Galaxy Photometry and Photometric Redshifts

Outline

- Stellar Photometry
  - Maximum likelihood
- Galaxy photometry
- Photometric redshifts
  - SED fitting
  - Training set, Bayesian methods

Lupton

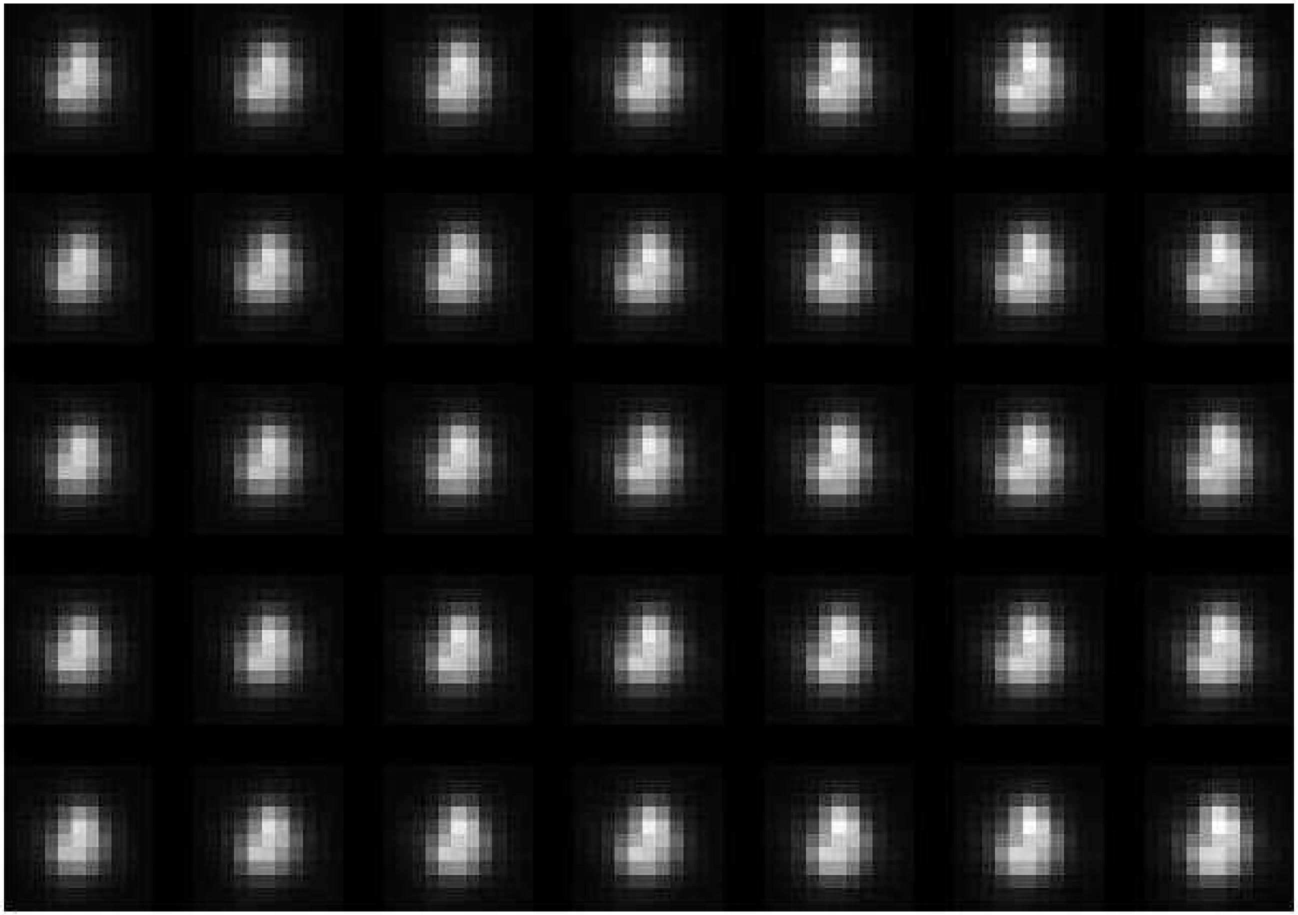


Fig. 4.— The estimated PSF for 35 positions in frame 756-z6-700, using a linear stretch. This is early SDSS data, and for one of the CCDs with worst image quality, and the astigmatism is clearly seen. The first component of Fig. 3 includes this astigmatism, although it is not obvious with the stretch used for that figure.

Stellar Photometry

Flux $$I(x) = S + A\phi(x - x_0) + \epsilon$$

PSF $$\sum \phi = 1$$

Gaussian noise $$\langle \epsilon(x)\epsilon(y) \rangle = \delta(x - y)\sigma^2(x)$$

Log likelihood

$$\ln L = -\sum \ln(2\pi\sigma^2) - \frac{1}{2}\sum \frac{(I - S - A\phi)^2}{\sigma^2}$$

Stellar Photometry

Maximum likelihood estimate

$$A_{\mathsf{MLE}} = \frac{\sum (I-S)\,\phi/\sigma^2}{\sum \phi^2/\sigma^2}.$$

$$\langle A_{\mathsf{MLE}} \rangle = A$$

Read and Poisson noise

$$\sigma^2 = B + A\phi$$

B=0

$$A_{\mathsf{MLE}} = \sum (I-S)$$

A<<B

$$A_{\mathsf{MLE}} = \frac{\sum (I-S)\,\phi}{\sum \phi^2}.$$

Galaxy Photometry

Peng

- Minimze reduced chi-squared

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

- σ is Poisson error
- Model is sum of fitting functions convolved with PSF

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

Galaxy Photometry with GALFIT

Sersic

$$\Sigma(r) = \Sigma_e e^{-\kappa[(r/r_e)^{1/n}-1]},$$

$$F_{\rm tot} = 2\pi r_e^2 \Sigma_e e^{\kappa} n \kappa^{-2n} \Gamma(2n) q / R(c)$$

Exponential

$$\Sigma(r) = \Sigma_0 e^{-(r/r_s)}$$

$$F_{\rm tot} = 2\pi r_s^2 \Sigma_0 q / R(c) \ ,$$

Nuker

$$I(r) = I_b 2^{(\beta-\gamma)/\alpha} \left(\frac{r}{r_b}\right)^{-\gamma} \left[1 + \left(\frac{r}{r_b}\right)^{\alpha}\right]^{(\gamma-\beta)/\alpha} .$$

Galaxy Photometry

Gaussian

$$\Sigma(r) = \Sigma_0 e^{-\left(r^2/2\sigma^2\right)}$$

$$F_{\text{tot}} = 2\pi\sigma^2 \Sigma_0 q / R(c)$$

Moffat

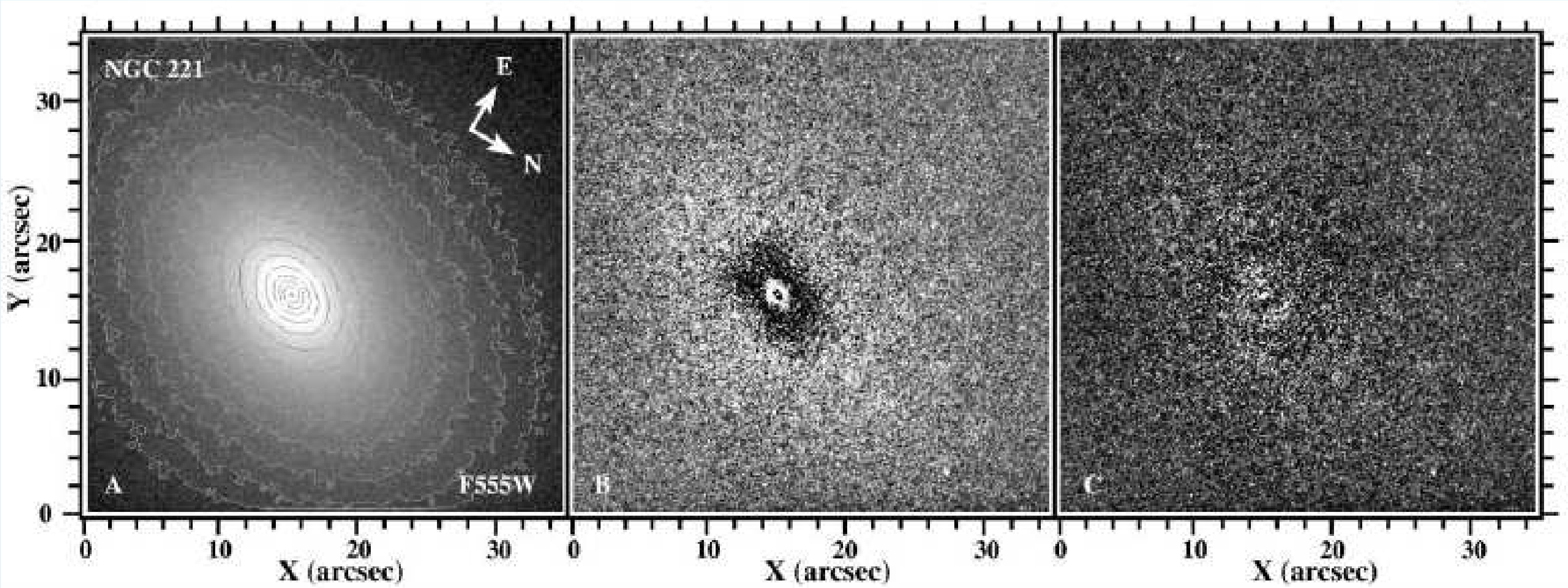
$$\Sigma(r) = \frac{\Sigma_0}{[1 + (r/r_d)^2]^n}$$

$$F_{\text{tot}} = \frac{\Sigma_0 \pi r_d^2 q}{(n-1)R(c)} \, ,$$

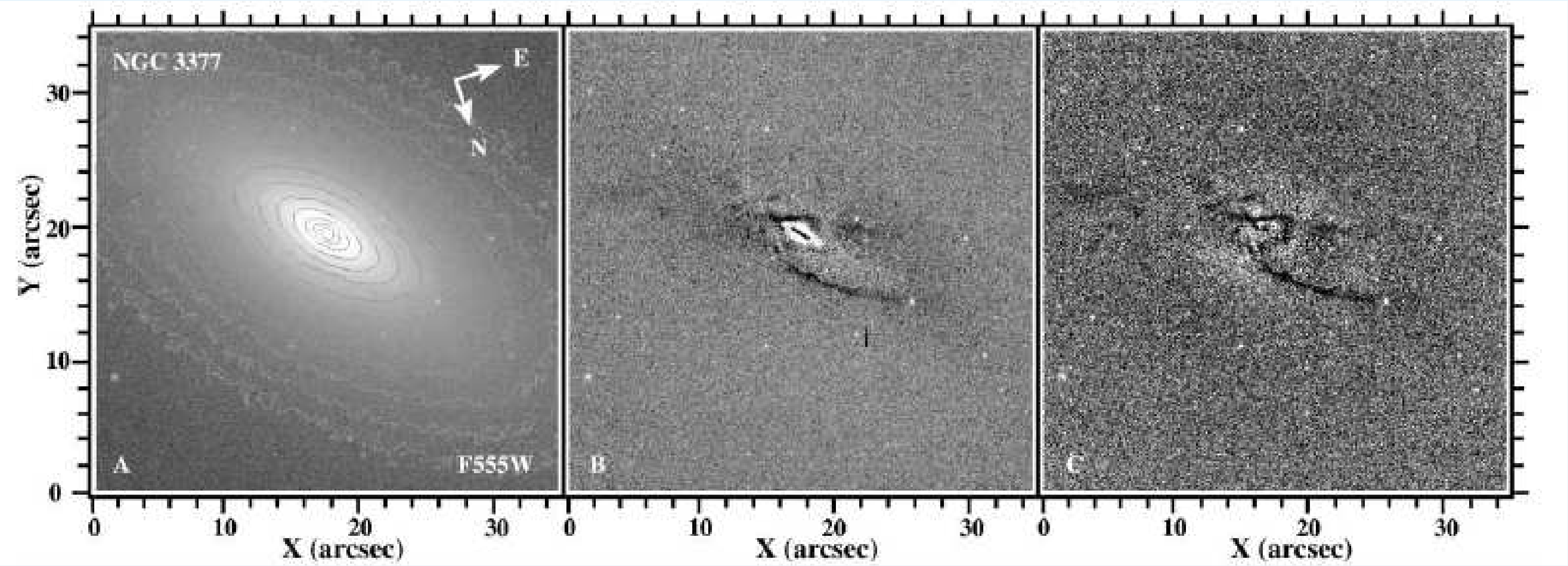
1. Normalize and prepare the PSF for convolution (item D in Fig. 1).
2. "Cut out" a section of the image centered on the object to fit from the original data image (item G in Fig. 1).
3. Create model images and derivative images based on new or initial input parameters.
4. Cut out the convolution region (items H and I) from the model and derivative images in the previous step and pad them around the edges with values of the models.
5. Convolve the convolution regions (both model and derivative images) in previous step with the PSF using a fast Fourier transform (FFT) technique.
6. Copy the convolution region back into the model/derivative images of step 3.
7. Compare with data image. Minimization is done using the Levenberg-Marquardt downhill-gradient method/parabolic expansion (Press et al. 1997).
8. Iterate from step 3 until convergence is achieved.
9. Output images and generate final parameter files.

Galaxy Photometry

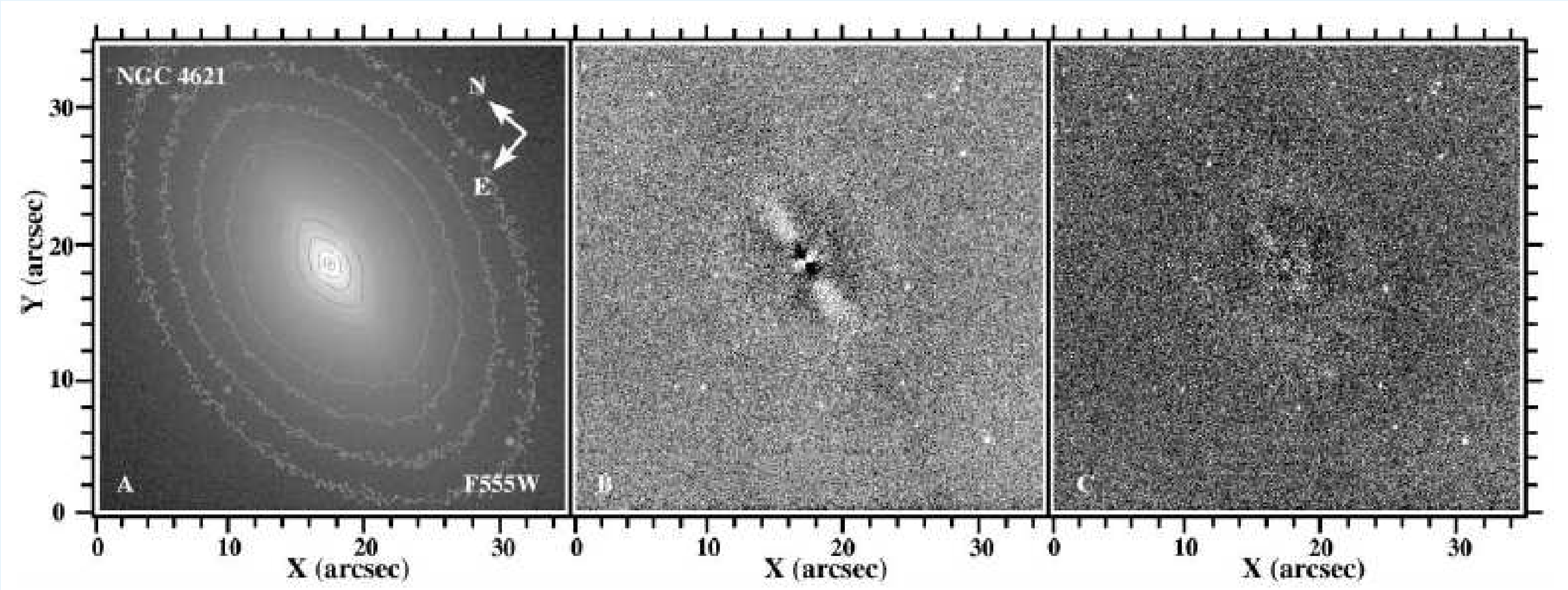
- Choices:
  - Fit 1D surface brightness profile
  - 2D fit to galaxy image
    - Study nuclear cusps, distinct nuclei, nuclear disks of stars and gas, dust lanes, nuclear spiral patterns



- Middle: 2D Nuker fit
- Right: Sersic + exponential disk



- Middle: Nuker bulge + exponetial disk
- Right: 4 Sersic components



- Middle: Nuker bulge + exponential disk
- Right: Nuker + 2 Sersic components

Photometric redshifts

Bolzonella

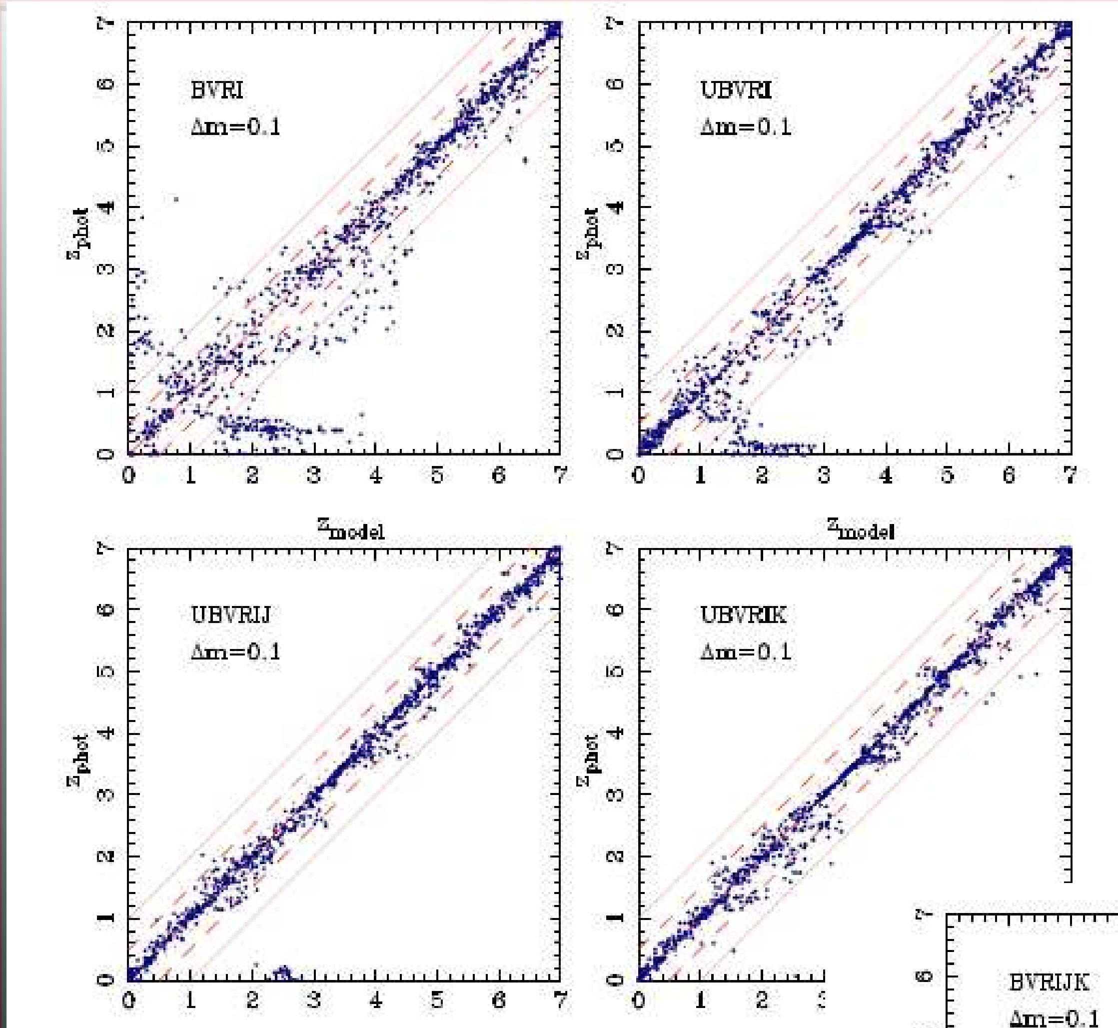
- Basic idea:
- Use finite number of filters to estimate location of 4000 A break, Balmer break, or other strong spectral features

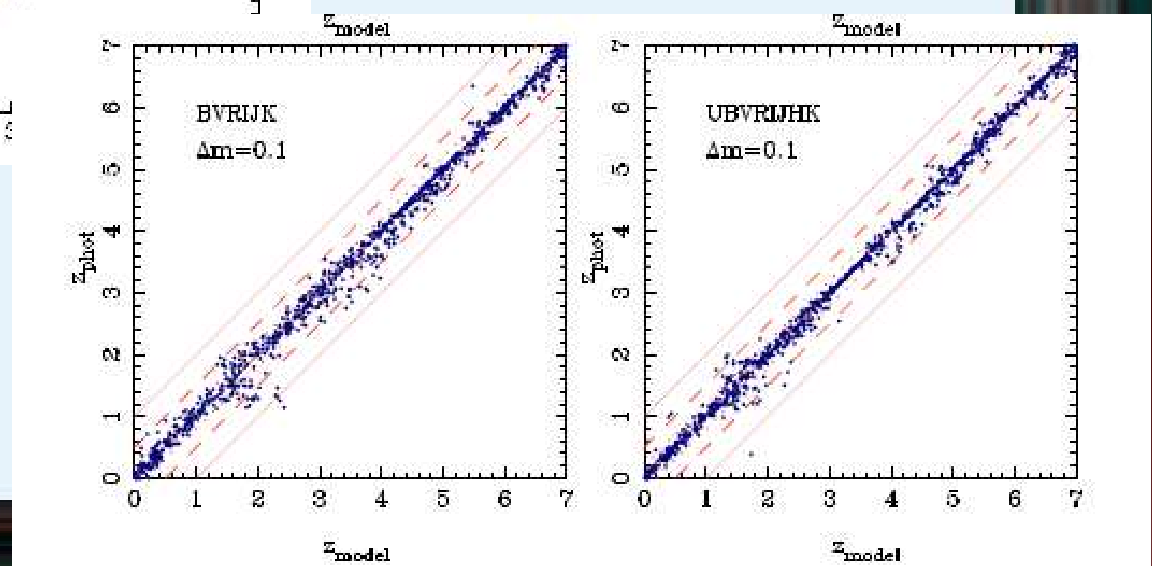
Filter	$\lambda_{\rm eff}$ [Å]	width [Å]
U	3652	543
B	4358	987
V	5571	1116
R	6412	1726
I	7906	1322
Z	9054	1169
J	12370	2034
H	16464	2863
K	22105	3705
F300W	3010	854
F450W	4575	878
F606W	6039	1882
F814W	8010	1451

Photometric Redshifts

$$\chi^2(z) = \sum_{i=1}^{N_{\rm filters}} \left[\frac{F_{{\rm obs},i} - b \times F_{{\rm temp},i}(z)}{\sigma_i} \right]^2 ,$$

- SED Templates produced by evolutionary code (e.g., Bruzual and Charlot)
- Model star-formation histories and assume an IMF (and metallicity)





- Simulated SED's
- Comparison to photometric redshift

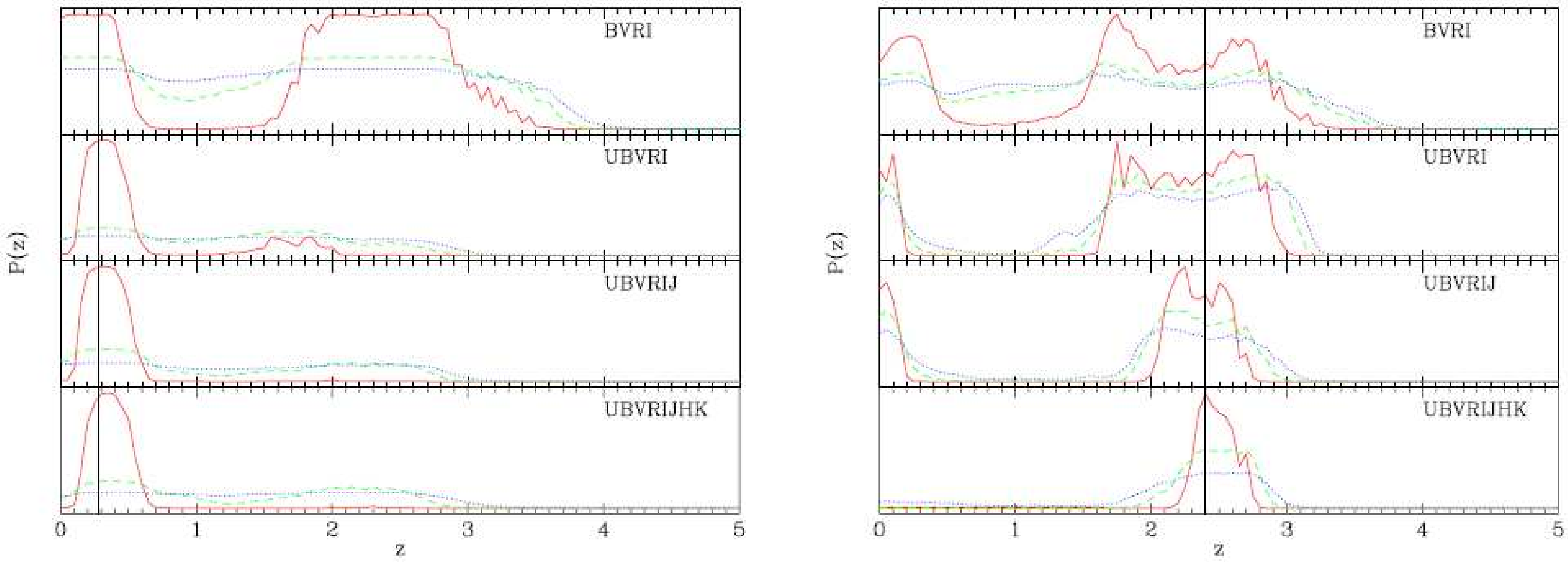


Fig. 3. Examples of the evolution of the probability distributions associated to $\chi^2(z)$ as a function of the filter set and photometric errors, for two simulated objects. Left: $z_{\rm model} = 0.282$. Right: $z_{\rm model} = 2.396$. Dotted lines refer to $\Delta m = 0.3$, dashed lines: $\Delta m = 0.2$, solid lines: $\Delta m = 0.1$. The vertical line marks the true $z_{\rm model}$ value.

- Probability distributions as a function of redshift for simulated galaxies

Photometric redshifts

- Alternatives
- Bayesian methods
  - Use priors and marginalization to include additional information such as expected shape of redshift distribution and known galaxy type fractions
- Training set methods
  - Use spectroscopy to build relation z=z(C,m)
    - Limited by spectroscopic redshift limit
    - Assumes single functional form for z(C,m)

References

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  ftp://ftp.astro.princeton.edu/jeg/Dubrovnik/Lupton/photoAstro.pdf
- Peng et al, Detailed Structural Decomposition of Galaxy Images (GALFIT), 2002
- Bolzonella et al, Photometric Redshifts based on standard SED fitting procedures, 2000
- Collister et al, ANNz: Estimating Photometric Redshifts Using Artificial Neural Networks, 2004
- Benitez, Bayesian Photometric Redshift Estimation, 2000