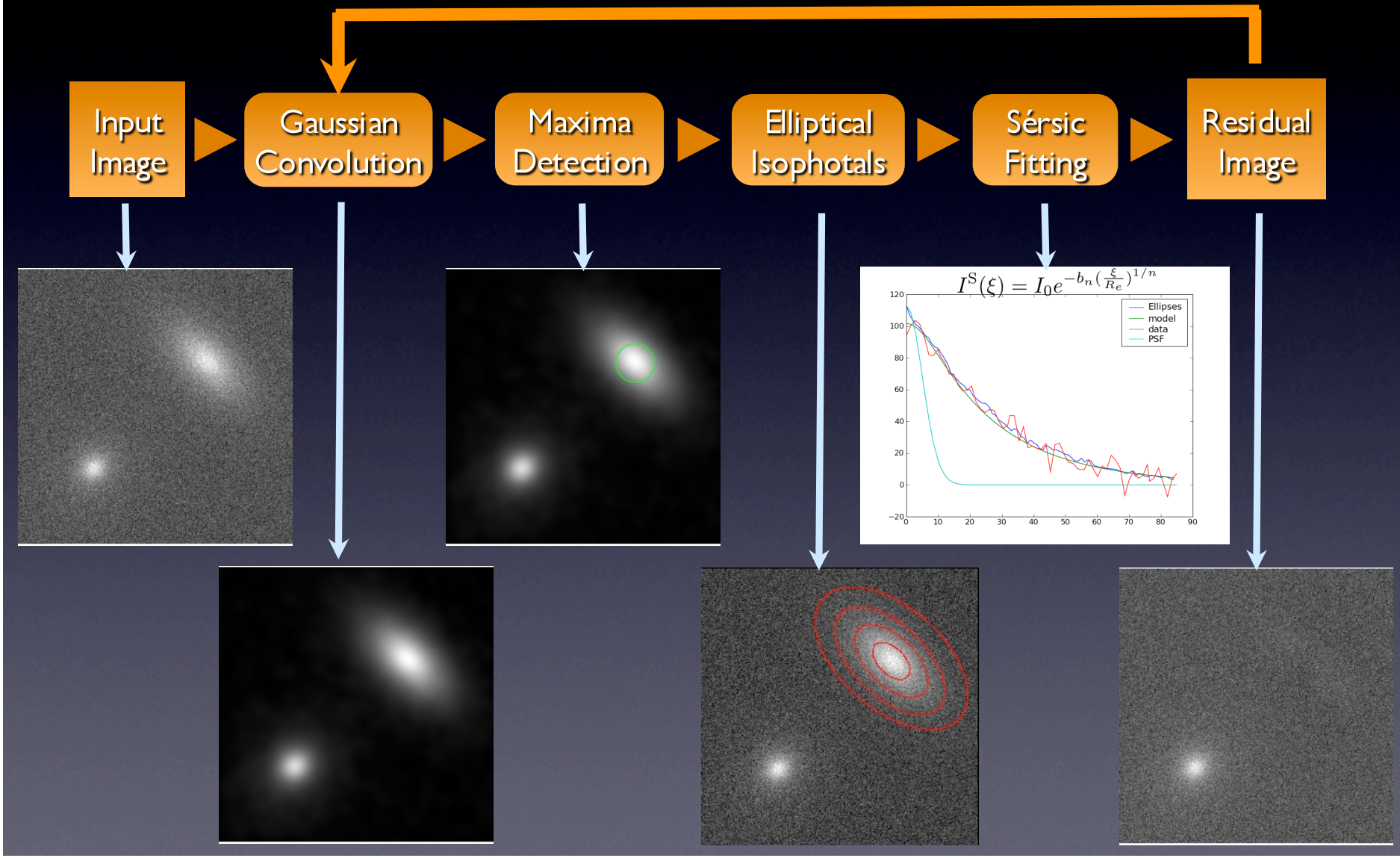
- Detection of objects inside astronomical images is not trivial
  - Background
  - PSF convolution
  - Noise
  - Deblending

$$D_i = (I * PSF)_i + b_i + \eta_i$$

Introduction

- DAOPHOT (Stetson, 1987)
- Source Extractor (Bertin & Arnouts, 1996)
- Multiscale Vision Model (Bijaoui & Rue, 1995)
- Uses of future large data-sets from next-generation surveys will benefit from a source extraction process which requires minimal a priori user input.

Modelling with Sersic Profiles

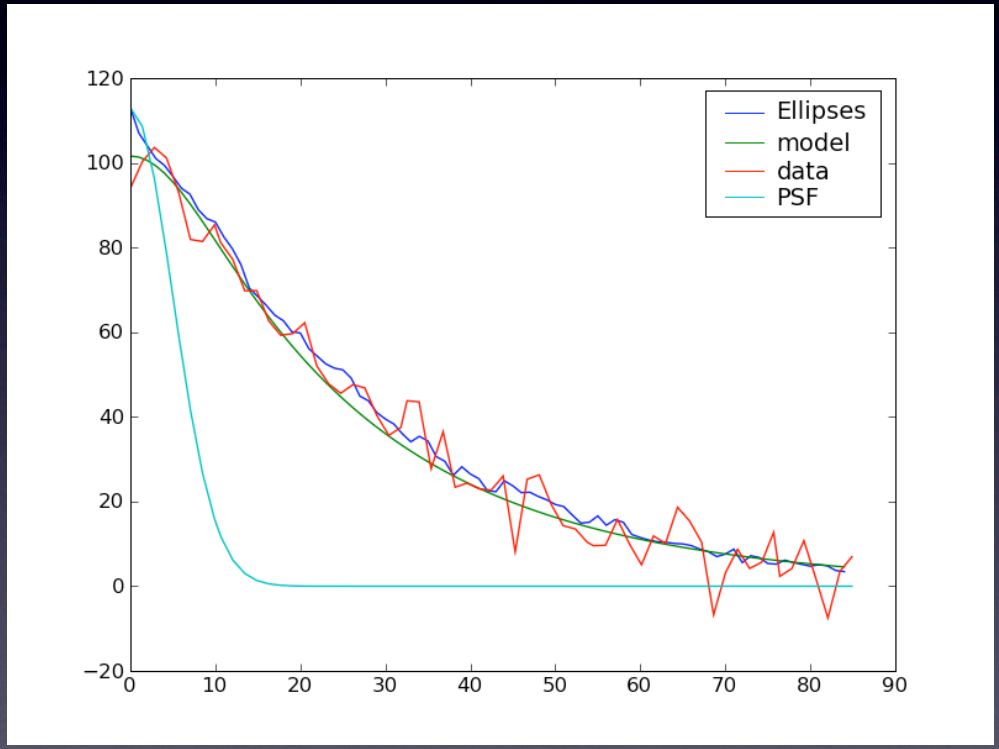


Modelling with Sersic Profiles

$$I^{\mathrm{S}}(\xi) = I_0 e^{-b_n(\frac{\xi}{R_e})^{1/n}}$$

$$\begin{aligned} x &= \xi \cos\theta \\ y &= \xi(1-\epsilon)\sin\theta \\ \xi &= \sqrt{x^2 + \frac{y^2}{1-\epsilon}} \end{aligned}$$

Modelling with Sersic Profiles



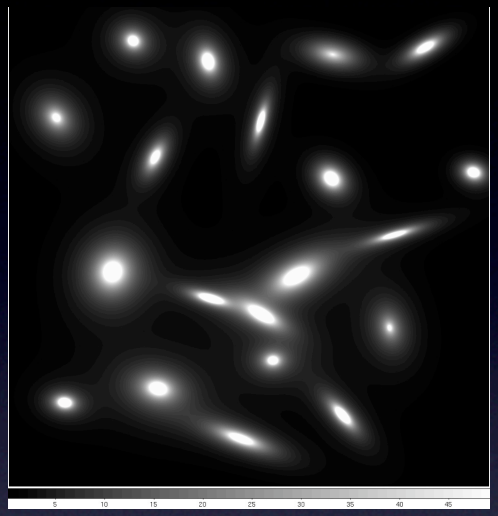
$$I^{\mathrm{S}}(\xi) = I_0 e^{-b_n(\frac{\xi}{R_e})^{1/n}}$$

Modelling with Sersic Profiles: Previous Approaches

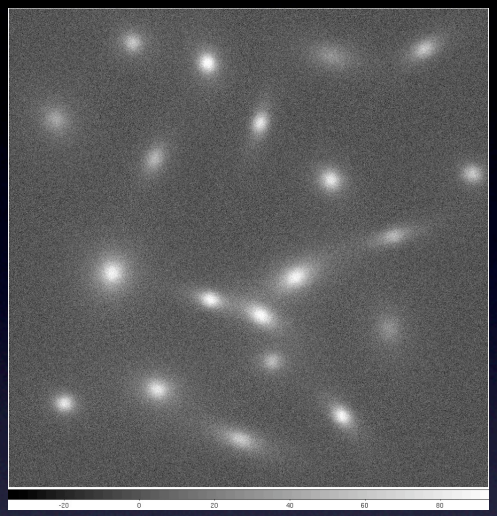
- 2D fitting algorithms:
  - GALFIT (Peng et al. 2002): Downhill gradient
  - GIM2D (Simard 1998): Metropolis
- Fit Sérsic profiles over circular annuli (Blanton et al. 2005).

Modelling with Sersic Profiles :

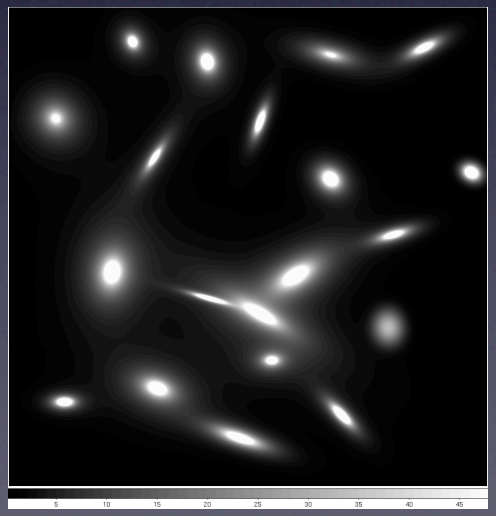
Results over simulations



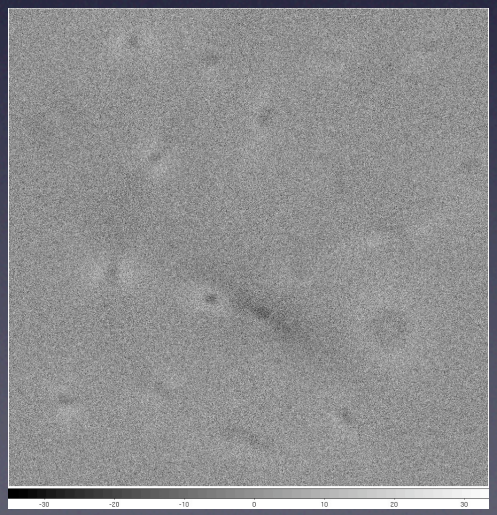
a



b



c



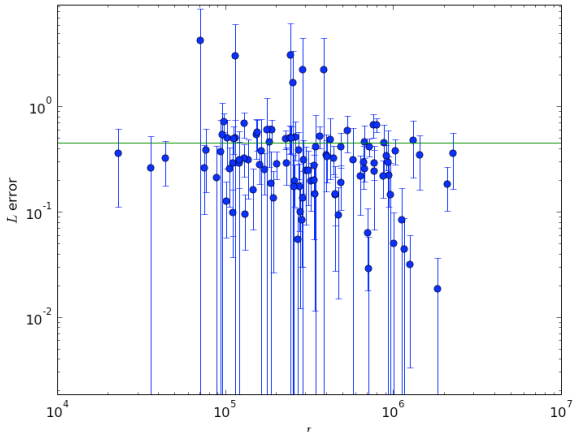
d

a) Original Profiles

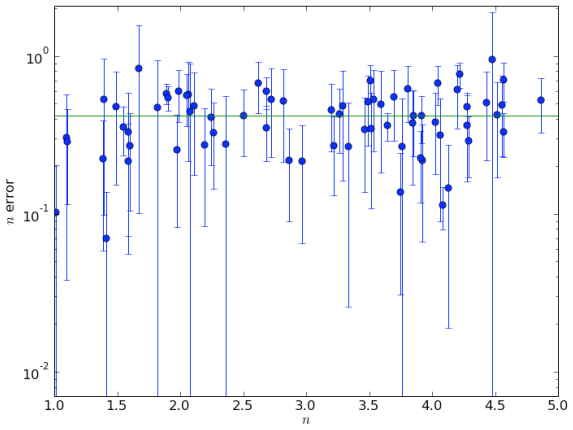
b) Mock image

c) Model

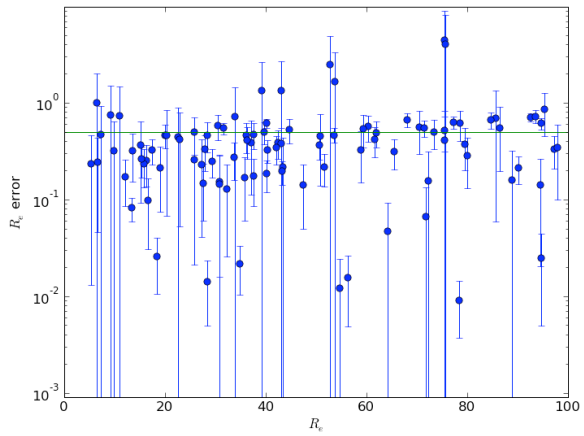
d) Residuals



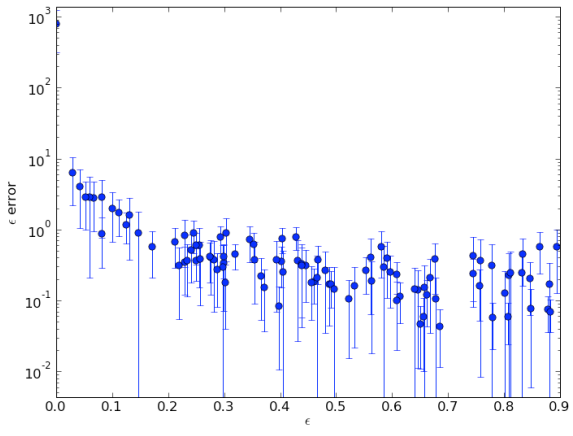
Total luminosity error.
Average error of 45.5%



Sérsic index error.
Average error of 42%



Effective radius error.
Average error of 49.4%



Ellipticity error. As the ellipticity is close to cero, the error increases.

Errors calculated as the absolute difference of the true value and the obtained value divided by the true value. Error bars show standard deviation over 10 values.

While our image residuals are very small, the fitted Sérsic parameters are only accurate to with 50%, consistent with the errors from GIM2D and GALFIT (Haussler et al. 2007) and the ones from Blanton et al. (2005), calculated over circular annuli.

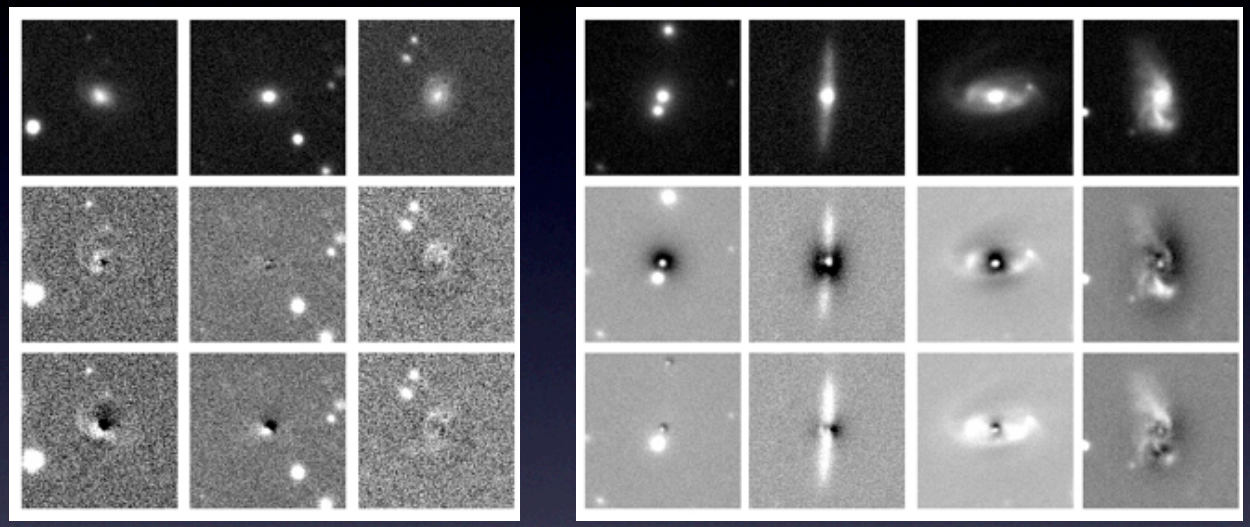
Modelling with Sersic Profiles :

Results Over Real Images

a)

b)

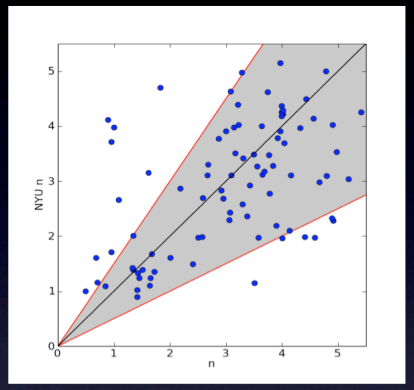
c)



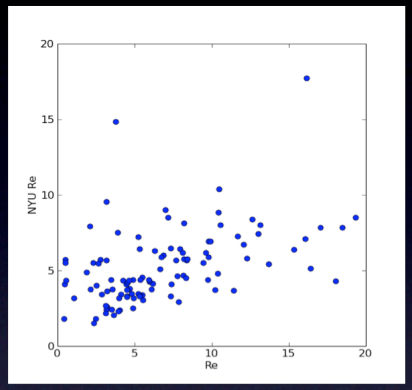
a) Original data objects.
b) Residuals obtained by our method (elliptical isophotal profiles)
c) Residuals obtained with Blanton et al. (2005) profiles (circular annuli)

Modelling with Sersic Profiles :

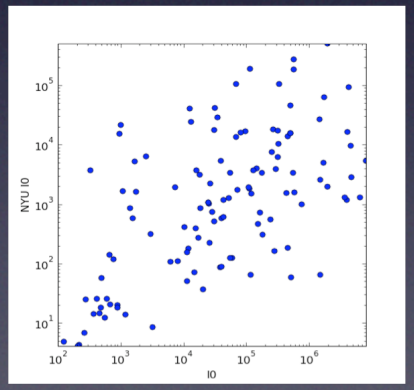
Results Over Real Images



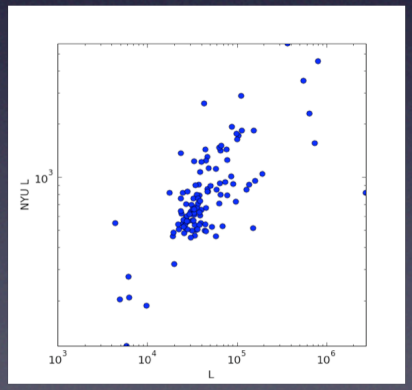
(a) Sersic index. The black line is a 1 to 1 relation. Red lines represent errors as described in Cabrera et al. (2010)



(b) Effective Radius. Values by Blanton et al. underestimate Re due to their circular annulus profiles.



(c) Central Intensity



(d) Integrated luminosity

Detected parameters vs Blanton et al. (2005) Sérsic parameters. Spearman ranked correlation test gives that the probabilities of variables to be correlated is grater than a 99.9%, or 3.7 sigma.

Conclusions

Simulations

• We have developed an automated method for detection of galaxies in astronomical images.

• While our image residuals over simulations are very small, the fitted Sérsic parameters are only accurate to with 50%, consistent with the errors from GIM2D and GALFIT (Haussler et al. 2007).

• The combination of the high quality of the fits and the large parameter errors indicates that there are degeneracies in the model parameters.

SDSS Data

• Our Sérsic indices, calculated over elliptical isophotal profiles, match the ones from Blanton et al. (2005), calculated over circular annuli, within the error bars obtained in our simulations.

• Spearman ranked correlations show that the probabilities of variables to be correlated are higher than a 99.9%

• New galaxy models may be added in order to take into account bulge/disk model profiles.

• Our next goal is to run our method over the all the SLOAN images using the UM and CMM HPCs.

• Need for structure detection.