LSST Photometric Redshifts and Applications

V.E. Margoniner (UC Davis), A. Connolly (U. Pittsburgh), J.A. Tyson (UC Davis)

Large Synoptic Survey Telescope

The redshift distribution of galaxies plays a fundamental role in the de-projection of the 2-dimensional distribution of galaxies on the sky into the real 3-dimensional Universe, as well as in any study of galaxy evolution, and in most methods useful in constraining cosmological parameters. A great strength of LSST is that from its ugrizy deep photometry we will be able to derive redshifts for each galaxy with a typical precision of ~0.07(1+z) per galaxy, without any pre-selection. Better precision may be obtained by adding combinations of magnitude and surface brightness priors or red sequence. We show from simulations and from existing HDFN data in similar photometric bands how this precision will be achieved, and we quantify the magnitude and impact of any redshift-dependent bias. The photo-z errors are not Gaussian, and we discuss modeling methods and calibration using a combination of selected area deep spectroscopic samples and optical+IR many band ultra photo-z.

1. Photo-z designer filters

Forecasts in this poster are based on the LSST parameters given in poster 26.14. Most important for photometric redshifts, this filter set covers a broad wavelength range and is designed for photo-z. Total system (atmosphere, optics, filter, detector) transmission curves are shown in Figure 1. These transmission curves are used by the LSST exposure time calculator at www.lsst.org. An LSST system with higher throughput in U and Y is likely.

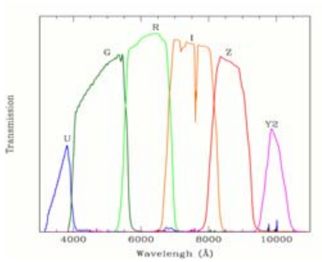

Figure 1: LSST total system transmission.

2. How accurate can photometric redshifts be?

Intrinsic limitations to photometric redshift arise from constraining z from a limited number of observations, with limited prior knowledge about the galaxy spectral energy distribution (SED) (and its evolution, reddening, etc.). The HDFN has been widely used as a standard data set for testing photometric redshifts techniques due to its depth, wavelength coverage, and number of photometric bands (7 total: HST~UBVI and ground JHK), and the best results obtained so far for this data set are σ_z ~0.06(1+z). Accuracy can be further improved if the SED is somehow known (for example focusing on LRGs). The difficulty is cleanly pre-selecting a certain type of galaxy, and the trade-off is that the density of objects decreases dramatically.

Representative spectroscopic training sets are difficult to obtain, especially for a deep survey. Therefore we focus on SED fitting methods, even though training set methods may still be useful for subsets of the LSST data.

3. LSST Simulations: synthetic galaxies

We simulate LSST photometric redshifts in two ways. The first approach is to use models of different galaxy SEDs at a range of redshifts, convolve them with LSST filter responses, add the estimated photon noise and then analyze the recovered photometric redshifts.

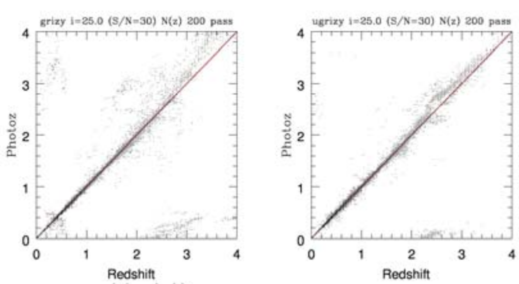

Figure 2: Photometric versus spectroscopic redshifts for grizy filter (left) and for the adopted ugrizy filter set (right) for the LSST survey after only 5 years. Catastrophic photo-z errors are decreased by adding the u band and can be further minimized via priors such as luminosity function (Fig 3) and surface brightness.

4. LSST Simulations: real galaxies

A second approach is based on real UBVIJ data. First, we convolve the HDFN UBVI space images with 0.7" FWHM seeing. Then we re-pixelize, add noise, and catalog the images to match the expected data quality for the final full depth stack of exposures. The final stack will go to 26.7AB and 25.4AB (10-sigma and 30-sigma in the i band.) The photometric redshift technique used here is based on SED fitting and on a magnitude or luminosity function prior (Figure 3). We achieve $\langle(z_{phot}-z_{spec})/(1+z_{spec})\rangle = 0.01 \pm 0.09$ for all the detected objects. If the 5% worst outliers are excluded, $\langle(z_{phot}-z_{spec})/(1+z_{spec})\rangle = 0.01 \pm 0.07$.

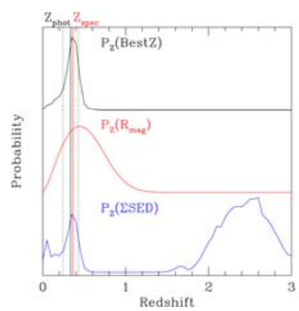

Figure 3: Redshift probability distributions for one example galaxy (offset vertically for clarity). The blue line indicates the probability derived from the chi-square fit of an object's colors to a set of SED templates. The red line shows the redshift probability estimated from the object's R magnitude. The black line is the combined probability. The vertical lines are: photometric redshift (black) and its 1-σ error (dotted black); and spectroscopic redshifts (red). This example is based on real BVRz data, which is not as constraining as the LSST filter set (ugrizy).

The final full-depth redshift distribution for LSST can be estimated from the photometric redshifts of all detected galaxies in the simulation:

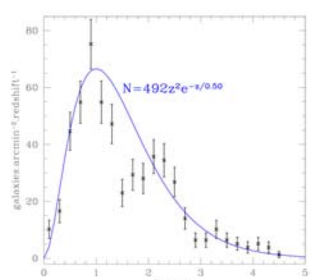

Figure 4: Estimated redshift distribution for the full-depth LSST survey for all galaxies detected in the i band. The plot is noisy because it is based on the small (3.95 arc min square) HDFN field of view. It will be necessary to calibrate LSST photo-z via ultra deep training sets over this wide redshift range in selected areas.

5. The need for a deep calibration sample

Several LSST probes of dark energy depend on accurate estimates of the photo-z scatter and bias vs z. As seen in Fig 2 the scatter and bias are well defined, but they must be measured (calibrated). An intensive campaign in selected areas is required. Indeed this is needed by the community. By necessity this will involve faint spectroscopic calibration of even fainter 10-15 band ultra photo-z data on a representative sample of 100,000 galaxies.

The LSST research and development effort is funded in part by the National Science Foundation under Scientific Program Order No. 9 (AST-0551161) through Cooperative Agreement AST-0132798.
Additional funding comes from private donations, in-kind support at Department of Energy laboratories and other LSSTC Institutional Members.