Photometric Redshifts
-
IPM School and Workshop on Weak Lensing and Photo-z Techniques

Hendrik Hildebrandt, Leiden Observatory

April 24, 2009

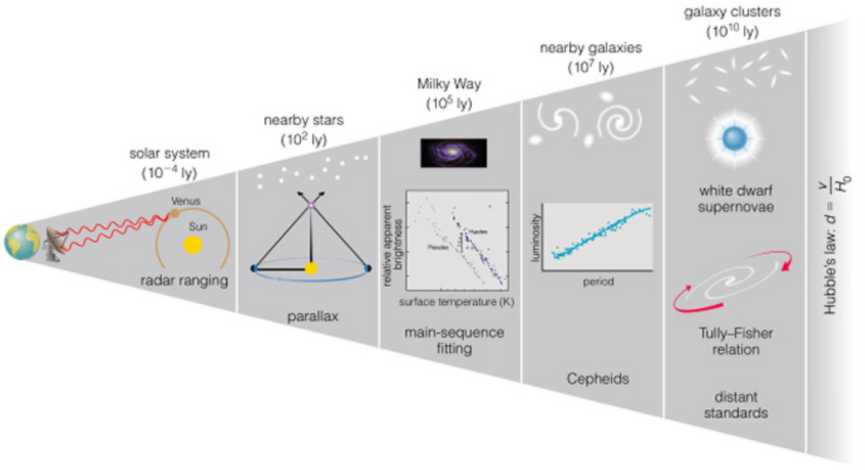
Outline

Two photons that simultaneously pierce the same pixel of a detector may have been emitted billions of years apart by regions of the universe that were in vastly different stages of evolution. One of the challenges in observational cosmology is to separate the layers of history that we on Earth receive superposed.

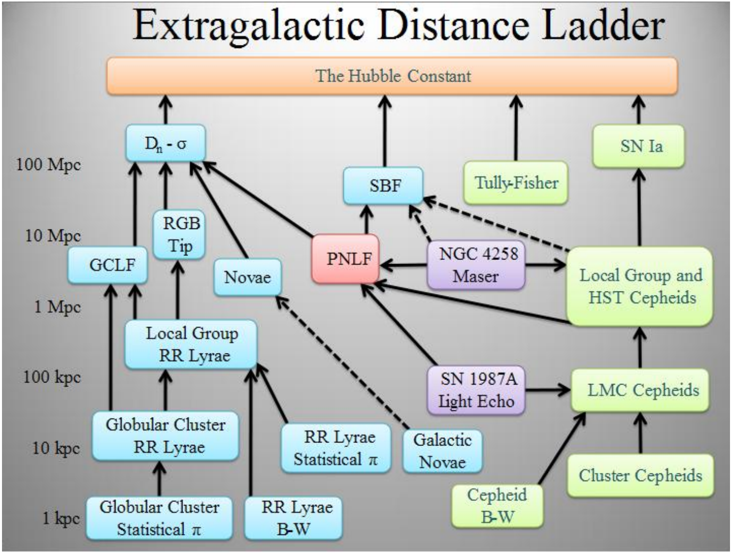
Adelberger et al. 2005, ApJ 619, 697

One way of doing this is the use of photometric redshifts.

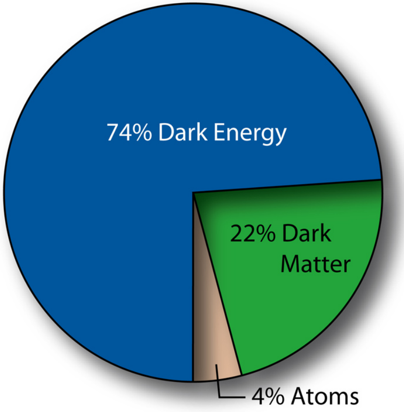
Cosmic Distance Ladder



Cosmic Distance Ladder



Concordance Cosmology



Cosmological Parameters from Spergel et al. (2007)

- $\Omega_\Lambda = 0.733 \pm 0.008$
- $\Omega_\mathrm{m} = 0.267 \pm 0.008$
- $\Omega_\mathrm{b} = 0.0441 \pm 0.0014$
- $H_0 = 70.4 \pm 1.5\ \frac{\mathrm{km}}{\mathrm{s \cdot Mpc}}$

Concordance Cosmology

Cosmology sets distance scale

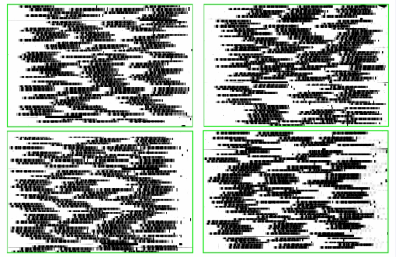
$$w(z) = D_\mathrm{H} \int_0^z \frac{\mathrm{d}z'}{E(z')}$$

with $D_\mathrm{H} = \frac{c}{H_0}$

and $E(z) = \sqrt{\Omega_\mathrm{m}(1+z)^3 + (1-\Omega_\mathrm{tot})(1+z)^2 + \Omega_\Lambda}$

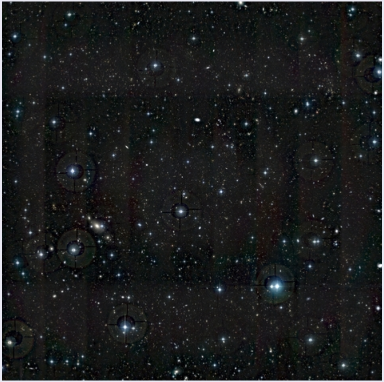
Spectroscopy vs. Photometry

VIMOS@VLT(8m)



$\sim$ 500 objects in one shot,
$t_{\mathrm{exp}} \approx 4\mathrm{h}$ for $I_{\mathrm{AB}} < 24$

MEGACAM@CFHT(4m)



$\sim$ 50 000 objects in one shot,
$t_{\mathrm{exp}} \approx 5\mathrm{h}$ for $I_{\mathrm{AB}} < 24$ in *ugriz*

Photo-z's have been in use for a long time...

This situation has led us to consider alternative methods by which redshifts beyond the present spectrographic range can be adequately estimated. There are, in fact, at least four magnitudes of unexplored territory between the spectrographic limit and the faintest galaxies detectable by direct photography, and it is now clear that observations within that territory will be vital to any definitive cosmological result. In addition, the high precision of spectrographic redshifts is not needed; we can well afford to trade a factor 10 in precision for the opportunity of reaching galaxies at larger distances.

Baum 1957, AJ 62, 6

Photometric Redshifts

- Get redshifts from (broad-band) imaging without spectroscopy.
- Accept the lower accuracy.
- Gain in depth.
- Gain in numbers of objects.

Approaches to photo-z's

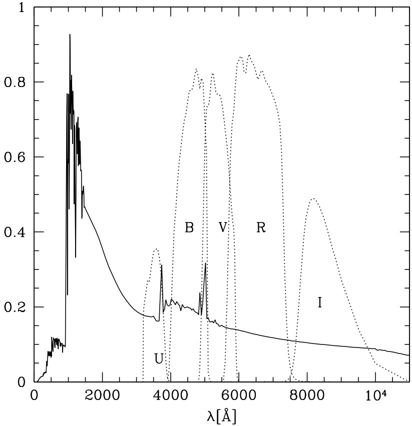
Empirical

- requires training sample
- establish relation betweem colours and spec-z
  - by a geometric fit
  - by artificial neural network
- high precision possible
- but less flexible

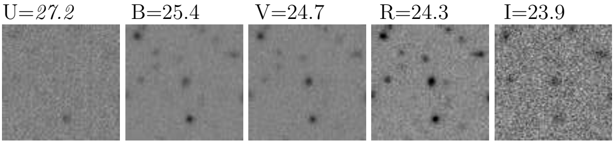
Template Fitting

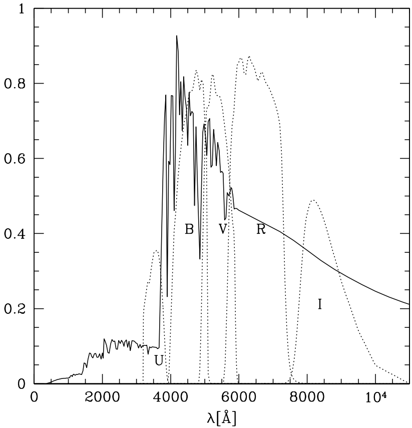
- based on SED template set
- needs instrumental response
- can include evolutionary effects
- can yield more than just the redshift
- can explore unknown territory
- but is prone to systematics

LBG selection

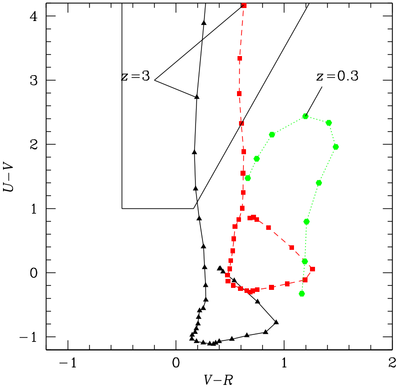


LBG selection

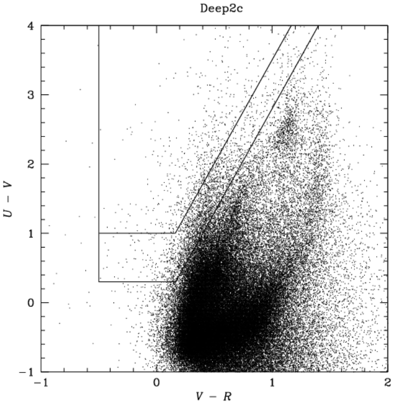




LBG selection

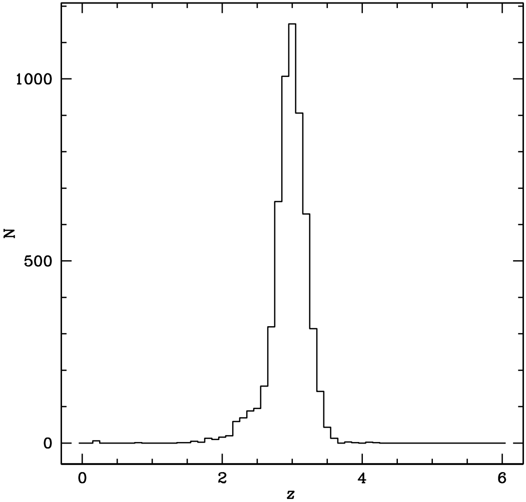


from Hildebrandt et al. 2005, A&A, 441, 905



from Hildebrandt et al. 2007, A&A, 462, 865

LBG selection



from Hildebrandt et al. 2007, A&A, 462, 865

LBG selection

Advantages:

- Cheap in terms of telescope time
- Well-tested
- Highly efficient
- Yields the largest high-z samples to date.

Disadvantages:

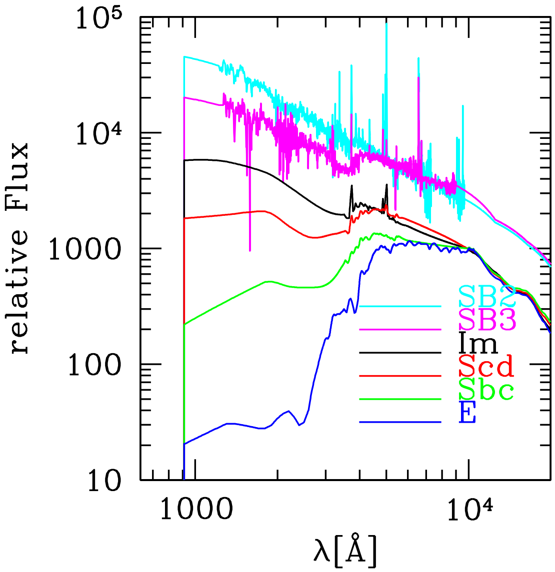
- Contamination
- Differences between samples at different z
- Colour selection $\Rightarrow$ not a fair sample
- **Only usable at high-z and for star-forming galaxies.**

BPZ - Bayesian Photometric Redshifts

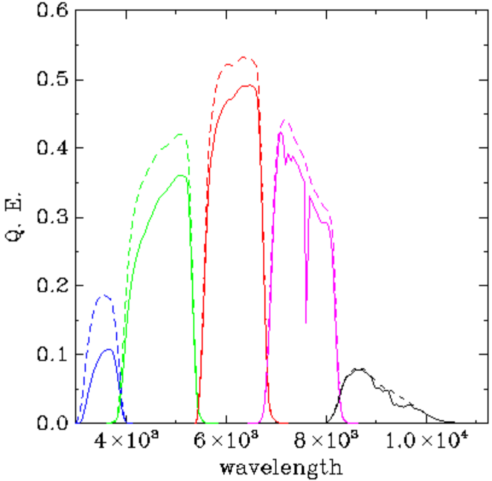
Ingredients

- SED Templates
- Filter Curves
- Apparent Magnitude Prior

The BPZ template set



Set of N Filter Curves



Model

Estimation of Model Colours

- Choose a zeropoint SED (either Vega or AB)
- Convolve this zeropoint SED with your N filter curves and integrate $\Rightarrow$ some pseudo-flux x_{i} for each filter i
- Redshift all templates in steps, stepsize Δz
- Convolve all these redshifted SEDs with your N filter curves and integrate $\Rightarrow$ some number $y_{z,\mathrm{j},\mathrm{i}}$ for each filter i and each template j at each redshift z
- Pseudo-flux: $f_{z,\mathrm{j},\mathrm{i}} = \frac{y_{z,\mathrm{j},\mathrm{i}}}{x_{\mathrm{i}}}$
- These pseudo-fluxes $f_{z,\mathrm{j},\mathrm{i}}$ are in no way normalised and may have funny absolute values. But the relative normalisation of the N fluxes for one SED-redshift-combination is correct.
- The $f_{z,\mathrm{j},\mathrm{i}}$ form a 3-dimensional hypercube

χ^2 Calculation

Calculate the χ^2 for each SED-redshift combination (neglecting correlated errors and errors in the template SED fluxes):

$$\chi^2_{\mathrm{j}}(z) = \sum_{\mathrm{i}=1}^{n} \left[\frac{a\, f_{z,\mathrm{j},\mathrm{i}} - f_{\mathrm{obs},\mathrm{i}}}{\sigma_{f_{\mathrm{obs},\mathrm{i}}}} \right]^2 ,$$

with $f_{\mathrm{obs},\mathrm{i}}$ and $\sigma_{f_{\mathrm{obs},\mathrm{i}}}$ being the observed flux in band i and its error, and a being a normalisation constant.

The normalisation a can either be fitted for each set of (z, j) or adjusted so that for some reference band:

$$a\, f_{z,\mathrm{j},\mathrm{ref}} - f_{\mathrm{obs},\mathrm{ref}} = 0 \,.$$

Likelihood

We are interested in the probability $p(z|F, m_0)$ that an object is at redshift z given its observed fluxes $F = \{f_{\rm obs,i}\}$ and an observed reference magnitude m_0.

Calculate the likelihood functions L for each template:

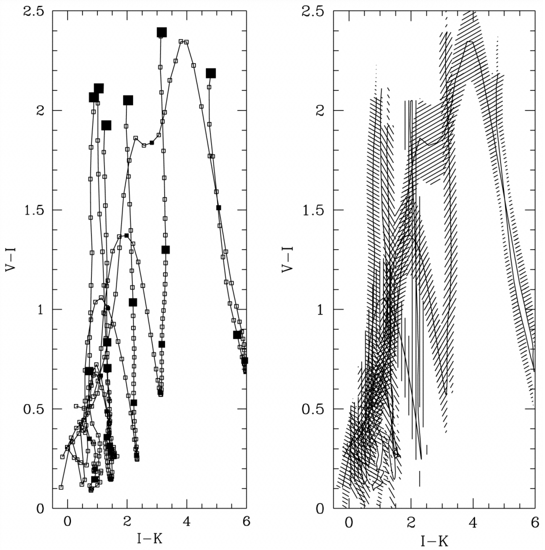
$$-\log\left[L_{\rm j}(z)\right] + \text{const.} \propto \chi^2_{\rm j}(z)\,.$$

L is the probability of observing the fluxes $F = \{f_{\rm obs,i}\}$ given the redshift z and the template j. One writes:

$$L_{\rm j}(z) \equiv p(F|z, {\rm j})\,.$$

Some codes (e.g. Hyperz) stop here and put out the most likely redshift, i.e. the z with the highest $L_{\rm j}(z)$ or the lowest $\chi^2_{\rm j}(z)$.

Colour-redshift tracks for the different templates



from Benitez 2000, ApJ 536, 571

Bayes' Theorem

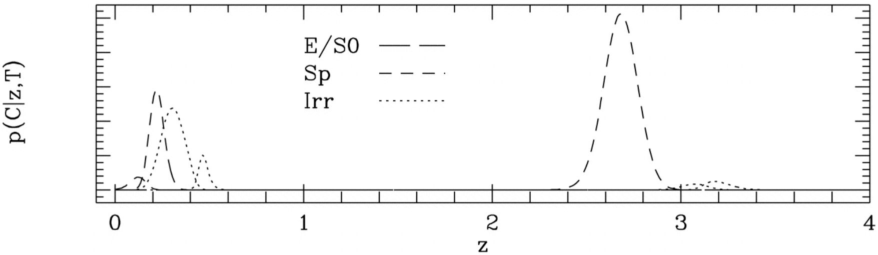
Bayes' Theorem connects the likelihood to the posterior probability:

$$p(z,\mathrm{j}|F,m_0) = \frac{p(z,\mathrm{j}|m_0) \times p(F|z,\mathrm{j})}{p(F)} \, ,$$

with $p(z,\mathrm{j}|m_0)$ being the prior probability and p(F) being a redshift-independent normalisation.

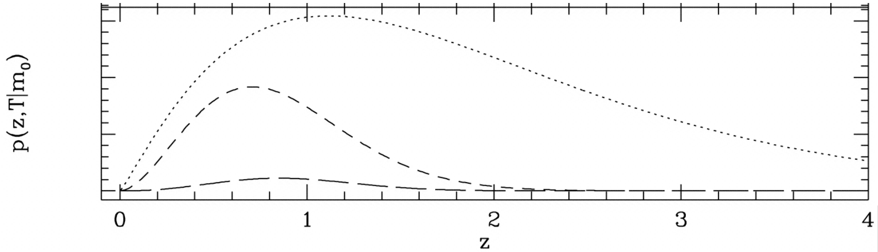
To get from $p(z,\mathrm{j}|F)$ to $p(z|F)$ you have to marginalise over the template axis.

Likelihood Functions for the different templates



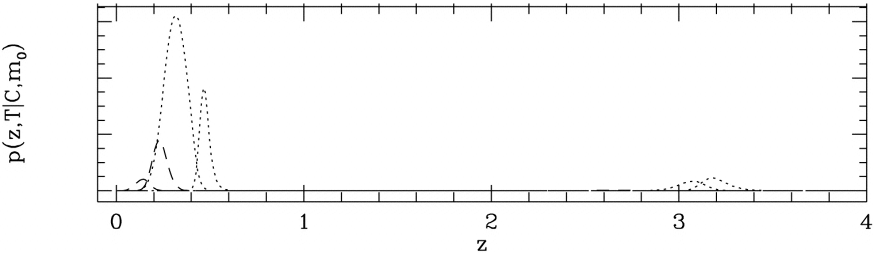
from Benitez 2000, ApJ 536, 571

Priors for the different templates and $m_{\rm obs,ref}$



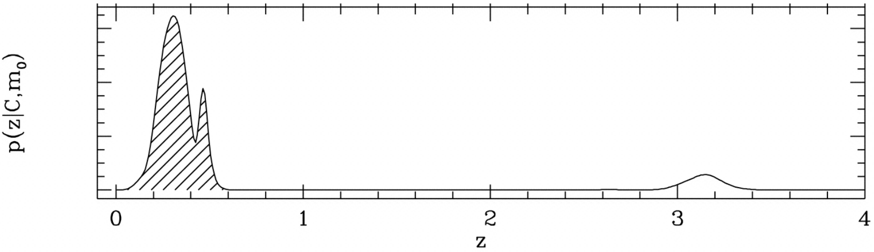
from Benitez 2000, ApJ 536, 571

Posterior probabilities for the different templates



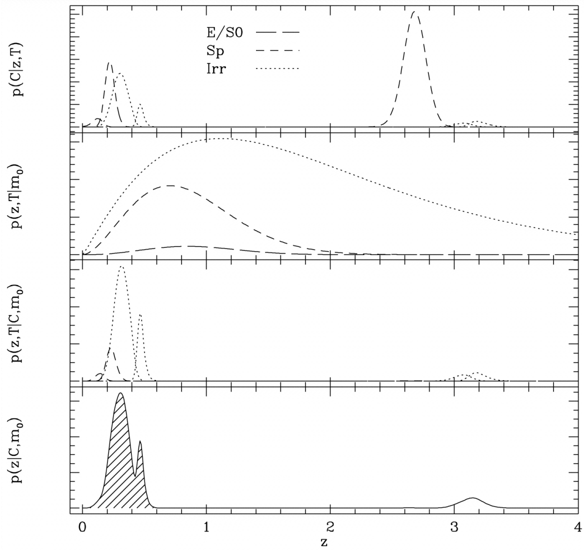
from Benitez 2000, ApJ 536, 571

Combined posterior probability



from Benitez 2000, ApJ 536, 571

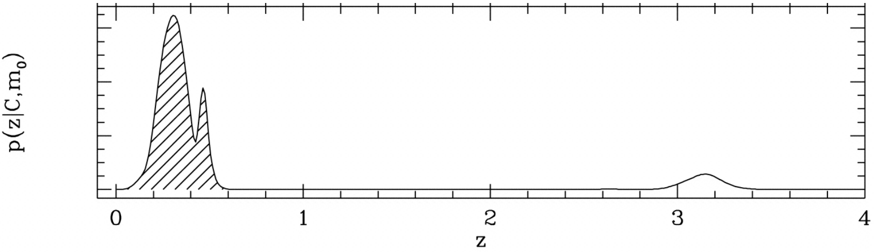
The whole story



from Benitez 2000, ApJ 536, 571

Empirical Odds

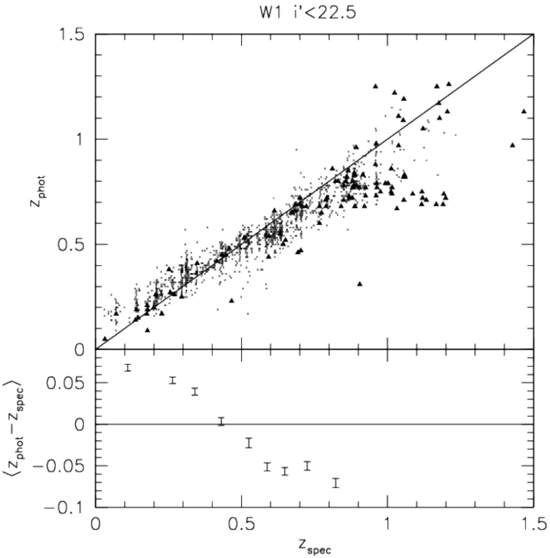
Besides reporting the most probable (in a Bayesian sense) redshift as Z_B, BPZ also puts out the empirical odds of this redshift solution.



from Benitez 2000, ApJ 536, 571

This ODDS output parameter is a very robust measure of the redshift quality. Low ODDS is a sign for double-peaked posterior probability functions.

Residual Systematics



from Erben et al. 2009, A&A, 493, 1197

Residual Systematics

How to remove them?

- Check your photometry.
- Re-calibrate your ZPs.
- Re-calibrate your templates.
- Adjust your prior.

Zeropoint Re-Calibration

How it's done:

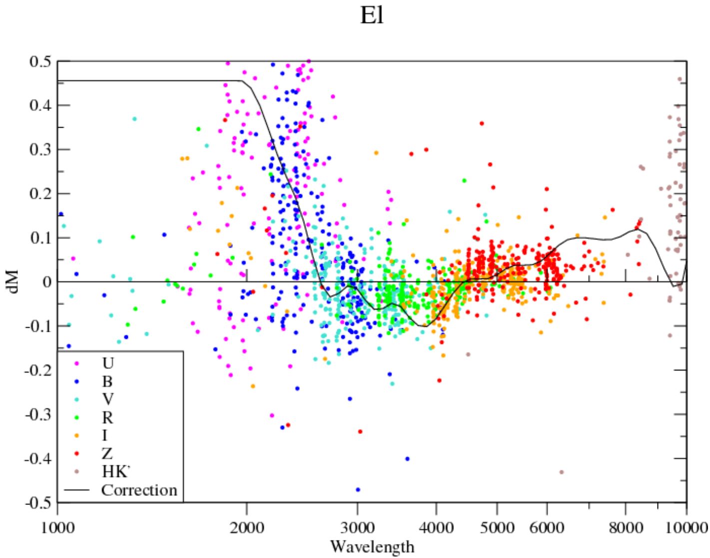
1. Select training set, i.e. objects with (secure) spectroscopic redshifts and good (high S/N) photometry.
2. Compute the best-fit template at z-spec. Basically run a photo-z code with redshift range $z_{\mathrm{spec}} \leq z \leq z_{\mathrm{spec}}$ for each object.
3. Calculate the magnitudes of the best-fit template in each filter i, $m_{\mathrm{model,i}}$. These are usually put out by the code.
4. Average over the magnitude differences to get the ZP offsets, $\Delta\mathrm{ZP_i} = \langle \Delta m_{\mathrm{i}} \rangle = \langle m_{\mathrm{obs,i}} - m_{\mathrm{model,i}} \rangle$
5. Apply these ZP offsets to your data and go back to 2.
6. Iterate until $\forall \mathrm{i} : \mathrm{ZP_i} < \mathrm{threshold}$.

Template Re-Calibration

How it's done:

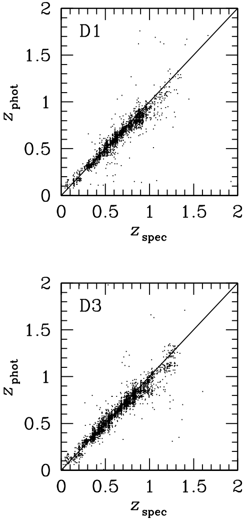
1. Take the training sample with re-calibrated ZPs.
2. Select all objects that were fitted by some particular template j.
3. Calculate the effective restframe wavelengths of each object in each filter i: $\lambda_{\mathrm{eff,rest,i}} = \lambda_{\mathrm{eff,i}} \left(1 + z_{\mathrm{spec}}\right)$.
4. Plot $\Delta m(\lambda_{\mathrm{eff,rest}})$ vs. $\lambda_{\mathrm{eff,rest}}$.
5. Fit some repair-function (e.g. cubic spline) to the points.
6. Convert into flux units.
7. Do this for each template and multiply the original templates by this repair function (in flux units).

Template Re-Calibration



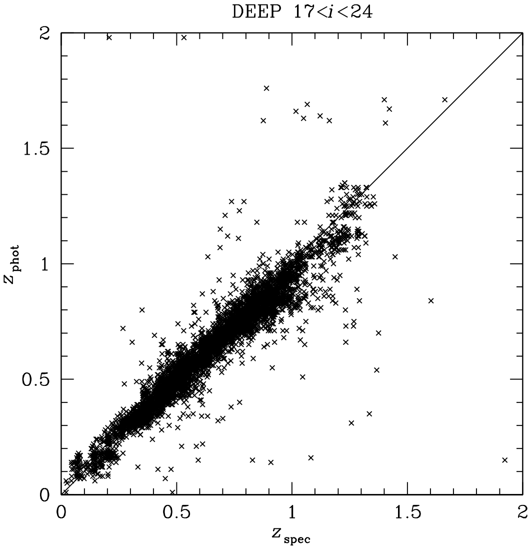
from Capak 2004, Ph.D. Thesis, AA (University of Hawai'i)

Bias-free photo-z's

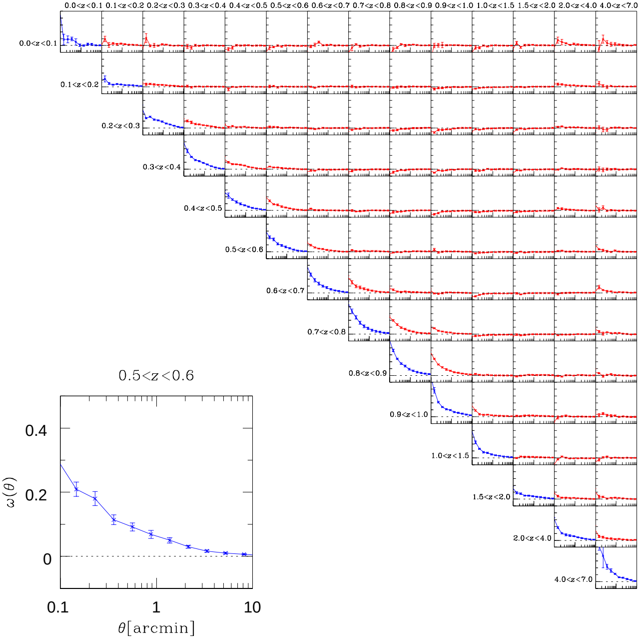


from Hildebrandt et al. 2009, accepted by A&A

Bias-free photo-z's



from Hildebrandt et al. 2009, accepted by A&A


0.0<z<0.1
0.1<z<0.2
0.2<z<0.3
0.3<z<0.4
0.4<z<0.5
0.5<z<0.6
0.6<z<0.7
0.7<z<0.8
0.8<z<0.9
0.9<z<1.0
1.0<z<1.5
1.5<z<2.0
2.0<z<4.0
4.0<z<7.0
0.5<z<0.6
ω(θ)
0.4
0.2
0
0.1
1
10
θ[arcmin]