QUANTIFYING PHOTOMETRIC REDSHIFT ERRORS IN THE ABSENCE OF SPECTROSCOPIC REDSHIFTS

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ABSTRACT

Much of the science that is made possible by multiwavelength redshift surveys requires the use of photometric redshifts. But as these surveys become more ambitious, and as we seek to perform increasingly accurate measurements, it becomes crucial to take proper account of the photometric redshift uncertainties. Ideally the uncertainties can be directly measured using a comparison with spectroscopic redshifts, but this may yield misleading results since spectroscopic samples are frequently small and not representative of the parent photometric samples. We present a simple and powerful empirical method to constrain photometric redshift uncertainties in the absence of spectroscopic redshifts. Close pairs of galaxies on the sky have a significant probability of being physically associated and therefore of lying at nearly the same redshift. The difference in photometric redshifts in close pairs is therefore a measure of the redshift uncertainty. Some observed close pairs will arise from chance projections along the line of sight, but it is straightforward to perform a statistical correction for this effect. We demonstrate the technique using both simulated data and actual observations, and discuss how its usefulness can be limited by the presence of systematic photometric redshift errors. Finally, we use this technique to show how photometric redshift accuracy can depend on galaxy type.

Key words: cosmology: observations – galaxies: distances and redshifts – methods: miscellaneous – surveys

Online-only material: color figures

1. INTRODUCTION

Redshift surveys are a major and growing industry in astronomical research. The use of photometric, as opposed to spectroscopic, redshifts in these surveys makes it possible to study a much larger number of objects for a given amount of telescope time and to study the faintest sources. However, photometric redshifts are susceptible to larger random and systematic errors, which can propagate into derived quantities; in order to derive meaningful results using photometric redshifts, it is crucial to understand their uncertainties. For instance, both random and systematic redshift errors can lead to systematic errors in the luminosity and mass functions (Chen et al. 2003; Marchesini et al. 2007). Studies of galaxy clustering can also be strongly affected (Adelberger 2005; Quadri et al. 2008). In both of these cases, it is possible to correct for the systematic errors in derived quantities if the distribution of photometric redshift errors is well understood, but in practice this is seldom the case. Surveys that are designed to constrain the cosmological parameters require especially tightly constrained photometric redshifts, and significant work has gone into establishing the photometric redshift accuracy and calibration requirements (e.g., Albrecht et al. 2006; Huterer et al. 2006; Mandelbaum et al. 2008).

The standard method used to estimate photometric redshift uncertainties is to directly compare the photometric redshifts with the spectroscopic redshifts for some subset of objects. However, spectroscopic samples are frequently not representative of the full photometric sample; at least at \( z \gtrsim 1 \), galaxies with high-confidence spectroscopic redshifts are often brighter, bluer, biased toward a specific sub-population (e.g., Lyman break galaxies or active galactic nuclei (AGNs)), or cover a different redshift range than the full photometric sample. Furthermore, if the parameters used to calculate photometric redshifts are tuned to minimize the differences between the photometric and spectroscopic redshifts, there is little guarantee that these parameters are optimal for the full photometric sample.

The photometric redshift calculation itself also naturally produces an estimate of the photometric redshift uncertainties. For template-fitting approaches (e.g., Bolzonella et al. 2000; Brammer et al. 2008), the uncertainties are derived from the \( \chi^2(z) \) of the template fits. However, in practice the uncertainties determined in this way (not to mention the photometric redshifts themselves) can depend quite sensitively on the shape and number of templates used. Similarly, the uncertainties derived when using empirical photometric redshift algorithms depend on the quality of the training set (e.g., Collister & Lahav 2004).

In this work, we describe a simple empirical method of using close pairs of objects on the sky to estimate the width and shape of the photometric redshift error distribution. Because galaxies are strongly clustered in real space, there is a high probability that any one galaxy has nearby neighbors. Therefore, close pairs of objects on the sky will have a significant probability of lying at the same redshift, and the differences in photometric redshifts of paired galaxies can be used to constrain the redshift errors. In effect, the method described here uses measurements of pairwise velocities, but in the case where the velocity differences are caused by redshift errors rather than true virial motions.

We first illustrate the procedure using a simulated data set and show examples using public data. Below we use the terms physical pairs when referring to objects that are physically associated with each other (and thus lie at similar redshifts), and projected pairs when referring to objects that lie at different redshifts. Additionally, to avoid confusion between an object’s actual redshift and its photometric redshift, we refer at times to the former quantity as its spectroscopic redshift. All magnitudes are on the AB system.

2. METHOD

2.1. Overview

Here we illustrate how it is possible to estimate the distribution of photometric redshift errors in a completely empirical
way, even in the absence of spectroscopic redshifts. The underlying principle is that galaxies in an ordinary astronomical image will show significant angular clustering (i.e., an excess number of near neighbors over what would be expected from a purely random distribution), which simply reflects the real-space clustering projected on the sky. But the angular clustering arises only from galaxies that are physically associated with each other and thus lie at (nearly) the same redshift. In other words, a sample of all close pairs of objects in an astronomical image will have a random contribution from projected pairs, and an excess contribution from pairs in which both objects lie at the same redshift.3

To demonstrate this principle, we use mock observations generated from the Millennium Simulation (Springel et al. 2005). The method used to create these “light cones” is described by Kitzbichler & White (2007). We obtain the positions and redshifts of all simulated galaxies down to $K = 23.9$ in a single $\sim$2 deg$^2$ light cone from the Millennium database.4 We select objects with $0.9 < z < 1.0$ in the light cone and determine the redshift distribution of all objects lying within a small angular separation of the selected objects. This is shown by the black histogram in Figure 1. The prominent spike at $0.9 < z < 1.0$ shows that many of these nearby neighbors lie at the same redshift. We then create “photometric redshifts” for all objects in the catalog by applying random Gaussian offsets to the true redshifts, and repeat this procedure. The blue dotted histogram shows the result; the spike is still present but has been broadened by the redshift errors. Finally, to estimate the contribution to $N(z)$ by close pairs that arise only in projection, we randomize the angular positions of objects in the catalog and repeat the procedure. This randomization removes the clustering of sources, so now the only pairs are projected pairs; the result is shown by the red dashed histogram. We can isolate the physical pairs, in a statistical sense, by subtracting the red histogram from the blue, and can estimate the distribution of photometric redshift errors from the width and shape of the spike.

2.2. Estimating Photometric Redshift Accuracy from Physically Associated Pairs

In the absence of spectroscopic redshifts, the dispersion of photometric redshifts can be estimated by comparing the difference in the photometric redshifts of the objects in physical pairs. To see how this is done, we model the photometric redshifts as being offset from the true redshifts using

$$z_{\text{phot}} = \delta_z \cdot (1 + z) + z^\text{true}$$

where $\delta_z$ is a random deviate. Equation (1) implicitly assumes that the uncertainties are constant in units of $(1 + z)$, but note that this condition is at best only approximately met in current data sets. Since typical photometric redshift uncertainties are significantly larger than the true redshift differences in physically associated pairs, we can assume that the true redshifts of both objects in a pair are identical.

The best estimate of the true redshift of a pair is its mean photometric redshift. We can then measure the quantity

$$\Delta z \equiv \frac{(z_{\text{phot},1} - z_{\text{phot},2})}{(1 + z_{\text{mean}})}$$

From Equations (1) and (2), it can be shown that

$$\Delta z \simeq \delta_1 - \delta_2 - \frac{1}{2}(\delta_1^2 - \delta_2^2)$$

where we have kept only the first- and second-order terms. If $\delta_z$ follows a Gaussian distribution, and if $\delta_z \ll 1$, then the dispersion in $\Delta z$ is related to the dispersion in $\delta_z$ by

$$\sigma(\Delta z) \simeq \sqrt{2}\sigma(\delta_z)$$

where we have additionally assumed that both objects in the pair have similar uncertainties. There may be times when it is useful to consider close pairs of different types of objects, such as bright-faint pairs, in which case this assumption will not hold and the uncertainties should be added in quadrature.

2.3. Subtracting Out the Projected Pairs

Unless pairs with only very small angular separations are used, the number of projected pairs will be comparable to, or significantly greater than, the number of physical pairs. It then becomes necessary to statistically subtract out the contaminants. The expected number and distribution of contaminants can be easily estimated by randomizing the positions of the galaxies from which the observed pairs are drawn (while keeping the redshifts the same) and by detecting the random pairs. The random positions should follow the same observing geometry constraints as the observed positions (i.e., avoiding the locations of bright stars or other image artifacts), and the process can be repeated several times to reduce the uncertainty. This method of subtracting out the uncorrelated pairs is the standard procedure in studies of galaxy clustering. In particular, it has been used to measure the strength of the “finger of god” effect (e.g., Coil et al. 2008) that is caused by velocity differences between pairs of objects, and which are analogous to the redshift differences that are the subject of the paper.

Figure 1. Redshift distribution of nearby neighbors of objects drawn from a light cone based on the Millennium Simulation. We select objects at $0.9 < z < 1.0$ and plot the redshift distribution of near neighbors (chosen, in this case, to have an angular separation $2:5 < \theta < 15''$ from the central object) as the black histogram. The spike shows that a significant number of the nearby neighbors lie at the same redshift as the central objects. The blue dotted histogram has been calculated in the same way as the black histogram, except that the redshifts have first been perturbed to simulate photometric redshift errors; the spike is still visible but has been broadened. The red dashed histogram shows the redshift distribution of neighbors after randomizing the galaxy positions and simply reflects the overall redshift distribution of all objects in the catalog; this can be taken as an estimate of the contribution to $N(z)$ of projected near neighbors.

(A color version of this figure is available in the online journal.)

3 Although we limit the discussion in this paper to pairs, it is possible to use larger $N > 2$ associations of objects.

4 see http://www.g-vo.org/Millennium
For purposes of illustration, we create “photometric redshifts” for objects in the light cone by perturbing the true redshifts with Gaussian random deviates with $\sigma = 0.06$, which is a typical error for high signal-to-noise ratio ($S/N$) objects in high-quality data sets at $z > 1$. We select objects in the light cone with $1 < z_{\text{phot}} < 2$ and identify all pairs with an angular separation $2.5''-15''$. The lower limit is applied to minimize the effect of blending on the object photometry (this is obviously not an issue for the simulated data used in this section, but will be an issue for actual data). The upper limit was chosen arbitrarily: a larger value would yield more pairs, and thus a more accurate estimate of the redshift uncertainties, but $15''$ is sufficient for our purposes and limits the computational expense. Some further technical details regarding the methods we use to select galaxy pairs can be found in the Appendix. The left panel of Figure 2 shows the distribution of $\Delta z_{\text{phot}}/(1+z_{\text{mean}})$ for both the observed pairs and the pairs found in the randomized catalog. In the right panel, we subtract the randomized histogram from the true histogram; this subtraction is a statistical correction for the projected pairs. Overplotted is the expected Gaussian, which from Equation (4) has width $\sigma = \sqrt{2} \times 0.06$. A Gaussian fit to the histogram yields $\sigma = 0.084 \pm 0.001$ with $\chi^2_{\text{DOF}} = 1.01$. We do not show this fit in the figure, as it is visually indistinguishable from the expected curve.

2.4. Non-Gaussian Errors

In the previous sections, we dealt with the case of Gaussian photometric redshift errors. But in actual data sets the average photometric redshift probability distribution will not generally be a perfect Gaussian, and hence $\Delta z$ will also deviate from a Gaussian. It is therefore of interest to consider other functional forms, particularly those with more prominent wings than a simple Gaussian. One possibility is to consider the case of error distributions that are the sum of two Gaussians. We first note that the distribution of $z_{\text{phot},1} - z_{\text{phot},2}$ is simply the error distribution convolved with itself.\textsuperscript{5} A single Gaussian convolved with itself will become broader by a factor of $\sqrt{2}$, which explains the presence of that factor in Equation (4). A double Gaussian convolved with itself results in a triple Gaussian (i.e., each of the two Gaussians convolved with themselves, plus a third Gaussian which is the two Gaussians convolved with each other).

To illustrate how this works, we produce “photometric redshifts” in the light cone by perturbing the spectroscopic redshifts by a double Gaussian, with widths $\sigma_1 = 0.03$ and $\sigma_2 = 0.09$, and we set the relative areas of the second to the first Gaussian to $r = 0.5$. This is the same as saying that $2/3$ of the objects have a redshift error given by $\sigma_1$ and $1/3$ have an error given by $\sigma_2$. We then calculate $\Delta z$ for the close pairs and fit a function of the form

$$F(x) = AG(x, 2\sigma_1^2) + 2rG(x, \sigma_1^2 + \sigma_2^2) + Ar^2G(x, 2\sigma_2^2),$$

(5)

where $G(x, \sigma^2)$ is a normalized Gaussian with variance $\sigma^2$ and $A$ is just an overall normalization factor. Thus, the fitting parameters are $(A, \sigma_1, \sigma_2, r)$, and we have increased the number of parameters relative to the single Gaussian case by two.

Figure 3 shows the result. We obtain $(\sigma_1, \sigma_2, r) = (0.0300 \pm 0.002, 0.087 \pm 0.007, 0.5 \pm 0.1)$, which is consistent with the expected values. This figure also shows the result of fitting a single Gaussian to the distribution; the fit is obviously not as good (with $\chi^2_{\text{DOF}} = 4.6$ versus $\chi^2_{\text{DOF}} = 1.2$ for the triple Gaussian fit) but still gives a reasonable estimate of the errors, with $\sigma = 0.062 \pm 0.001$. In practice, fits using Equation (5) can become somewhat unstable in certain regimes of parameter space due to covariance in the fitting parameters or due to poor $S/N$. It is useful to constrain the fitting parameters so they do not reach very small, or negative, values.

In practice, it is convenient to use any functional form that adequately describes the observed distribution of $\Delta z$, has a limited number of free parameters, and is simple to deconvolve. In the case of non-Gaussian tails, a simpler alternative to the double Gaussian parameterization described above is the Lorentzian distribution, $L(x, \gamma)$ (this distribution has been used previously by Marchesini et al. 2007 to describe photometric redshift errors). This formula has only two free parameters and has the convenient property that the convolution of a Lorentz distribution with itself results in another Lorentz distribution where $\gamma$ is increased by a factor of 2 (Dwass 1985). So in this

\textsuperscript{5} Rigorously speaking, the distribution is cross-correlated with itself rather than convolved with itself, but the two operations are equivalent for the even functions considered here.
case the fitting function of $\Delta z$ would be

$$F(x) = A L(x, 2\gamma),$$

where the fitting parameters are $(A, \gamma)$.

### 2.5. The Effects of Catastrophic Failures

Thus far we have modeled the photometric redshift errors as small perturbations on the true redshifts. However, actual photometric redshifts are subject to “catastrophic failures.” These outliers may be caused by artifacts in the data, multiple minima in $\chi^2(z)$, or may arise from a mismatch between the observed galaxy spectral energy distributions (SEDs) and the galaxy templates used when calculating photometric redshifts.

In a close-pairs analysis, outliers will result in an excess of pairs with widely discrepant photometric redshifts.

Here we demonstrate the effects of two types of catastrophic failures. In the first, we generate “photometric redshifts” for each object in the light cone as described in Section 2.3, but now include outliers by assigning random redshifts that are constrained to be at least $5\sigma$ away from the true redshift for $30\%$ of the objects (the catastrophic failure rate is lower than this for normal galaxies in current multiwavelength surveys, but we exaggerate the effect to provide a clear illustration).

In the general case it is not trivial to estimate the rate of catastrophic failures using a pairs analysis. In part this is due to a degeneracy between detected pairs in which one object scatters into the redshift selection window and pairs in which an object scatters out. In the former case, the objects that scatter in will be uncorrelated with the objects that were already inside the window and thus will not contribute to the core of the distribution of $\Delta z$ once the correction for projected pairs has been performed. However, those objects will remain correlated with objects outside the redshift window and will thus contribute to pairs at large values of $|\Delta z|$. Similarly, objects that were originally in the redshift selection window but scattered out will remain correlated with objects inside the window and will also contribute at large values of $|\Delta z|$.

In the case where the number of pairs with large redshift separation is dominated by objects that scattered out of the window, the outlier rate can be estimated approximately as the fractional area under the histogram at large $|\Delta z|$. In the left panel of Figure 4, the area at $|\Delta z| > 0.35$ is $30\% \pm 1\%$, in agreement with the expected value of $30\%$. However, this good...
agreement is due to the fact that the redshift selection window of $1 < z < 1.5$ is near the peak of the overall redshift distribution of objects in the light cone, and so more objects can scatter out than can scatter in. Repeating the analysis with a redshift window of $2 < z < 2.5$ yields a fractional area of $46\% \pm 2\%$.

In the right panel, the fractional area at $|\Delta z| > 0.35$ is $42\% \pm 2\%$, which is larger than the input catastrophic failure rate of $30\%$. This is due to the fact that there is a large contribution of objects that scatter from $0 < z < 0.5$ into the redshift window of $2 < z < 3$. If we reduce the catastrophic failure rate of objects at $0 < z < 0.5$ to $5\%$, while keeping this value at $30\%$ for objects at $2 < z < 3$, then the fractional area is $35\% \pm 4\%$.

This shows that, using the simple estimate described here will frequently lead to an approximate upper limit on the true catastrophic failure rate. A more rigorous analysis is possible and would require knowledge of the intrinsic redshift distribution of close pairs. Such an analysis is beyond the scope of this paper but would proceed along the lines of that described by Benjamin et al. (2010), who use a cross-correlation between different redshift bins (see also Erben et al. 2009). In fact, the method of measuring the fraction of pairs at large $|\Delta z|$ is closely related to that technique, as it relies on counting the number of pairs in widely separated redshift bins.

3. THE EFFECTS OF SYSTEMATIC ERRORS IN THE PHOTOMETRIC REDSHIFTS

In the previous section, we demonstrated the close-pairs technique on mock data. Here we use the technique to determine the photometric redshift errors in an actual data set and discuss the effects of systematic redshift errors.

The Cosmic Evolution Survey (COSMOS; Scoville et al. 2007) is a 2 deg$^2$ multiwavelength survey and was conducted with the primary goal of studying the relationship between galaxy evolution and large-scale structure. A unique aspect of this survey is the number of observed filters, with 30 bands from the ultraviolet to the mid-infrared. Particularly valuable is the deep medium-band optical imaging, which traces galaxy SEDs with much higher resolution than is possible with standard broadband filters. Ilbert et al. (2009) present photometric redshifts for the COSMOS field. They use a template-fitting approach to derive the photometric redshifts, paying particular attention to the choice of templates and to the effects of emission lines. The medium-band imaging allows Ilbert et al. (2009) to achieve extremely accurate photometric redshifts out to $z \sim 1$; for the brightest sources, with $I < 22.5$, they quote a typical error in $|\Delta z|/(1 + z)$ of 0.007.

Another unique aspect of this field is the large number of spectroscopic redshifts available from the zCOSMOS survey (Lilly et al. 2009). For the purposes of this paper, these spectroscopic redshifts are extremely useful as the zCOSMOS-bright sample has a high level of completeness for $I < 22.5$, and the objects with secure spectroscopic redshifts are a relatively unbiased subset of the parent population. Thus, we can use these spectroscopic redshifts to obtain an independent test of the photometric redshift errors. In what follows, we reject objects classified as stars or X-ray sources in the photometric catalog and make use of only the highly secure spectroscopic redshifts (with confidence class 3 or 4). We also apply small random perturbations to the photometric redshifts to eliminate discretization effects.

To demonstrate how well we can recover the photometric redshift errors from real data using the technique described in this paper, we begin by comparing our estimate of the errors to a direct measurement of the errors made by comparing photometric and spectroscopic redshifts for individual galaxies. For this we use the zCOSMOS-bright sample. The left panel in Figure 5 shows the $\Delta z_{\text{phot}}/(1 + z_{\text{mean}})$ for galaxies with $17.5 < I < 22.5$. The blue curve shows the best fit, using the fitting function (Equation (5): $\chi^2_{\text{DOF}} = 1.7$). The right panel shows the direct measurement of the photometric redshift errors in a standard $(z_{\text{phot}} - z_{\text{spec}})/(1 + z_{\text{spec}})$ plot, and the blue curve shows the predicted errors from the fit in the left panel. Although to first order we do recover the typical magnitude of the errors reasonably well, the distribution of errors is obviously not perfect (with $\chi^2_{\text{DOF}} = 7.3$) as the central region is too strongly peaked.

This effect can be seen more strongly at fainter magnitudes, as demonstrated in Figure 6. The left panel shows $\Delta z_{\text{phot}}/(1 + z_{\text{mean}})$ for galaxies with $24 < I < 25$, along with the best fit ($\chi^2_{\text{DOF}} = 1.4$). Here the error distribution appears highly non-Gaussian, with broad tails and a very narrow peak. In this case, we cannot directly measure the photometric redshift errors as done in Figure 5 since there are few spectroscopic redshifts available for galaxies at these faint magnitudes. Thus, we follow Figure 5. Left: the distribution of $\Delta z_{\text{phot}}/(1 + z_{\text{mean}})$ for galaxies with $17.5 < I < 22.5$ in the COSMOS field. The blue curve is a fit. Right: the distribution of $(z_{\text{phot}} - z_{\text{spec}})/(1 + z_{\text{spec}})$ for objects with spectroscopic redshifts from zCOSMOS, again for galaxies with $17.5 < I < 22.5$. The curve is the error distribution that would be inferred from the fit in the left panel. Although the typical size of the errors is recovered well to first order, the shape of the error distribution is not perfect. (A color version of this figure is available in the online journal.)
a different approach of estimating the error distribution from photometric–spectroscopic pairs, i.e., we measure the redshift separation of close pairs where one object has a spectroscopic redshift from the zCOSMOS-bright sample and the other object has $24 < I < 25$. In this case, the projected pairs can be subtracted out in a manner analogous to that described in Section 2.3, except that the positions of spectroscopic sample are fixed and only the positions of the photometric sample are randomized. The photometric redshift errors estimated in this way are shown in the right panel of Figure 6. Again, the solid blue curve (with $\chi^2_{\text{DOF}} = 4.3$) shows the error distribution that would have been predicted from the fit in the left panel. Obviously, the strong central peak is an artifact and does not represent the true errors. The red dashed curve in this panel is a fit using a double-Gaussian-fitting function ($\chi^2_{\text{DOF}} = 0.95$), and the red curve in the left panel shows the resulting prediction for $\Delta z_{\text{phot}}/(1 + z_{\text{mean}})$ ($\chi^2_{\text{DOF}} = 3.9$).

The fact that many close pairs of objects have photometric redshifts that are closer than expected based on the true errors is largely due to an artifact of the photometric redshift algorithm. It is a common feature of many data sets that there are artificial spikes in the photometric redshift distribution. These spikes may result from the particular filter/template combination or may be due to systematic errors in object colors. For instance, if the observed galaxy colors in two closely spaced filters are systematically too red—due to poor point-spread function (PSF) matching or zero-point errors—then the photometric redshift code may interpret the red colors as being due to 4000 Å breaks in the galaxy SEDs, with the effect that many objects will have artificially similar photometric redshifts.

This illustrates the fundamental limitation of the technique described in this paper, which is that its usefulness is reduced in the case of significant systematic redshift errors. A more frequently discussed type of systematic error, in which all photometric redshifts are overestimated or underestimated, will go completely undetected using the method described in Section 2 (however in some cases such biases are relatively unimportant, so long as they are small; Quadri et al. 2007). Artificial spikes in the photometric redshift distribution are somewhat different type of systematic error; this type of error is not nearly as noticeable in most data sets as it is in Figure 6, and we have made use of the COSMOS field here primarily for its illustrative value.

This does not necessarily mean that the COSMOS photometric redshifts suffer from redshift “attractors”—also sometimes called “redshift focusing”—more than other photometric redshift catalogs; it may simply mean that the random errors are so small in this case that the systematic errors become important.

### 4. Differential Photometric Redshift Errors

In this section, we investigate how photometric redshift errors depend on redshift, S/N, and galaxy type. Because in most data sets the photometric redshifts are constrained primarily by the locations of Lyman break and/or the Balmer/4000 Å break, objects with weak or undetected breaks will have comparatively uncertain photometric redshifts. It is therefore expected that redshift accuracy will have some dependence on galaxy type, not only because of differences in the SED shapes but also because of possible correlations between galaxy type and S/N. Here we use public data in the field observed by the UKIDSS Ultra-Deep Survey (UDS; Lawrence et al. 2007; Warren et al. 2007). We use an updated version of the UDS catalog that was presented by Williams et al. (2009), and details of the data, photometry, and redshifts can be found in that work. Briefly, this catalog includes near-infrared (NIR) imaging from the UDS, optical imaging from the Subaru-XMM Deep Survey (SXDS; Furusawa et al. 2008), infrared imaging from the Spitzer Wide-Area Infrared Extragalactic Survey (SWIRE; Lonsdale et al. 2003). The field size with complete multicolor coverage is ∼0.65 deg$^2$. The latest version of our catalog includes $H$-band imaging in the NIR from the UDS data release 3 and $V$-band imaging from the SXDS data release 1. We have also added $u^\prime$-band imaging from the Canada–France–Hawaii Telescope (CFHT) that was taken as part of Program ID 07BC25 (P.I. O. Almaini) and was downloaded from the CFHT archive. Those data were kindly reduced for us by H. Hildebrandt using the procedures described in Erben et al. (2009) and Hildebrandt et al. (2009). Thus, the updated catalog has complete $u^\prime BVRIz' JHK3.6 \mu m \ 4.5 \mu m$ photometry.

The photometric redshifts were calculated from the updated catalog using the EAZY code (Brammer et al. 2008). We did not perform any tuning of the default EAZY parameters, with the single exception of reducing the amplitude of the template error function to 0.5, which has been found to provide better...
results in several different data sets (G. Brammer 2010, private communication). Additionally we use an updated template set with a new treatment of emission lines (G. Brammer et al. 2010, in preparation).

To illustrate the effect of galaxy type on redshift accuracy, we separate galaxies into star-forming and quiescent populations according to the bimodality in a rest-frame $U-V$ versus $V-J$ color–color diagram (Williams et al. 2009). We limit the sample to $K < 22.9$ and reject galaxies with high $\chi^2$ values from the template fits as those objects tend to have very inaccurate photometric redshifts and are frequently AGNs.

We estimate accuracy in $\Delta(z)/(1 + z)$ in four redshift bins: $0.3 < z_{\text{phot}} < 0.7$, $0.7 < z_{\text{phot}} < 1.2$, $1.2 < z_{\text{phot}} < 1.7$, and $1.7 < z_{\text{phot}} < 2.2$. Within each redshift bin, we separate galaxies into a bright and faint subsample according to the median $S/N$ of all galaxies in that bin. Although most studies classify galaxies according to the $S/N$ in the detection band, it is not obvious that this is an especially relevant statistic. In this case, the detection band is $K$, which does not actually play a major role in constraining the redshifts at $z < 2$. Since photometric redshifts are most strongly constrained at these redshifts by the identification of the 4000 Å break, we use the $S/N$ in the closest band redward of the break. Thus, an old galaxy with a strong break, which may have high $S/N$ redward of the break and low $S/N$ blueward of the break, will be appropriately classified as high $S/N$ since the location of the break will be tightly constrained.

For each galaxy sample, we fit the distribution of $\Delta z_{\text{phot}}/(1 + z_{\text{mean}})$ using Equation (5). Figure 7 shows the result in the $1.2 < z_{\text{phot}} < 1.7$ redshift bin (without splitting the samples by $S/N$). It is immediately apparent that the quiescent galaxies have more accurate redshifts than the star-forming galaxies. This is more clearly demonstrated in Figure 8, which shows the $68\%$ uncertainty in $\Delta(z)/(1 + z)$ that we estimate by integrating the inferred photometric redshift error distribution. The red and blue solid curves show how this quantity changes with redshift for the quiescent and star-forming galaxies, respectively. The upper and lower dashed curves show the accuracy for the fainter and brighter subsamples of each population.

The quality of the photometric redshifts in the UDS is impressively good. The quiescent galaxies, in particular, have extremely accurate redshifts at $z \lesssim 1$. This is confirmed by a direct comparison of photometric with spectroscopic redshifts using the substantial spectroscopic sample of $z \sim 1$ pas-

![Figure 7](image_url) Distribution of $\Delta z_{\text{phot}}/(1 + z_{\text{mean}})$ for star-forming galaxies and quiescent galaxies at $1.2 < z_{\text{phot}} < 1.7$ in the UDS. The quiescent galaxies have more accurate photometric redshifts.

(A color version of this figure is available in the online journal.)

![Figure 8](image_url) $68\%$ errors in $\Delta(z)/(1 + z)$ as a function of redshift for star-forming (blue curves) and quiescent (red curves) galaxies. The solid curves are for the full sample of $K < 22.9$ objects, while the lower dashed curves are for bright galaxies and the upper dashed curves are for faint galaxies. A galaxy is classified as bright (faint) if the $S/N$ in the band immediately redward of the 4000 Å break is higher (lower) than the median for all galaxies in that redshift bin.

The quiescent galaxies do show significantly more accurate photometric redshifts than the star-forming galaxies over all redshifts probed here. For certain types of studies, such differential photometric redshift errors can adversely affect the results. For instance, the increased errors for star-forming galaxies can lower the inferred correlation length (Quadri et al. 2007), leading to an artificial trend of clustering with star formation properties. Another example is the mass/luminosity function: redshift errors will tend to flatten these functions relative to their true values (Chen et al. 2003; but see Marchesini et al. 2007) and can lead to an artificial difference between these functions for star-forming and quiescent galaxies.

The result that quiescent galaxies have more accurate redshifts is obviously somewhat dependent on image depth and filter coverage; our deep images and closely spaced optical and NIR filters allow us to pinpoint the location of the Balmer/4000 Å break for quiescent galaxies quite accurately, while the lack of ultraviolet imaging means that we cannot detect the Lyman break of star-forming galaxies at these redshifts. It is
entirely possible that with different data the star-forming galaxies would have photometric redshift accuracy comparable to, or even better than, the quiescent galaxies.

5. SUMMARY AND DISCUSSION

The use of photometric, as opposed to spectroscopic, redshifts makes it possible to study a much larger number of objects for a given amount of telescope time. But photometric redshift errors will propagate through many different types of analyses, and in practice may comprise a significant source of error in derived quantities. For this reason, a realistic estimate of the distribution of photometric redshift errors is necessary. Obtaining large, representative samples of spectroscopic redshifts with which to directly measure the photometric redshift errors is observationally expensive and often completely unfeasible. It is therefore of great interest to have a method to estimate the size and distribution of such errors that can be applied with limited, or even non-existent, spectroscopic samples.

In this paper, we have presented such a method. It is based on the idea that a close association of two or more galaxies on the sky may represent a true physical association, in which case the objects will lie at nearly the same redshift and the differences between their photometric redshifts constrain the typical errors. We have described a simple implementation of this idea that makes use of close galaxy pairs, where the best estimate of the true redshift of a pair is taken to be the mean of the photometric redshifts. We have described how to estimate the photometric redshift error distribution from the difference in photometric redshifts and discussed the effects of catastrophic failures. This technique requires applying a statistical correction for pairs that arise from chance projections along the line of sight, and this is easily done by randomizing the galaxy positions and repeating the analysis. Although in this paper we have focused on the redshift range $0.5 \leq z \leq 2$, the basic technique can be applied at both significantly lower and higher redshifts.

As a first application of our method, we have shown that quiescent galaxies will on average have more accurate photometric redshifts than star-forming galaxies in broadband optical/NIR surveys out to at least $z \sim 2$. This is because quiescent galaxies have a strong break in their SEDs near 4000 Å, and if the location of this break can be pinpointed using the observed photometry, the redshift will be tightly constrained. Star-forming galaxies, on the other hand, have weaker features in their SEDs over the range of observed wavelengths. Differential photometric redshift errors can lead to differential effects in derived quantities, such as luminosity or mass functions, and should be taken into account when comparing such quantities between samples.

A significant limitation of the method presented in this paper arises from systematic errors in the photometric redshifts. One type of systematic error, in which all photometric redshifts are biased in one direction, will go completely undetected. However, if a particular class of galaxies (e.g., galaxies on the red sequence) is subject to such a bias, whereas another class (in the blue cloud) is not, then this bias will become apparent by looking at cross-pairs (red–blue pairs). Another type of systematic error is when the photometric redshift distribution shows artificial spikes. This is particularly problematic, as it means that the photometric redshifts of a pair of objects may both be drawn into the spike, leading to a smaller relative redshift difference and an underestimate of the true redshift errors. In extreme cases, when this type of error is comparable to the random errors, this effect can lead to highly disturbed error distributions (Figure 6). Both of these types of systematic errors can, however, be accounted for by using pairs where one object has a known spectroscopic redshift.

The concept of using angular associations between galaxies to constrain their redshifts is not entirely new. For instance, Newman (2008) and Matthews & Newman (2010) use a cross-correlation between a spectroscopic and a photometric sample of galaxies to infer the true redshift distribution of the photometric sample. Erben et al. (2009) use the cross-correlation between galaxies selected in two disjoint photometric redshift bins to quantify the photometric redshift errors (see also Schneider et al. 2006; Benjamin et al. 2010). Kováč et al. (2010) modify the photometric redshift probability distribution of objects on the basis of the spectroscopic redshifts of nearby objects. The technique presented here has the advantage that it is simple to implement, the results are easy to interpret, it can be applied with limited (or even with a complete lack of) spectroscopic information, and it can provide useful constraints with even relatively small galaxy samples.

Much of the previous work on techniques to calibrate photometric redshift uncertainties was conducted in the context of planning for redshift surveys that are designed to constrain the fundamental cosmological parameters. For such studies, it is often the overall redshift distribution $N(z)$ of some sample of objects that is of interest. In contrast, studies of galaxy evolution are frequently—but not always—more concerned with the typical redshift uncertainties for different classes of objects. The discussion in this paper has been oriented toward the latter type of study, and our techniques do not directly constrain the $N(z)$. Future work will be required to assess how useful these techniques are for cosmological studies and to determine how they may best be incorporated.

One fundamental difference between the methods described in this work and the cross-correlation methods used in some previous work is that standard cross-correlation methods rely on the amplitude of the correlation function, which follows directly from the observed number of pairs. In contrast, our method does not depend on the number of pairs, but rather on the redshift differences of objects that do appear in pairs; i.e., it is width, and not the amplitude, of the histogram in the right panel of Figure 2 that is of interest. This means that our method does not depend on estimates of the galaxy bias (but evolution in the bias will affect an analysis of the catastrophic failures; see Section 2.5). However, in the case of wide redshift bins, a non-flat galaxy redshift distribution and/or evolution in the bias will lead to a second-order effect in which galaxy pairs at one end of the redshift bin will be more numerous than galaxy pairs at the other end and will thus contribute disproportionately to the inferred redshift errors. In practice, it is advisable to use relatively narrow redshift bins.

A related issue is that results from the close-pairs technique may be subject to subtle biases due to the relationship between galaxy properties and local environment. For instance, if red sequence galaxies preferentially appear in groups, then they will be overrepresented in a sample of close pairs. Similarly, galaxies with boosted star formation due to close interactions may also be overrepresented. On the other hand, such galaxies may be relatively rare, and it is worthwhile to remember that the number of pairs in a sample is a strong function of the sample size itself, growing like $N^2 - N$. Another potential problem is that close pairs of objects may have inaccurate photometry due to blending or poor background subtraction, so it is important to apply a sensible lower limit for the pair separations.
Our method of using angular associations of galaxies to constrain both the redshifts and the redshift errors can be applied and extended in various ways. Particularly intriguing is the possibility of incorporating information from angular associations directly into photometric redshift codes. A step in this direction has already been taken by Kovacevic et al. (2010), who modify the photometric redshift probability distributions of objects that have near neighbors with spectroscopic redshifts; here we simply note that this same idea may be extended to neighbors with only photometric information. Regardless of how the ideas discussed in this paper are used in future, the close-pairs technique is straightforward to apply and should prove to be a useful tool in analyzing data from redshift surveys.

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APPENDIX
IDENTIFYING GALAXY PAIRS: SOME PRACTICAL CONSIDERATIONS

In this appendix, we briefly discuss some technical considerations that may be of interest to readers implementing the procedures described above.

It can be numerically intensive to identify all of the close pairs in an image. Especially if one wishes to perform the analysis for different samples of objects—for instance, for objects in bins of redshift or S/N, or for pairs with different ranges of angular separation—then it would take significant computational time to identify each of the pairs that meet each set of selection criteria. In practice, we identify all close pairs in an image (out to some maximum angular separation) only once and store the ID numbers and angular separations for each pair in a file. Then, for any desired selection criteria, we can read in the file and discard those pairs that do not meet the criteria.

When creating the histogram of \( \Delta z \equiv (z_{\text{phot},1} - z_{\text{phot},2})/(1 + z_{\text{mean}}) \), it should be noted that it is not only the unique pairs which are counted, since pairs in which both objects lie within the redshift range of interest are counted twice. In the example described in Section 2.3, a pair where both objects lie at \( 1 < z_{\text{phot}} < 2 \) contributes twice to the histogram of \( \Delta z \), whereas a pair where only one object lies in that redshift range contributes once.

Similar considerations apply for the randomized catalog that is used to correct for the projected pairs. Rather than creating a new random catalog for each galaxy sample under consideration, we create a single large catalog of random points, identify the (unique) pairs, and store a list of angular separations in a file. Then we can quickly mimic the random catalogs described above by assigning to each value of the pair separation a value of \( \Delta z \)—where the photometric redshifts in Equation (2) are drawn at random from the data—and by rejecting those pairs that do not have the correct angular separation or do not have at least one object that falls within the redshift range of interest. As with the data catalog, pairs in which both objects fall within the redshift selection window are counted twice. The remaining step is to scale the histogram of \( \Delta z \) to the amplitude that it would have if the random catalog had the same number of objects as the data catalog. The area of the scaled histogram should be equal to \( \frac{1}{\pi} n_D (n_D - 1) f_z f_r \), where \( n_D \) is the number of points in the data catalog, \( f_z \) is a geometrical correction factor which is equal to the fraction of all pairs that have the right range of angular separations, and \( f_r \) is a redshift correction factor that is equal to the number of selected pairs in the random catalog that fall within the redshift selection window divided by the total number of unique pairs (note that this factor can be greater than 1, since pairs where both objects fall within the window are counted twice).

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