

DARK ENERGY SURVEY

Photo-z's: Methods, Errors and CatSim1

Marcos Lima, Carlos Cunha, Hiroaki Oyaizu

Kavli Institute for Cosmological Physics University of Chicago

> DES Collaboration Meeting Michigan - October 28, 2005



Collaborators

Huan Lin Josh Frieman Ofer Lahav Adrian Collister Zhaoming Ma Dragan Huterer Wayne Hu

Fermilab

Fermilab, University of Chicago

University College of London

University of Cambridge

University of Chicago

University of Chicago

University of Chicago



SURVEY

Outline

Photo-z Methods (Marcos)

- Error Estimators (Carlos)
- CatSim1 results (Hiro)



Photo-z methods

- Probe strong spectral features (4000 Å break)
- Difference in flux through filters as the galaxy is redshifted.





Template Fitting methods

- Use a set of standard SED's templates (CWW, etc.)
- Calculate fluxes in filters of redshifted templates.
- Match object's fluxes (χ² minimization)
- Outputs type and redshift
- Examples

Hyper-z (Bolzonella et al. 2000)

BPZ (Benitez 2000)



Training Set Methods

DARK ENERGY SURVEY

• Determine functional relation between *m* and *z*_{phot} using a training set

 $z_{phot} = z_{phot}(m,c)$

Examples



(Firth et al. 2003, Collister & Lahav 2004)



DES5YR (Huan Lin)

DARK ENERGY SURVEY

Cunha et al. in prep. 2005. DES griz filters



Limiting Magnitudes g 24.6 r 24.1 i 24.0

Ζ

23.65





DES+IR

DARK ENERGY SURVEY

Cunha et al. in prep. 2005. DES + VISTA grizYJHKs filters

Similar improvements by adding one single filter if it is J or redder.





Extrapolations

- VIMOS VLT Deep Survey (VVDS) Le Fevre et al. 2005
- Training set: VVDS i magnitude distribution

i < 24 and i < 22.5



Cunha et al. in prep. 2005.



DARK ENERGY SURVEY

Photometric Redshift Errors



Error Estimators

- Don't require training set:
 - $-\chi^2$ based methods
 - Propagation of magnitude differentials
 - Monte Carlo magnitude resampling (MCMR)
- Require training set:
 - Nearest Neighbor (NNE)
 - Kd Tree



Nearest Neighbors Error

- Nearest Neighbor Error is the width (σ_{68}) of the (z_{phot} - z_{spec}) distribution of 100 nearest training set objects in magnitude space
- Assumption is that nearby objects in magnitude space have similar error characteristics



Nearest Neighbors Error

- We prefer NNE, because:
 - It works better (and we need a training set anyways).
 - Does not require knowledge of magnitude errors and magnitude error correlations



NNE at work



- $z_p z_s =$ wrongness
- Errors can only be statistically



NNE at work



- $z_p z_s =$ wrongness
- Errors can only be tested statistically



- What bias?
 in z_{phot} bins
 in z_{spec} bins
- Can only remove bias caused by catastrophics





- What bias?
 in z_{phot} bins
 in z_{spec} bins
- Can only remove bias caused by catastrophics





- What bias?
 in z_{phot} bins
 in z_{spec} bins
- Can only remove bias caused by catastrophics





Removing Objects

DARK ENERGY SURVEY



10% objects removed \Rightarrow 30% improvement in dispersion



Removing Objects





Error distributions





Redshift Distributions





DARK ENERGY SURVEY

CatSim1 Results



CatSim1 Results

- Galaxies from the N-body based bright object catalog and the faint object catalog
 - Mixed with 1:3 ratio, i.e., 1 bright catalog object for every 3 faint object catalog
- Training Size: 50,000 galaxies
- Photometric size: 50,000 galaxies







SURVEY

i < 24









SURVEY

CatSim1: Summary

- RMS scatter ~ 0.1 for i < 24
- Results are comparable to (if not better than) the original DES catalog simulation by Huan Lin
- NNE error estimates are good
- Further testing on cluster galaxies may be necessary



Conclusions

- Training set methods are better suited for DES
- NNE estimator works like a charm
- Most catastrophic objects can be removed
- CatSim1 results look good