

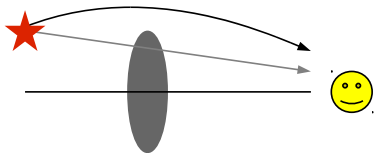
# Multi-Epoch Galaxy Modeling

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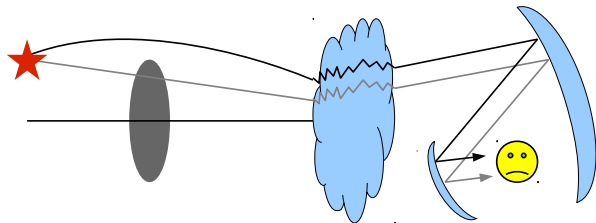
Cosmology in Northern California 2010

# Gravitational lensing: the dirty truth.



- ▶ Mass deflects light - we can infer mass!

# Gravitational lensing: the dirty truth.



- ▶ Mass deflects light - we can infer mass!
- ▶ Atmosphere and telescope also deflect light, but we can infer the properties of the atmosphere and telescope from stars.

# Defining the shear measurement problem

- ▶ We have many exposures of each patch of sky, with different orientations and observing conditions. We might even want to combine observations from multiple telescopes.
- ▶ For each exposure, we have a model of the PSF and the geometric distortion.
- ▶ We want to measure an ellipticity for each galaxy, in a way that is
  1. unbiased,
  2. fast,
  3. and accurate(in that order of importance).

# Handling multi-epoch data: other options

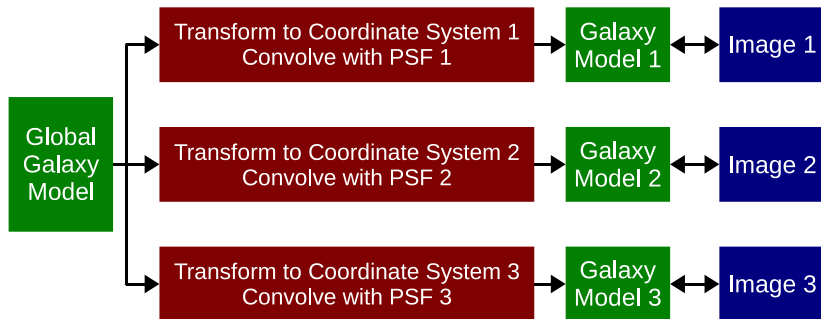
	supports non-modeling analyses	works in short-exposure limit	optimal PSF weights	supports calibration marginalization	exact treatment of per-pixel errors
<b>analysis on coadd</b>	✓	✓	?*	✗	✗
<b>analysis on exposures</b>	✓	✗	✓	✓	✓
<b>simultaneous multifit</b>	✗	✓	✓	✓	✓
<b>serial likelihood sampling</b>	✗	✓**	✓	✓	✓

\* requires special coadd algorithm (Kaiser), which assumes stationary noise, non-spatially varying PSF, no missing pixels

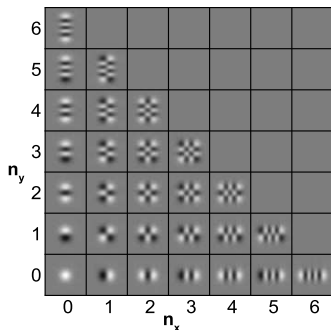
\*\* only optimal if there's no galaxy parameter marginalization before combining likelihoods (e.g. LENSFIT, Miller et al 2007)

# Multifit

- ▶ Fit a transformed galaxy to each image, convolving with the PSF for that image.
- ▶ It's crucial to fit *simultaneously*, or the fit isn't robust.



# Introduction to shapelets



$$\Phi_{n_x n_y}(x, y) = \frac{H_{n_x}(\mu) H_{n_y}(\nu) e^{-\frac{\mu^2 + \nu^2}{2}}}{2^{n_x + n_y} \beta \sqrt{\pi n_x! n_y!}}$$

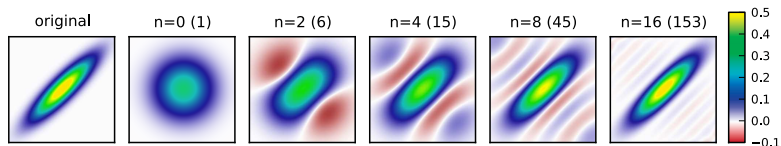
$$\mu = \frac{x - x_0}{\beta}$$

$$\nu = \frac{y - y_0}{\beta}$$

- ▶ Eigenfunctions of the 2-d quantum harmonic oscillator (orthonormal, complete).
- ▶ Zeroth order is a circular Gaussian.
- ▶ *Analytic convolution!*

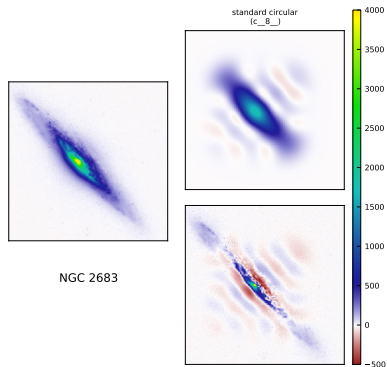
Figures from *Massey & Refregier (2005)*

# Shapelets are broken at high ellipticity



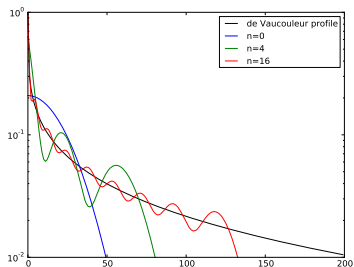
elliptical gaussian ( $q = \frac{1}{4}$ )  $\uparrow$

edge-on spiral  $\Rightarrow$

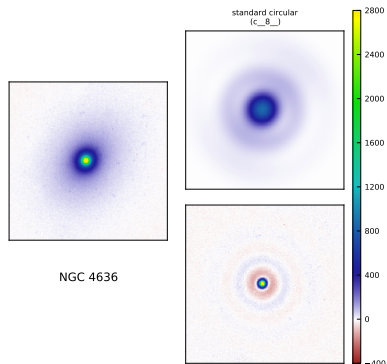




# Shapelets are broken at high Sérsic index



de Vaucouleur profile ( $n = 4$ )



elliptical galaxy

# Elliptical Shapelets

We can make a shapelet expansion around an elliptical gaussian by transforming the coordinate grid (this actually works for any 2-d function):

$$\Phi_{\mathbf{n}}(\mathbf{x}|\mathbf{e}) = \Phi_{\mathbf{n}}(\mathbf{S}_e^{-1}\mathbf{x})$$
$$\mathbf{S}_e = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} a & 0 \\ 0 & b \end{bmatrix}$$

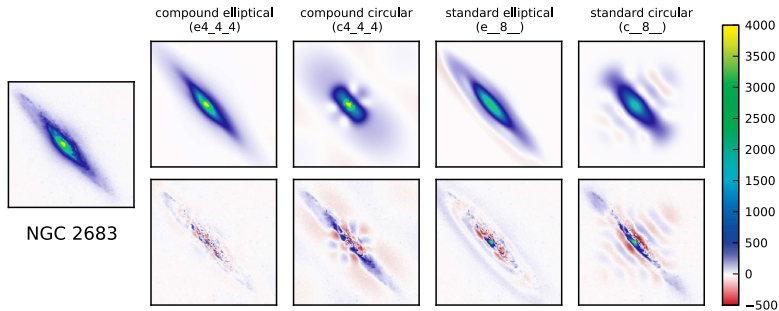
- ▶ The most common shapelet convolution relation (Refregier and Bacon 2003) requires galaxy and PSF to have the same ellipticity
- ▶ Standard procedure is to use an approximate shear operator on the galaxy or PSF to allow its use.
- ▶ It's important to use an exact elliptical convolution relation (Hirata and Seljak (2003) for Gauss-Laguerre, or Bosch (2010) for Gauss-Hermite).

# Compound Shapelets

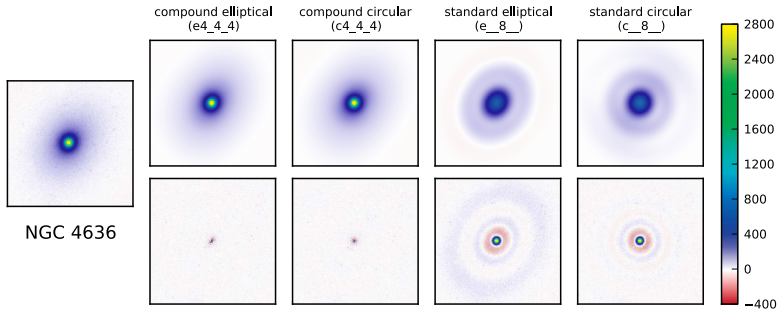
Simple idea: combine multiple low-order shapelet expansions with different radii into a single basis.

- ▶ Shapelet functions with small radii model the core.
- ▶ Shapelet functions with large radii model the wings.
- ▶ Result is better than a single high-order expansion with the same number of basis functions.

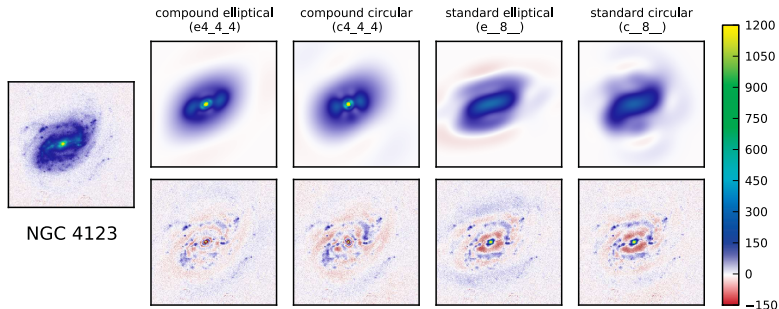
# Results



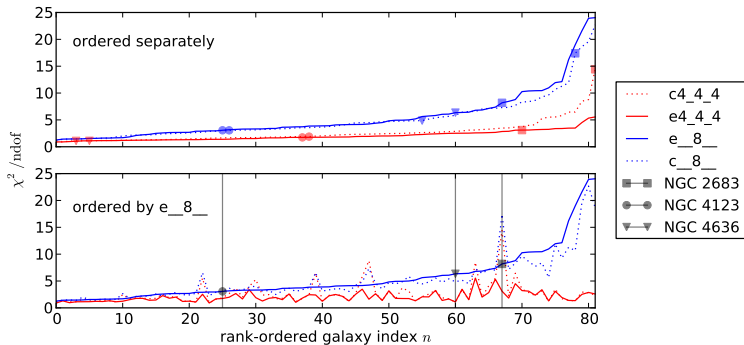
# Results



# Results



# Results



# Training an “eigenmorphology” basis

Given a high S/N, well-resolved sample of galaxies, and an initial compound basis:

1. Fit a compound elliptical shapelet model to each galaxy, obtaining a vector of coefficients  $\mathbf{a}_i$  and Fisher information matrix  $\mathbf{F}_i$  for each galaxy  $i$ .
2. Optimize

$$\min_{\mathbf{M}} \sum_i \left[ (\mathbf{a}_i - \mathbf{M}\mathbf{b}_i)^T \mathbf{F}_i (\mathbf{a}_i - \mathbf{M}\mathbf{b}_i) + \ln \left| \mathbf{M}^T \mathbf{F}_i \mathbf{M} \right| \right],$$
$$\mathbf{b}_i \equiv \left( \mathbf{M}^T \mathbf{F}_i \mathbf{M} \right)^{-1} \mathbf{M}^T \mathbf{F}_i \mathbf{a}_i$$

subject to the constraint  $\mathbf{M}^T \mathbf{M} = \mathbf{I}$ , one column at a time.

3.  $\mathbf{M}$  maps the original basis to a new basis, ordered such that the first  $n$  basis functions are the  $n$  most important linear combinations of original basis functions.



# Working with a compound basis

## It's easy to...

- ▶ reorthogonalize it
- ▶ convolve it with a PSF expressed in shapelets
- ▶ evaluate it on a pixelized grid
- ▶ apply a linear coordinate transform
- ▶ project out basis functions that are degenerate with the ellipse parameters.

## It's hard to...

- ▶ ensure the model has positive flux where there's no data
- ▶ determine an optimal set of shapelet radii and orders
- ▶ interpret best-fit basis coefficients

# Summary and Future Work

## What you've heard

- ▶ Given a good model, simultaneous fitting is the safest way to analyze data from multiple exposures; be careful with coadds!
- ▶ Compound elliptical shapelet models are perfect for simultaneous fitting.

## On the horizon

- ▶ testing the eigenmorphology metric
- ▶ morphological classification
- ▶ multi-band photometry
- ▶ deblending dense fields