

# Three data analysis problems

Andreas Zezas

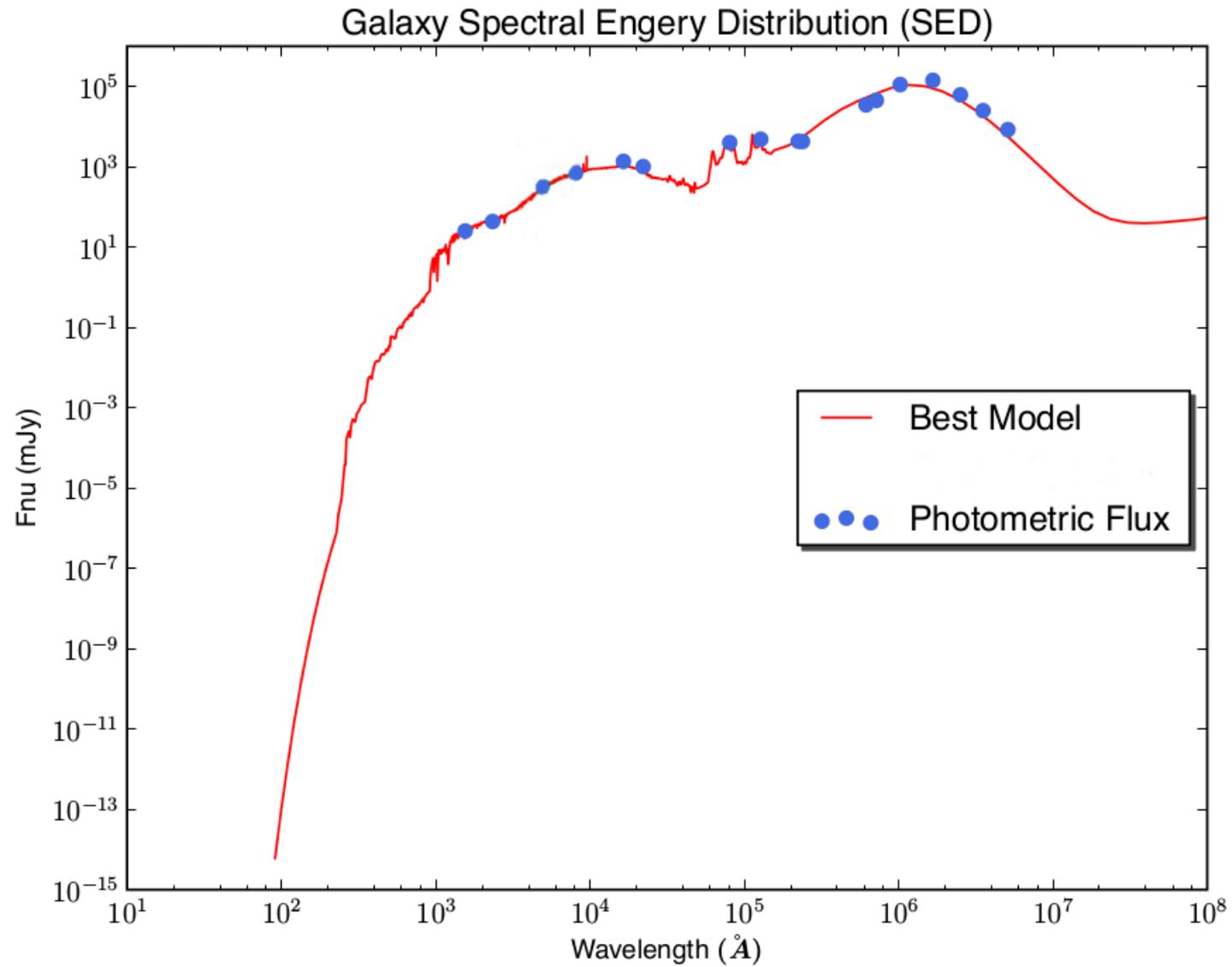
*University of Crete*

*CfA*

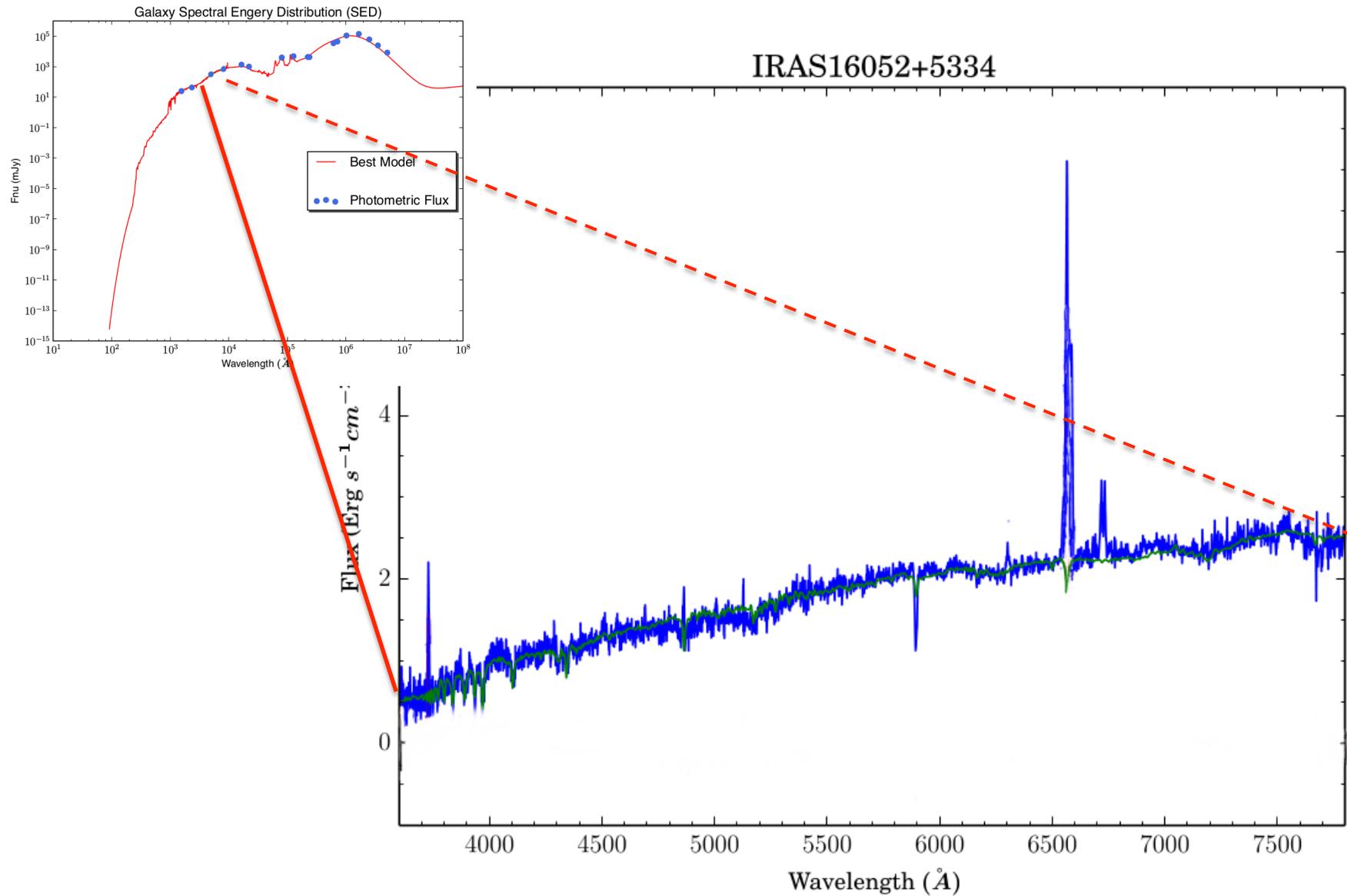
## Two types of problems:

- Fitting
- Source Classification

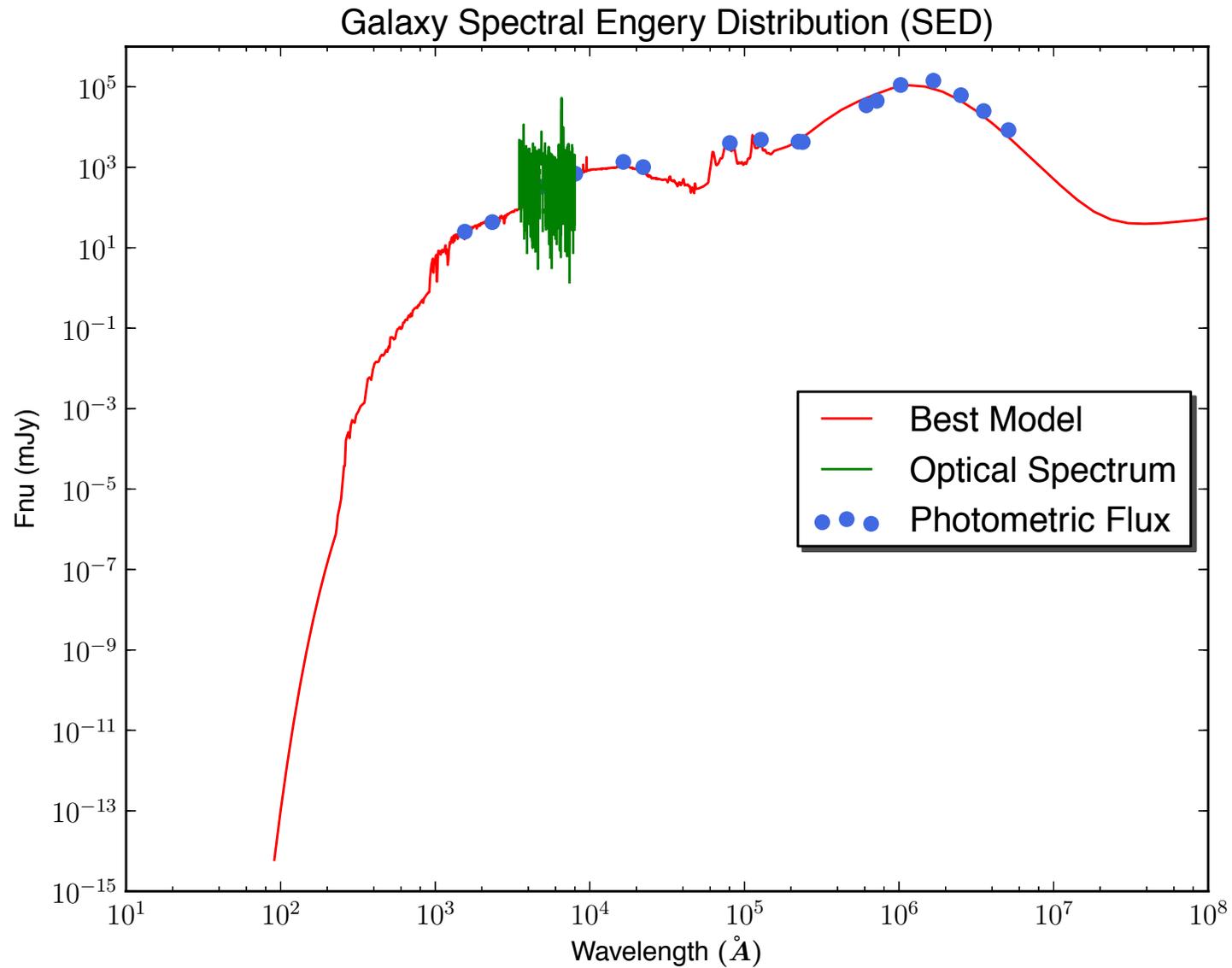
# Fitting: complex datasets



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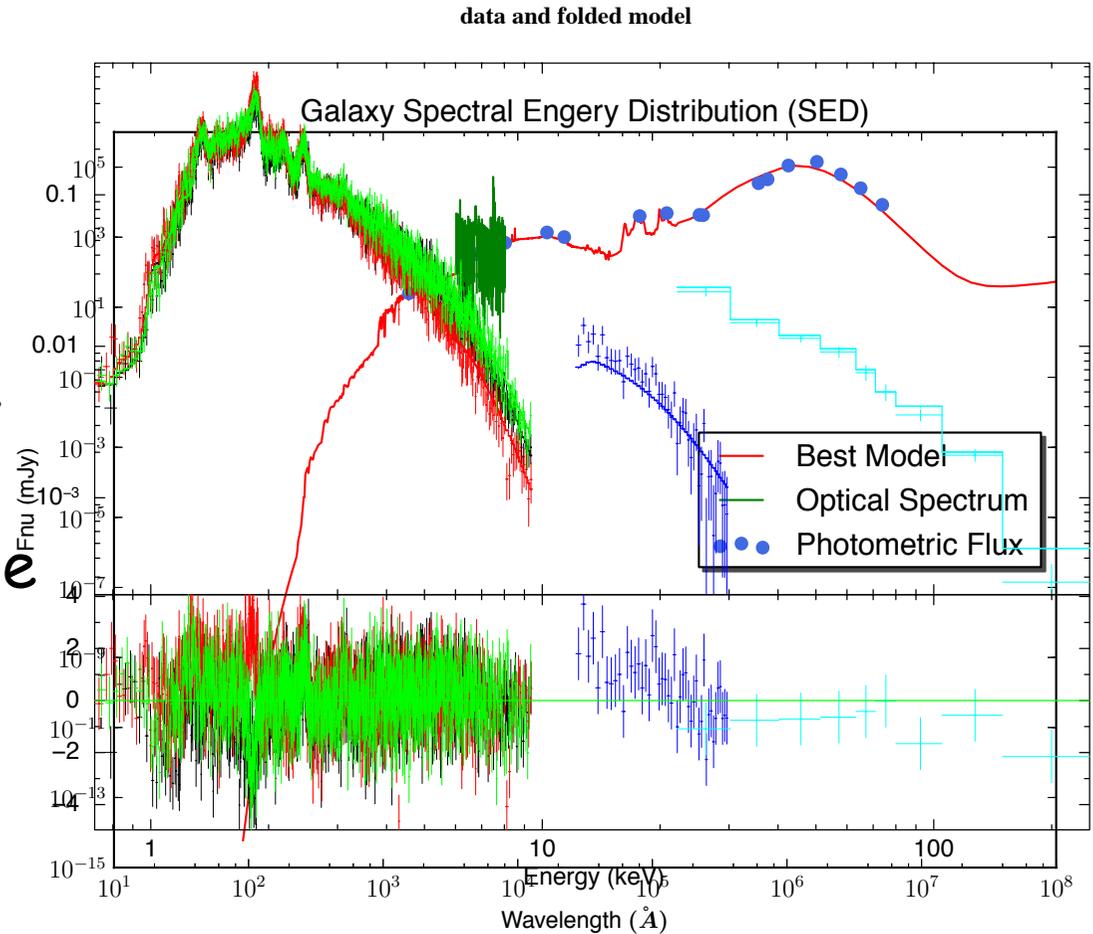


# Fitting: complex datasets

Iterative fitting may work, but it is inefficient and confidence intervals on parameters not reliable

How do we fit jointly the two datasets ?

VERY common problem !



# Problem 2

Model selection in  
2D fits of images

# A primer on galaxy morphology

Three components:

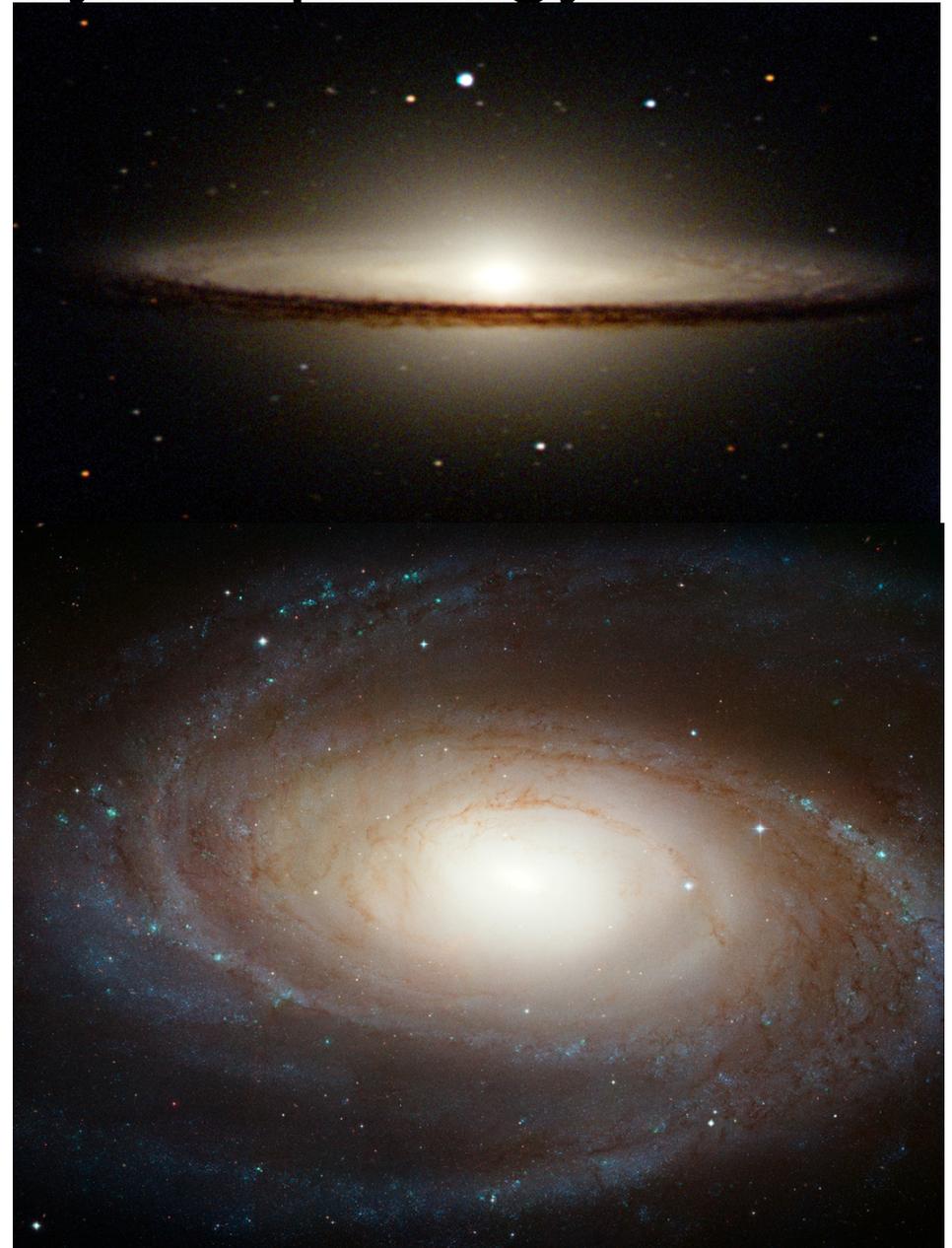
spheroidal

$$I(R) = I_e \exp \left[ -7.67 \left[ \left( \frac{R}{R_e} \right)^{1/4} - 1 \right] \right]$$

exponential disk

$$I(R) = I_0 \exp \left( -\frac{r}{r_h} \right)$$

and nuclear point source (PSF)



# Fitting: The method

Use a generalized model

$$I(R) = I_e \exp \left[ -k \left[ \left( \frac{R}{R_e} \right)^{1/n} - 1 \right] \right] \quad \begin{array}{l} n=4 : \text{spheroidal} \\ n=1 : \text{disk} \end{array}$$

Add other (or alternative) models as needed

Add blurring by PSF

Do  $\chi^2$  fit (e.g. Peng et al., 2002)

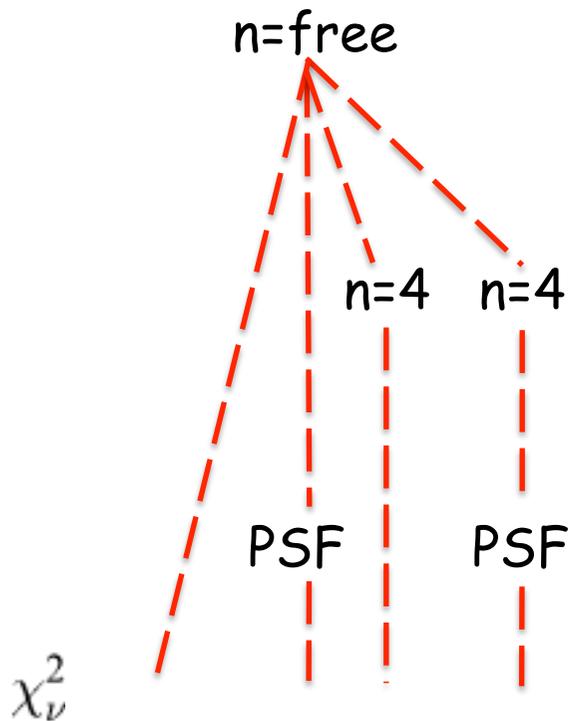
$$\chi^2 = \frac{1}{N_{\text{dof}}} \sum_{x=1}^{nx} \sum_{y=1}^{ny} \frac{(\text{flux}_{x,y} - \text{model}_{x,y})^2}{\sigma_{x,y}^2}$$

$$\text{model}_{x,y} = \sum_{\nu=1}^{nf} f_{\nu,x,y}(\alpha_1 \dots \alpha_n)$$

# Fitting: The method

Typical model tree

$$I(R) = I_e \exp \left[ -k \left[ \left( \frac{R}{R_e} \right)^{1/n} - 1 \right] \right]$$



# Fitting: Discriminating between models

Generally  $\chi^2$  works

BUT:

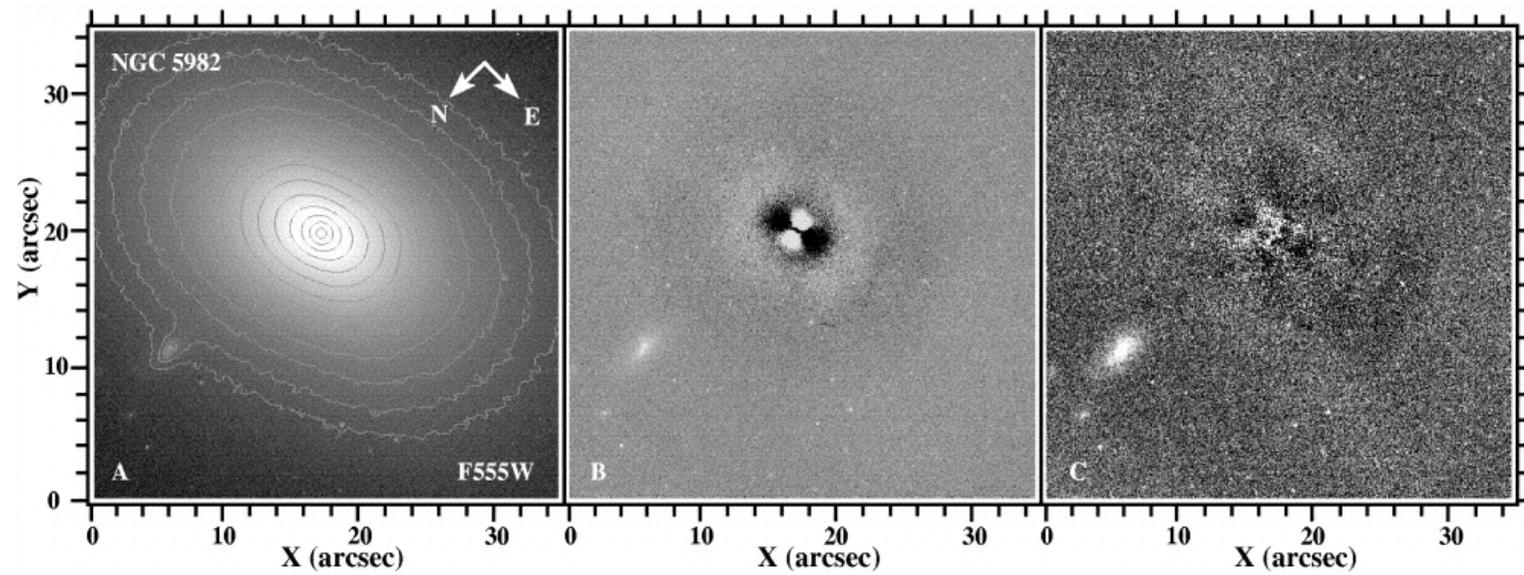
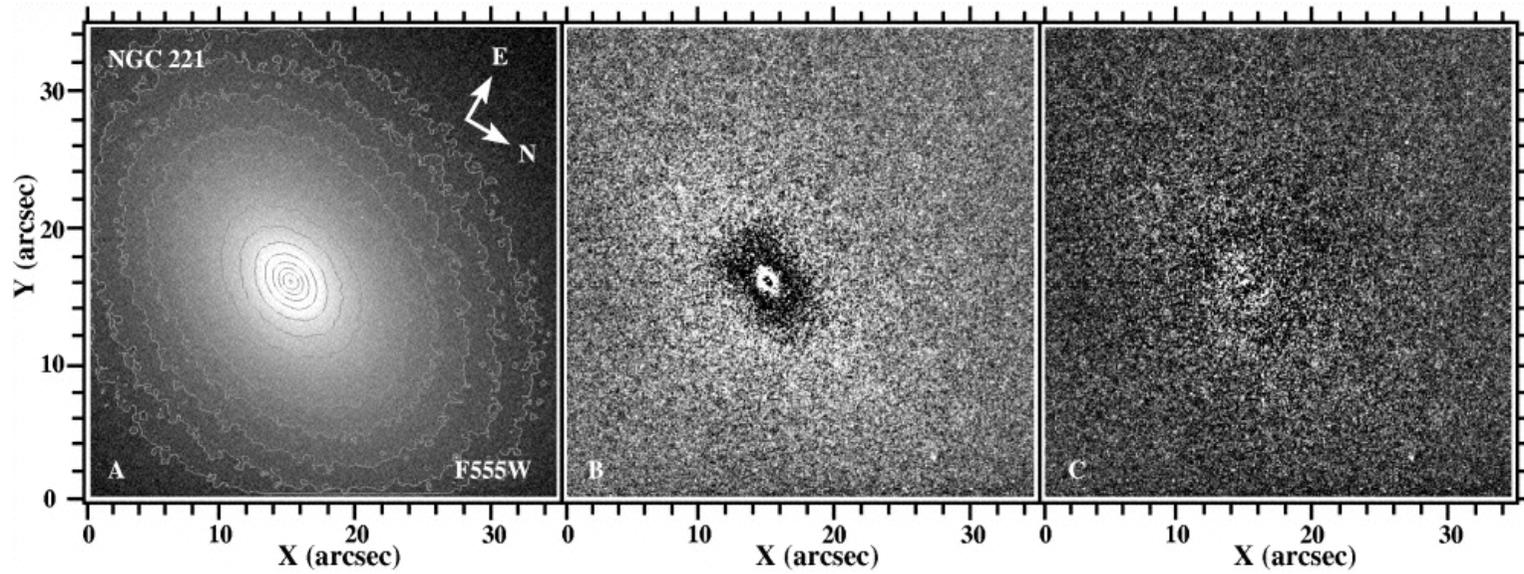
Combinations of different models may give similar  $\chi^2$

How to select the best model ?

Models not nested: cannot use standard methods

Look at the residuals

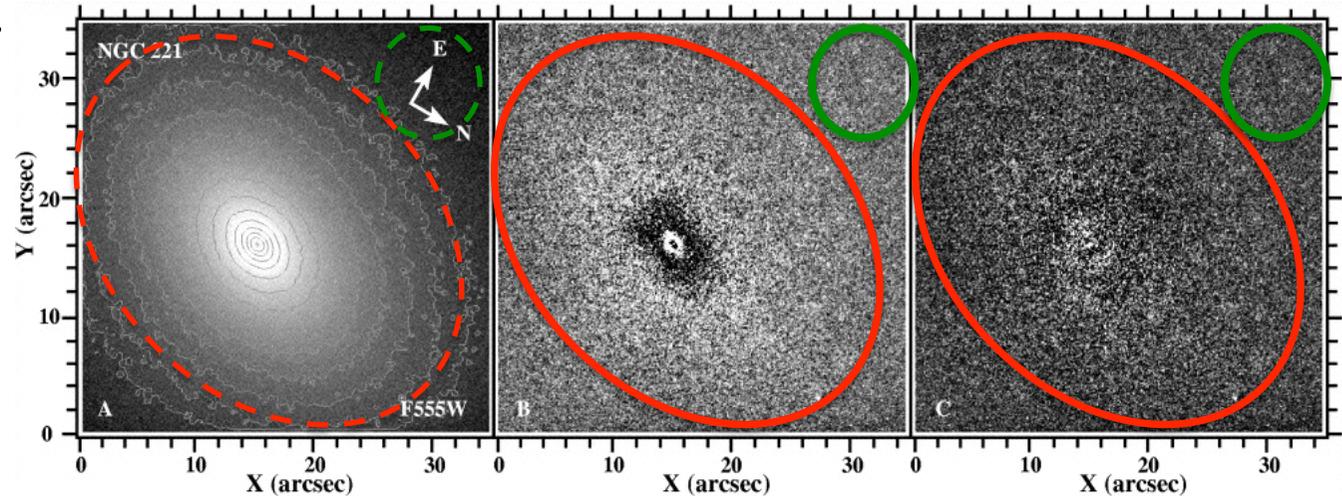
# Fitting: Discriminating between models



# Fitting: Discriminating between models

Excess variance

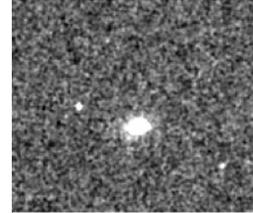
$$\sigma_{XS}^2 = \sigma_{obj}^2 - \sigma_{sky}^2$$



Best fitting model among least  $\chi^2$  models  
the one that has the lowest exc. variance

# Fitting: Examples

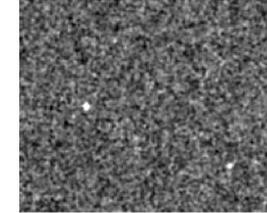
DATA



MODEL

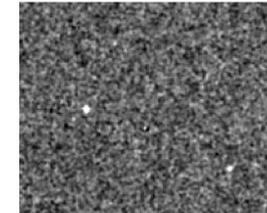
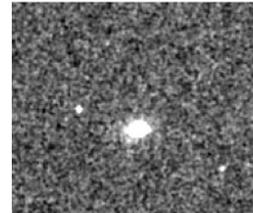


RESIDUALS

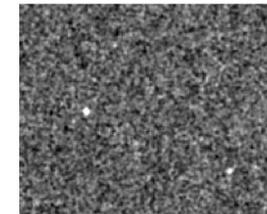
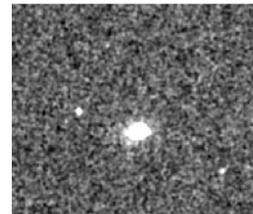


Sérsic

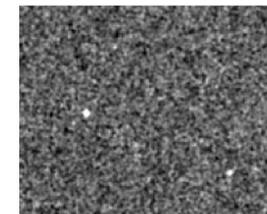
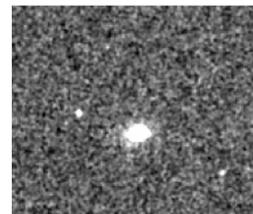
Model	$\chi^2_\nu$	$\sigma^2_{XS}$
(1)	(2)	(3)
Sérsic	1.107	1.722(0.120)
Sérsic + psfAgn	1.107	1.657(0.118)
Sérsic + exDisk	1.107	1.770(0.121)
Sérsic + psfAgn + exDisk	1.106	1.472(0.113)



Sérsic + psfAgn



Sérsic + exDisk



Sérsic + psfAgn + exDisk

Bonfini et al. in prep.

# Fitting: Problems

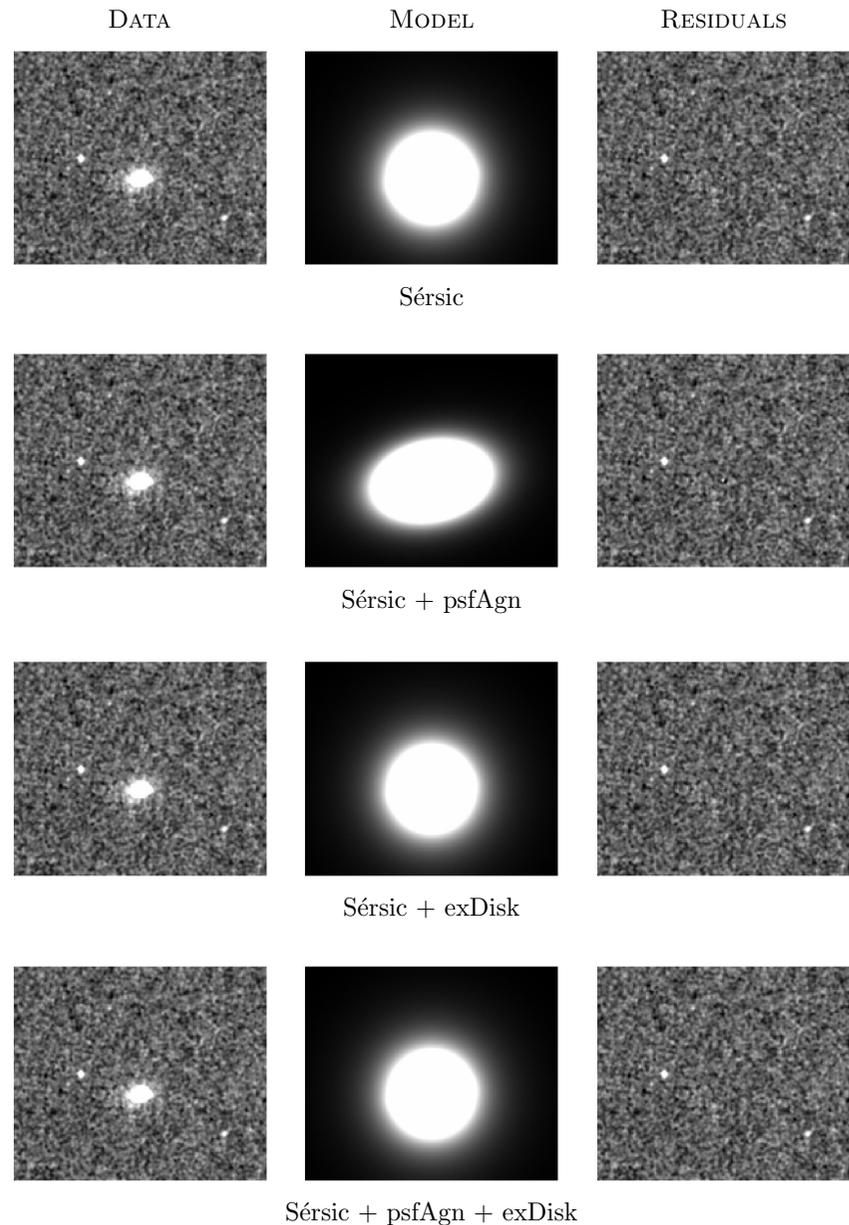
However, method not ideal:

It is not calibrated

Cannot give significance

Fitting process  
computationally intensive

Require an alternative,  
robust, fast, method



# Problem 3

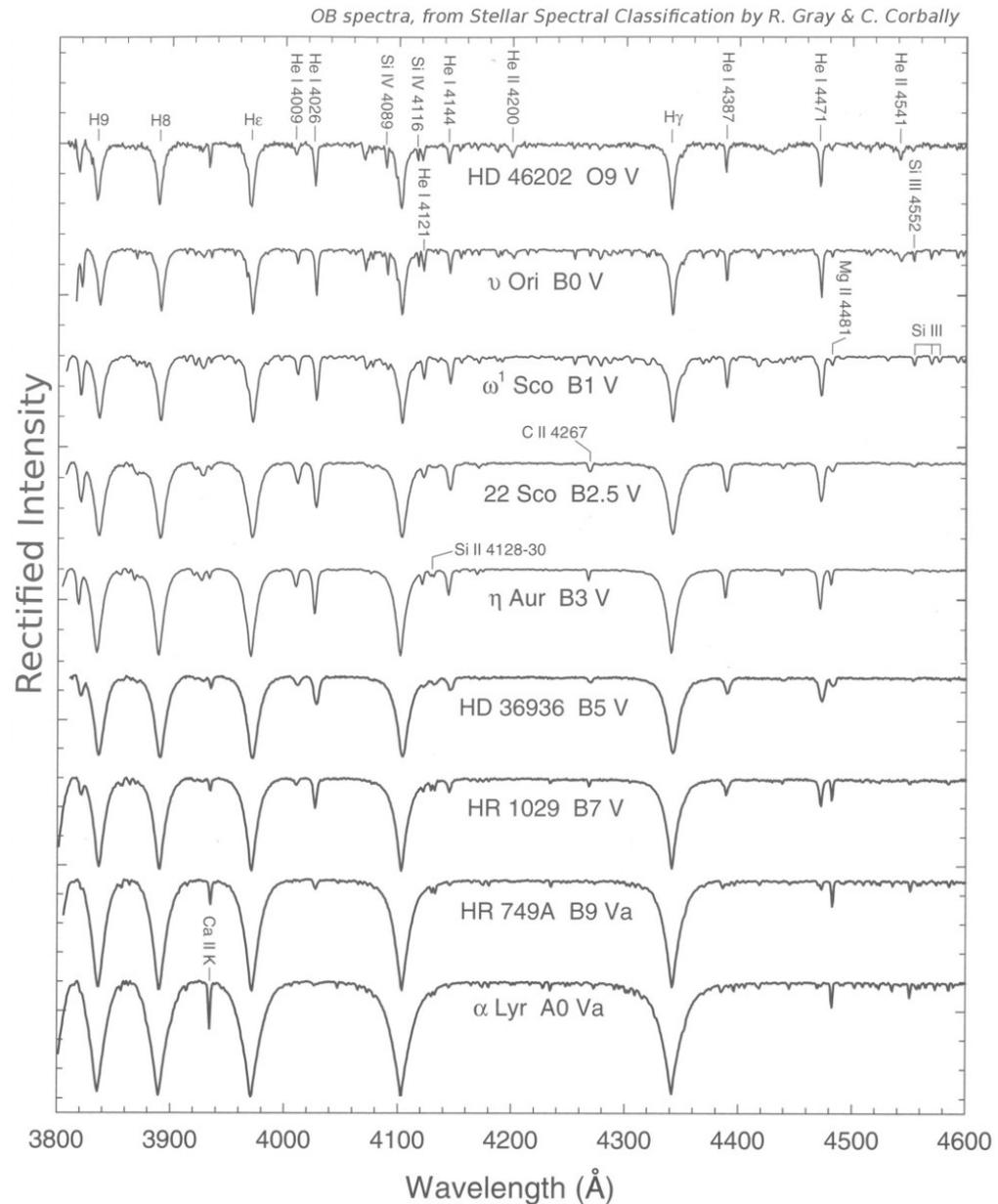
## Source Classification

### (a) Stars

# Classifying stars

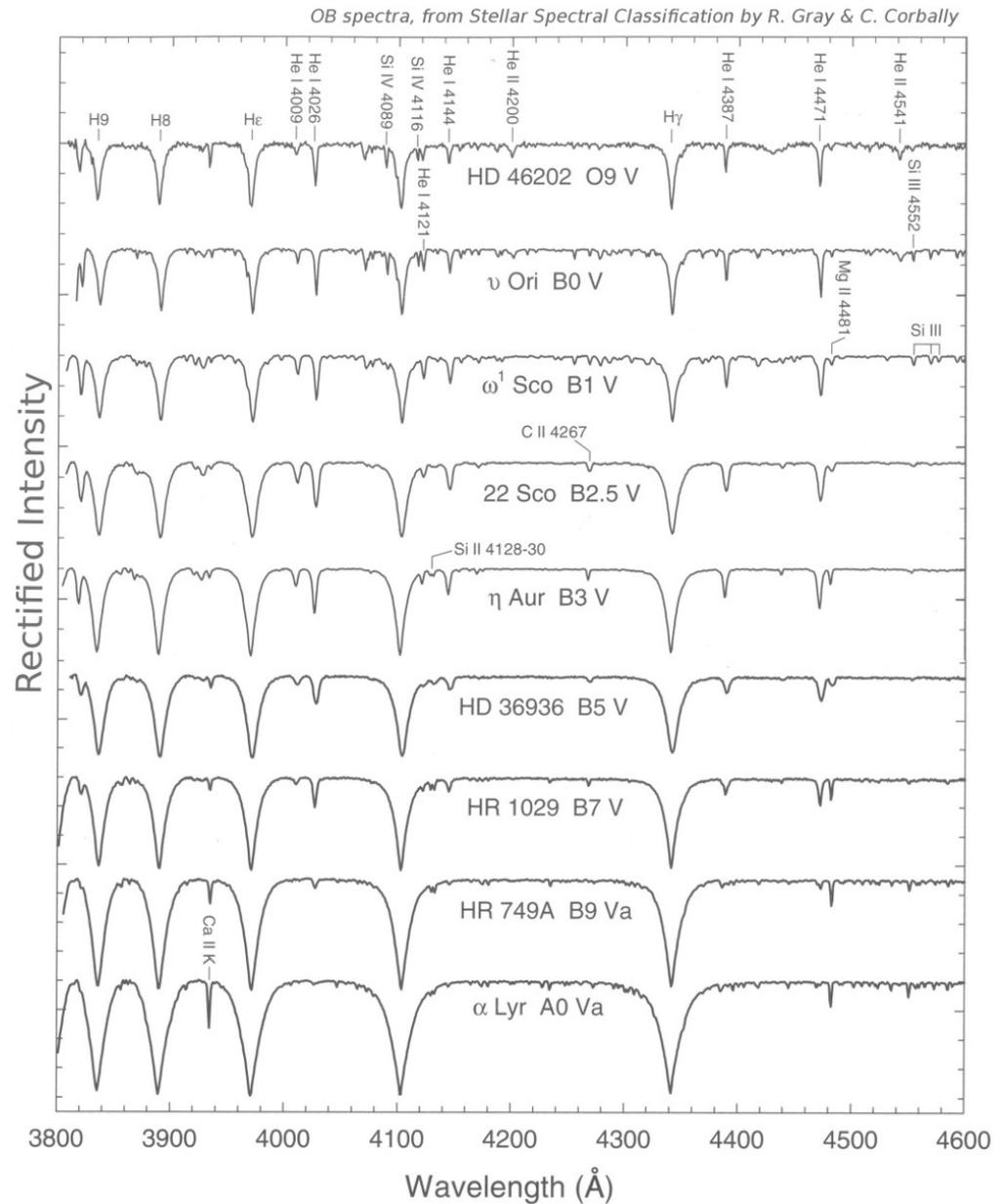
Relative strength of lines discriminates between different types of stars

Currently done "by eye"  
or  
by cross-correlation analysis

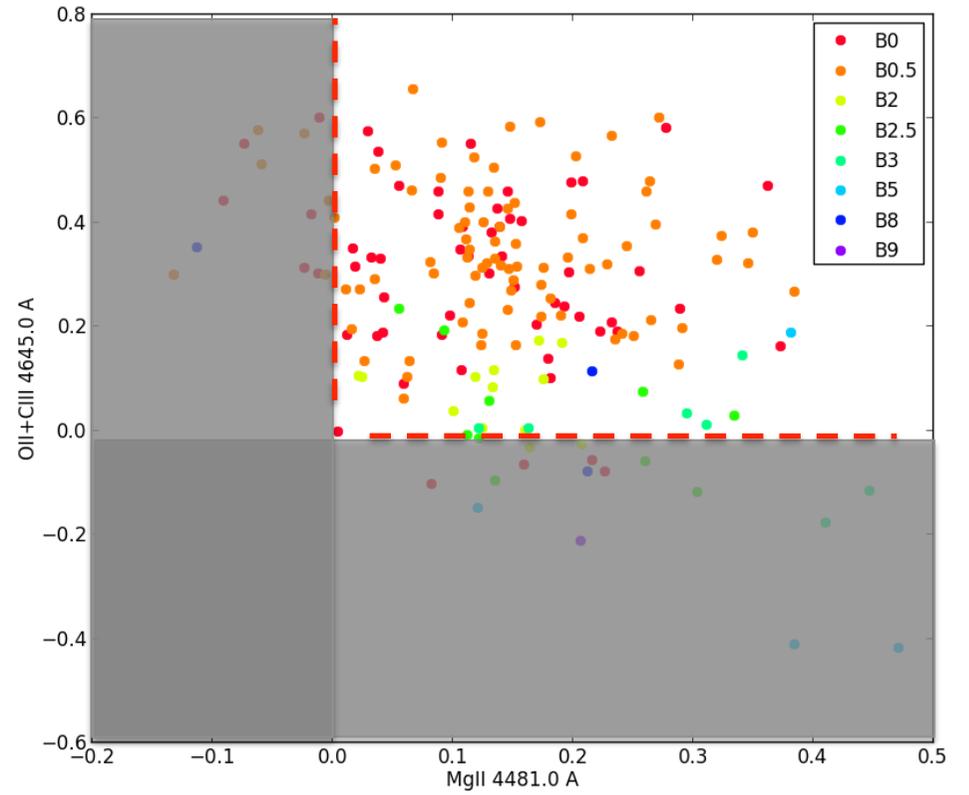
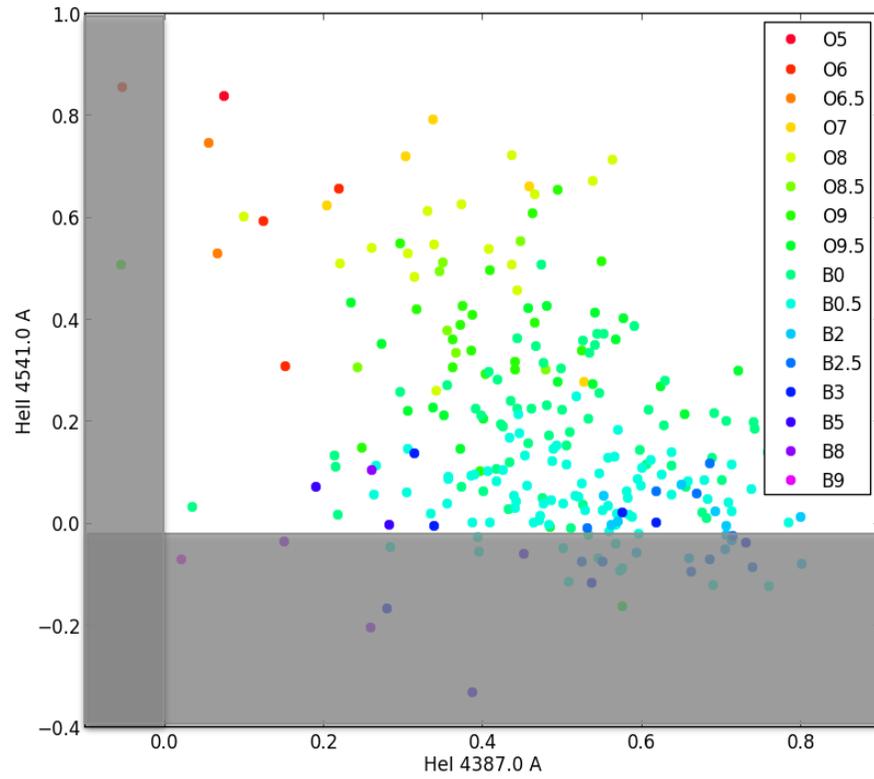


# Classifying stars

Would like to define a quantitative scheme based on strength of different lines.



# Classifying stars

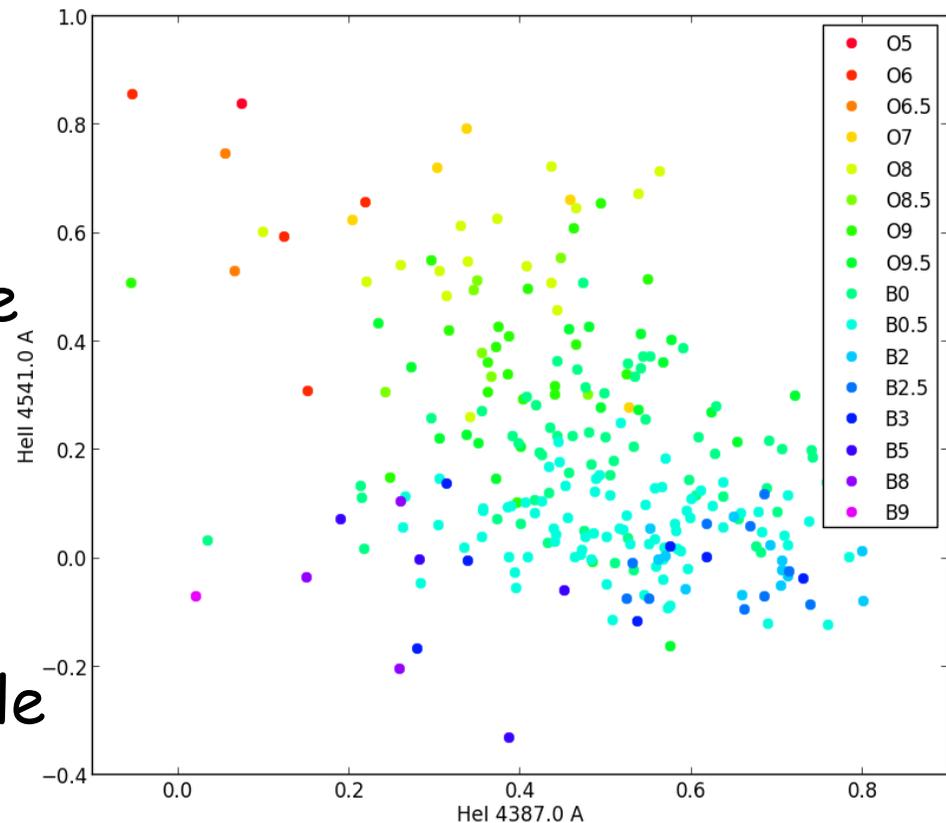


Maravelias et al. in prep.

# Classifying stars

Not simple....

- Multi-parameter space
- Degeneracies in parts of the parameter space
- Sparse sampling
- Continuous distribution of parameters in training sample (cannot use clustering)
- Uncertainties and intrinsic variance in training sample

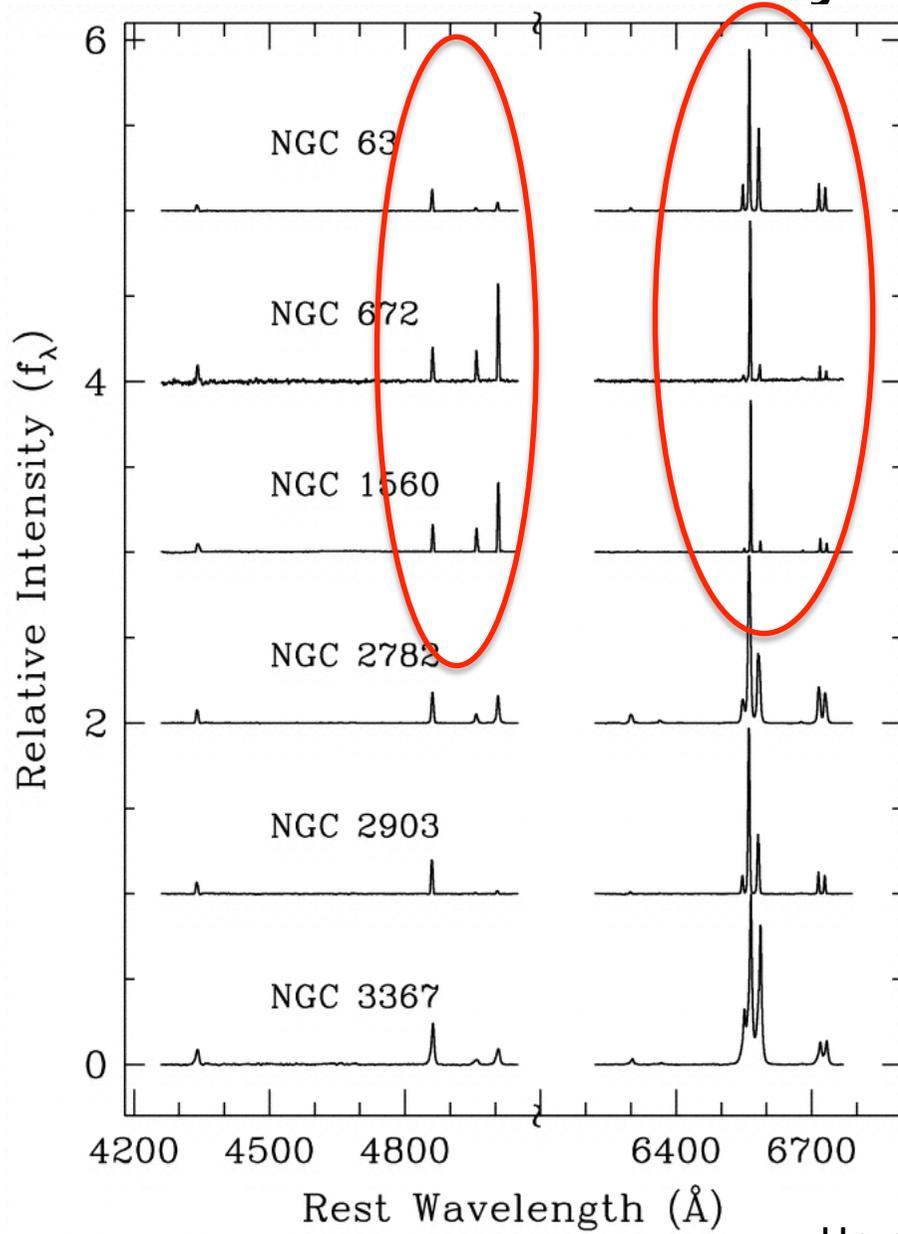


# Problem 3

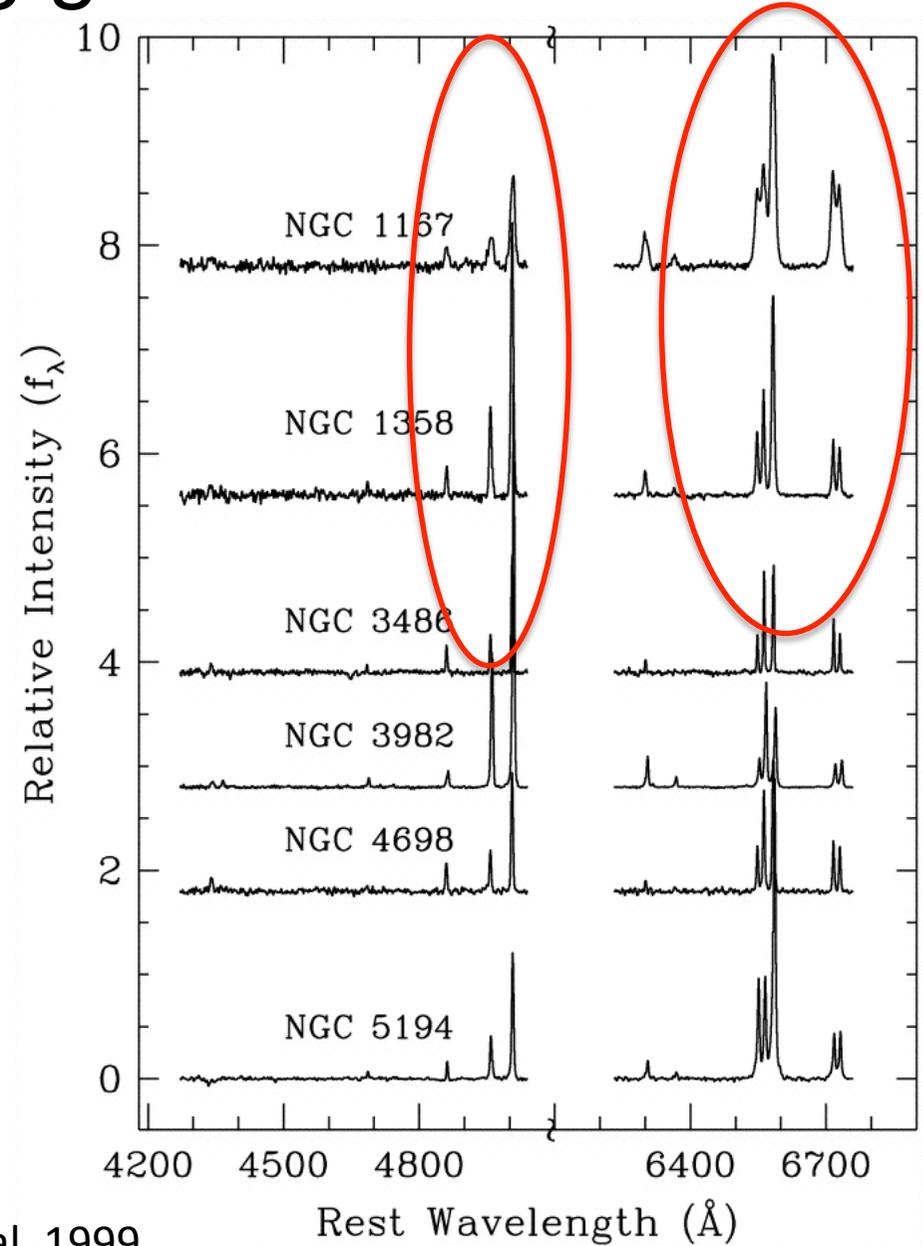
## Source Classification

### (b) Galaxies

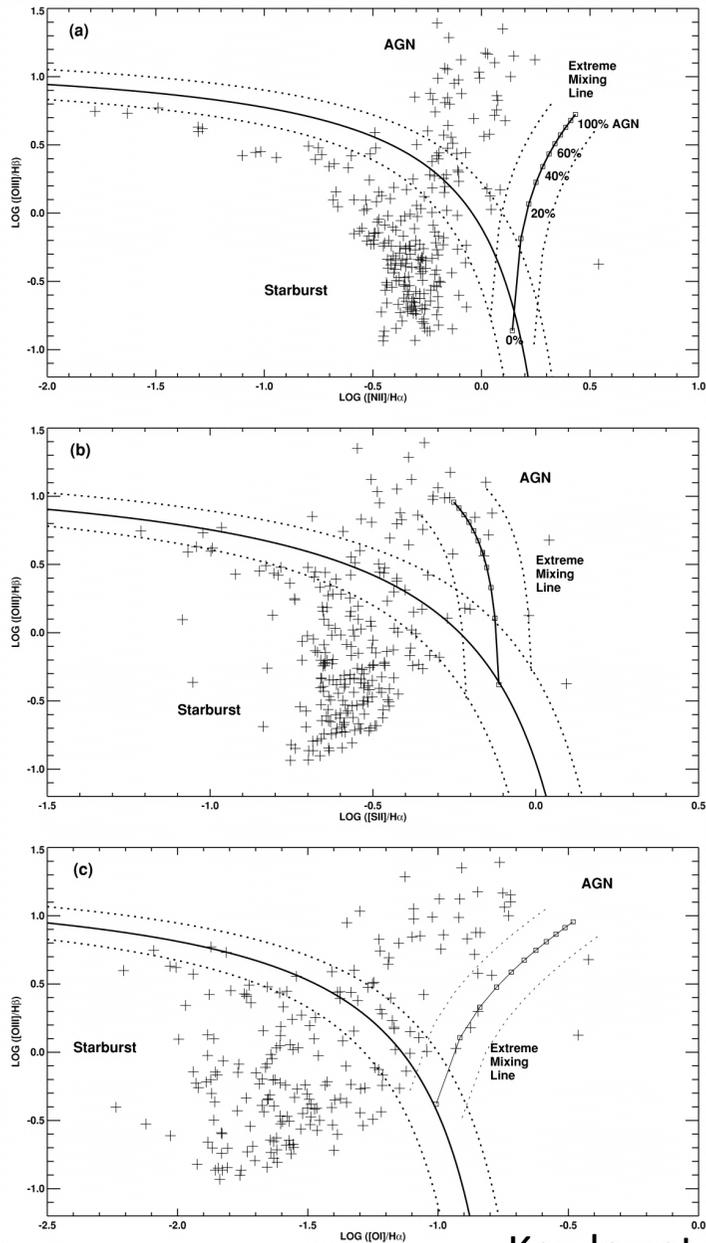
# Classifying galaxies



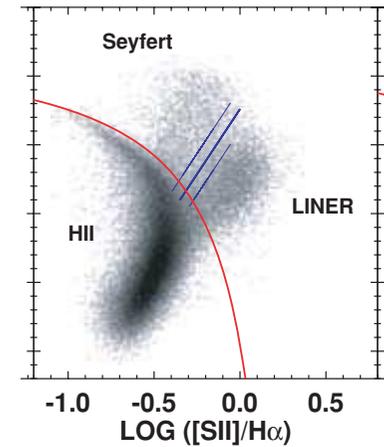
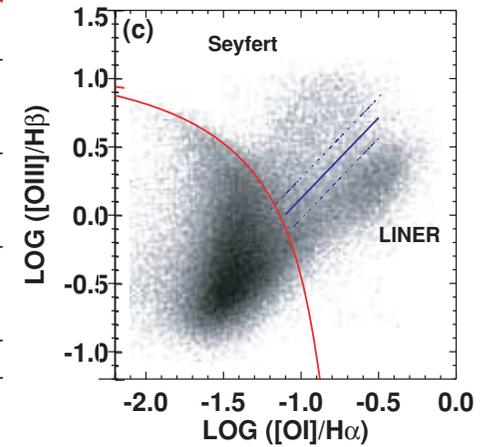
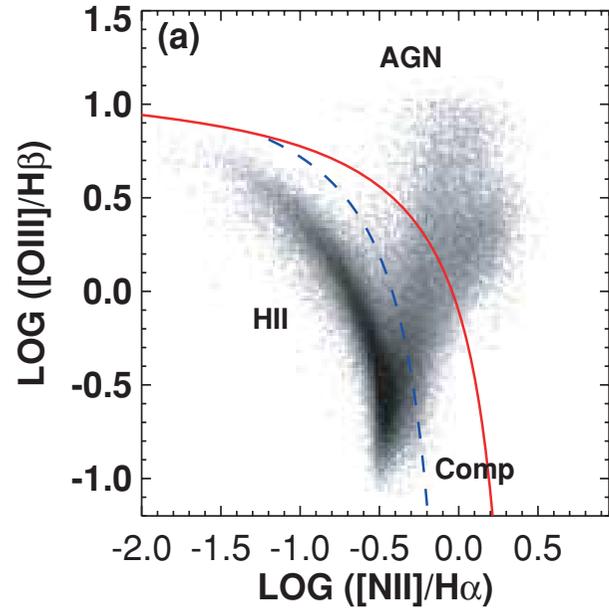
Ho et al. 1999



# Classifying galaxies



Kewley et al. 2001

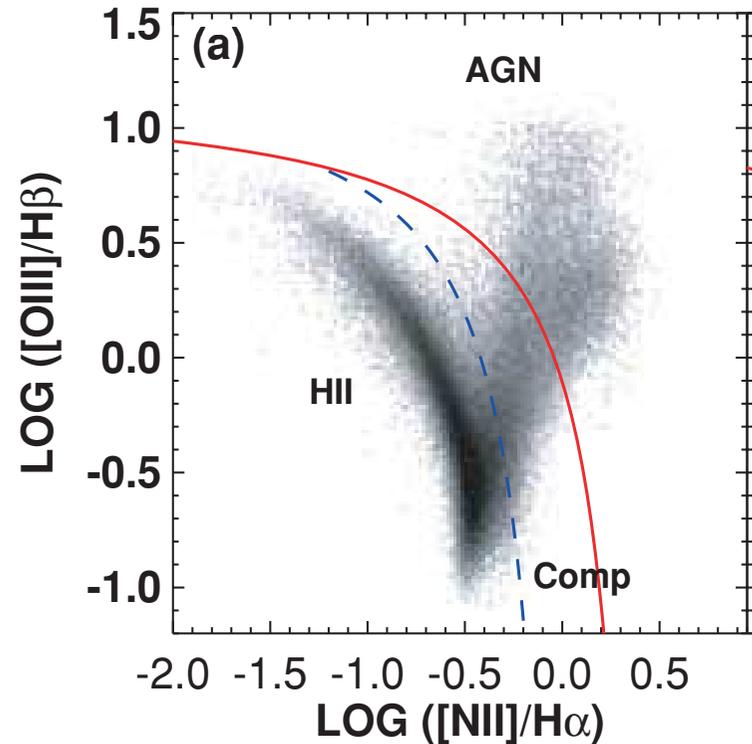


Kewley et al. 2006

# Classifying galaxies

Basically an empirical scheme

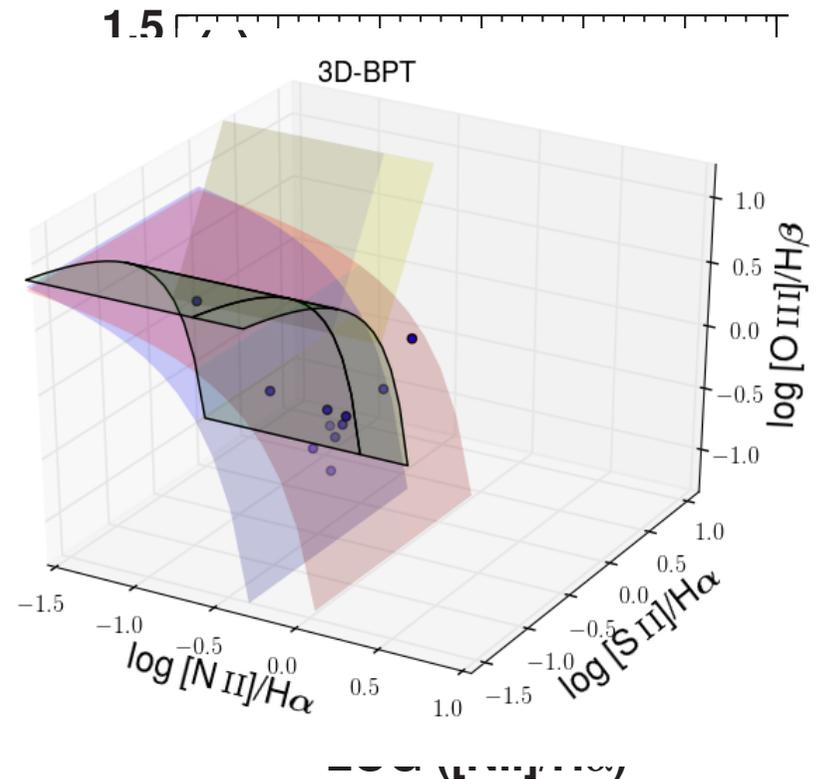
- Multi-dimensional parameter space
- Sparse sampling - but now large training sample available
- Uncertainties and intrinsic variance in training sample



→ Use observations to define locus of different classes

# Classifying galaxies

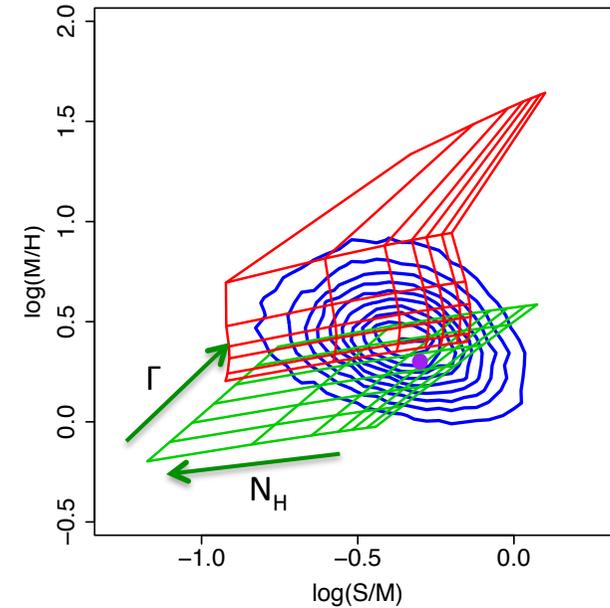
- Uncertainties in classification due to
    - measurement errors
    - uncertainties in diagnostic scheme
  - Not always consistent results from different diagnostics
- Use ALL diagnostics together
- Obtain classification with a confidence interval



Maragoudakis et al in prep.

# Classification

- Problem similar to inverting Hardness ratios to spectral parameters
- But more difficult
  - We do not have well defined grid
  - Grid is not continuous



		$N_H$					
		0.250–0.500	0.125–0.250	0.075–0.125	0.050–0.075	0.025–0.050	0.010–0.025
$\Gamma$	1.75–2.00	<b>11.36%</b>	<b>13.93%</b>	<b>3.35%</b>	<b>1.00%</b>	0.53%	0.24%
	1.50–1.75	<b>5.56%</b>	<b>13.70%</b>	<b>5.99%</b>	<b>2.34%</b>	<b>1.70%</b>	0.67%
	1.25–1.50	<b>1.80%</b>	<b>7.76%</b>	<b>5.61%</b>	<b>3.11%</b>	<b>2.82%</b>	<b>1.56%</b>
	1.00–1.25	0.38%	<b>2.71%</b>	<b>2.87%</b>	<b>2.26%</b>	<b>2.33%</b>	<b>1.58%</b>
	0.75–1.00	0.07%	0.54%	<b>0.82%</b>	0.75%	<b>1.00%</b>	0.81%
	0.50–0.75	0.01%	0.09%	0.15%	0.18%	0.23%	0.17%

# Summary

- Model selection in multi-component 2D image fits
- Joint fits of datasets of different sizes
- Classification in multi-parameter space
  - Definition of the locus of different source types based on sparse data with uncertainties
  - Characterization of objects given uncertainties in classification scheme and measurement errors

All are challenging problems related to very common data analysis tasks.

Any volunteers ?