The Efficacy of Galaxy Shape Parameters in Photometric Redshift Estimation: A Neural Network Approach

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ABSTRACT. We present a determination of the effects of including galaxy morphological parameters in photometric redshift estimation with an artificial neural network method. Neural networks, which recognize patterns in the information content of data in an unbiased way, can be a useful estimator of the additional information contained in extra parameters, such as those describing morphology, if the input data are treated on an equal footing. We use imaging and five band photometric magnitudes from the All-wavelength Extended Groth Strip International Survey (AEGIS). It is shown that certain principal components of the morphology information are correlated with galaxy type. However, we find that for the data used the inclusion of morphological information does not have a statistically significant benefit for photometric redshift estimation with the techniques employed here. The inclusion of these parameters may result in a tradeoff between extra information and additional noise, with the additional noise becoming more dominant as more parameters are added.

Online material: color figure

1. INTRODUCTION

Obtaining sufficiently accurate photometric redshift estimates is of the utmost importance for the current and coming era of large multiband extragalactic surveys (see, e.g., Huterer et al. 2006 for a recent review). Unlike spectroscopic redshift determination, photometric redshift (photo-$z$) estimation is highly subject to systematic errors and confusion, because the spectral information of a galaxy is limited to the magnitude or flux in a number of wavelength bands.

Photo-$z$ estimation techniques have traditionally been divided into two main classifications. So-called template-fitting methods (for example, the popular Lephare package, as described in Ilbert et al. 2006 and Arnouts et al. 1999, and Bayesian photometric redshift, as described in Benítez 2000), involve correlating the observed band photometry with model galaxy spectra and redshift, and possibly other model properties. In contrast, so-called empirical or training set methods, such as artificial neural networks (e.g., ANNz package; Collister & Lahav 2004) and boosted decision trees (e.g., Gerdes et al. 2010), develop a mapping from input parameters to redshift with a training set of data in which the actual redshifts are known, then apply the mappings to data for which the redshifts are to be estimated. There are advantages and disadvantages to each class of methods. Template-fitting methods require assumptions about intrinsic galaxy spectra or their redshift evolution, and empirical methods require the training set to be complete in the sense that it is representative of the target evaluation population in bulk in all characteristics.

In regard to photo-$z$ estimations, science goals such as using weak lensing for cosmology are most affected by the number of outliers—those objects whose photo-$z$ estimations are far from the actual redshifts (e.g., Hearin et al. 2010). In general, data sets with bands extending into the infrared (e.g., $J$, $H$, and $K$ bands) have more accurate photo-$z$ estimation and fewer outliers. However, most upcoming large surveys, such as the Large Synoptic Survey Telescope (LSST; Ivezić et al. 2008), will have optical and near-infrared data only.

It is a reasonable hypothesis that galaxy morphology and redshift are correlated in such a way that the addition of morphological information could improve photo-$z$ estimation. Reasons include the larger frequency of mergers at higher redshifts and, perhaps more importantly, the general evolutionary trend from spiral to elliptical shapes.

The inclusion of morphological parameters in photo-$z$ estimation has also been studied by Tagliaferri et al. (2003) with an artificial neural network determination and by Vince & Csabai (2006) and Way & Srivastava (2006) with other methods. All three works use Sloan Digital Sky Survey (SDSS) data. Tagliaferri et al. (2003) find possible modest improvement with the inclusion of shape information, although they restrict their analysis to quite low redshift ($z \leq 0.7$) galaxies. Way & Srivastava (2006) consider several empirical methods and show marginal
improvement for some methods with the addition of morphological information. Vince & Csabai (2006) claim an improvement of between 1 and 3% in the rms error in photo-$z$ determination; however, it is not noted whether this result is significant, and the method of photo-$z$ estimation is not discussed. We note that SDSS galaxy photometric data is a bit unusual in the context of data that will be used to constrain cosmological parameters from surveys such as LSST, in that SDSS photometric data has a greater representation of nearby galaxies and thus fewer potential outliers.

In this work, we explore the efficacy of adding parameters describing the morphological information of galaxies, in the context of a neural network estimation technique for photo-$z$ estimations.

2. DATA SET AND SHAPE PARAMETERS

For this analysis we desire data with magnitudes in a number of optical bands, spectroscopic redshifts, and enough imaging resolution to determine morphological parameters. We use observations of the Extended Groth Strip from the All-wavelength Extended Groth Strip International Survey (AEGIS) data set (Davis et al. 2007), which contains photometric band magnitudes in $u, g, r, i,$ and $z$ bands from the Canada-France-Hawaii Telescope Legacy Survey (CFHTLS; Gwyn 2008), imaging from the Advanced Camera for Surveys on the Hubble Space Telescope (HST/ACS; Koekemoer et al. 2007), and spectroscopic redshifts from the DEEP2 survey using the Deep Imaging Multi-Object Spectrograph (DEIMOS) on the Keck telescope. The limiting $i$-band AB magnitude of the CFHTLS survey is 26.5, that of HST/ACS is 28.75 in the $V$ (F606W) band, and that of DEEP2 is 24.1 in the $R$ band.

From the HST/ACS imaging data in two bands, $V$ (F606W) and $I$ (F814W), we form a set of parameters characterizing the morphological properties of the galaxies as follows:

1. Concentration parameter $C = 5\log(r_{50}/r_{20})$ defines the central density of the light distribution with radii $r_{50}$ and $r_{20}$ at, correspondingly, 80% and 20% of the total light.

2. Asymmetry parameter $A = \frac{[(\Sigma_{x,y}|I(x,y) - I_{180}(x,y)|)/(2\Sigma_{x,y}|I(x,y)|)] - B_{180}}$ characterizes the rotational symmetry of the galaxy’s light, with $I(x,y)$ being the intensity at point $(x,y)$ and with $I_{180}(x,y)$ being the intensity at the point rotated $180^\circ$ about the center from $(x,y)$, with $B_{180}$ being the average asymmetry of the background calculated in the same way. It is the difference between object images rotated by $180^\circ$.

3. Smoothness parameter $S = \frac{[(\Sigma_{x,y}|I(x,y) - I_{S}(x,y)|)/(2\Sigma_{x,y}|I(x,y)|)] - B_{S}}$ is used to quantify the presence of small-scale structure in the galaxy. It is calculated by smoothing the image with a boxcar of a given width and then subtracting that from the original image. In this case $I(x,y)$ is the intensity at point $(x,y)$, $I_{S}(x,y)$ is the smoothed intensity at $(x,y)$, and $B_{S}$ is the average smoothness of the background, calculated in the same way. The residual is a measure of the clumpiness due to features such as compact star clusters. In practice, the smoothing scale length is chosen to be a fraction of the Petrosian radius.

4. Gini coefficient $G = [1/\hat{X}n(n - 1)]\sum_{i=2}^{n}(2i - n - 1)X_{i}$ describes the uniformity of the light distribution, with $G = 0$ corresponding to the uniform distribution and $G = 1$ corresponding to the case when all flux is concentrated in to one pixel. $G$ is calculated by ordering all pixels by increasing flux $X_{i}$. $\hat{X}$ is a mean flux and $n$ is the total number of pixels.

5. $M_{20} = \log \Sigma M_{i}/M_{\text{tot}}$ is the ratio of the second-order moment of the brightest 20% of the galaxy to the total second moment. This parameter is sensitive to the presence of bright off-center clumps.

6. Ellipticity parameter $e = 1 - (b/a)$, where the values $a$ and $b$ are the semimajor axis and semiminor axis of the galaxy.

A number of these parameters are discussed in Scarlata et al. 2007. The remaining two parameters are two of the fitting parameters to the Sérsic profile form $\Sigma_{e}(r) = \Sigma_{0}e^{-k(r/r_{e})^{1/(n-1)}}$ (e.g., Graham & Driver 2005), where $\Sigma_{0}$ is the surface brightness at radius $r_{e}$, and $k$ is defined such that half of the total flux is contained within $r_{e}$.

7. The penultimate parameter is the Sérsic power law index $n$.

8. The final parameter is $r_{e}$, the effective radius of the Sérsic profile.

Morphological parameters $C, A, S, G,$ and $M_{20}$ are determined for these galaxies in Lotz et al. (2008), while $\varepsilon, n,$ and $r_{e}$ are determined by Griffith et al. (2011) using the Galfit package (Peng et al. 2002; Häusler et al. 2007). For this analysis we require a magnitude in each band, a spectroscopic redshift, and sufficient HST/ACS image resolution to construct all eight shape parameters. A total of 2612 galaxies spanning redshifts from 0.01 to 1.57, with a mean redshift of 0.702 and a median of 0.725, and $i$-band magnitudes ranging from 24.43 to 17.62 are in the data set used here. The redshift distribution of this particular set of galaxies arises because of the intentional construction of the portion of the DEEP2 spectroscopic catalog within the AEGIS survey to have roughly equal numbers of galaxies below and above $z = 0.7$; therefore, it is not an optimized training set for any given photometric data evaluation set, although a more optimized training set for a generic photometric data evaluation set could be constructed from it. We emphasize that because in this analysis random subsets from the same 2612 galaxy catalog are used for training and evaluation, the representativeness of the training set is not an issue here for this analysis.

Template-based photometric redshifts estimations for all of the galaxies used in this analysis have been reported in Ilbert et al. (2006). This estimation also provides a most likely galaxy type among template spectra, corresponding to elliptical, Sbc, Scd, irregular, or starburst.
3. MORPHOLOGICAL PRINCIPAL COMPONENTS

In order to most efficiently determine the effect of the extra information provided by morphological parameters on the photo-$z$ estimation, we form principal components of the morphological parameters. The morphological principal components are given as linear combinations of the eight morphological parameters discussed in § 2 by Table 1.

Principal components (e.g., Jolliffe 2002) are the result of a coordinate rotation in a multidimensional space of possibly correlated data parameters into vectors with maximum orthogonal significance. The first principal component is along the direction of maximum variation in the data space, the second is along the direction of remaining maximum variation orthogonal to the first, the third is along the direction of remaining maximum variation orthogonal to both of the first two, and so on.

Given the available galaxy type estimations discussed at the end of § 2, we can check for correlations between principal components of the morphological parameters and galaxy type, as in Figure 1. It is seen that the first principal component is well correlated with galaxy type, and correlations persist through several of the other principal components. These correlations indicate that the morphology may provide an additional handle on the photo-$z$ estimation, since outliers often occur because a spectral feature (such as a break) of one galaxy type at a given redshift may be seen by the observer to be at the same wavelengths as a spectral feature of another galaxy type at a different redshift. Thus, morphological information indicative of galaxy type may help break this degeneracy.

4. PHOTO-$z$ ESTIMATION METHOD

Artificial neural network techniques have been popular empirical methods for photo-$z$ estimation, including with such software packages as ANNz (Collister & Lahav 2004). In the case of neural network photo-$z$ determination, the network functions as a black box that finds patterns contained in the relation between band magnitudes (and, in principle, other information) and redshift in an unbiased way. Thus, a neural network photo-$z$ estimation can be a useful tool to explore whether additional parameters beyond the band magnitudes, such as morphology in this case, provide additional useful information.

An artificial neural network, in analogy with a biological one, contains layers of nodes called “neurons” and relationships between neurons in different layers of varying weights that can be altered. Each neuron in the network beyond the input layer assumes a value determined by passing through an activation function the sum of the product of all of the values of the neurons feeding the neuron in question times the weight of the connection between the two neurons. Neurons at the input accept values of data and the output of the network is the value of one or more output layer neurons.

The weights between neurons are adjusted by training the network to best give desired outputs for a set of inputs. Training is dependent on a training set containing a number of cases with inputs and outputs. In the case of photo-$z$ estimation, the training set contains band magnitudes and possibly other information as inputs and the actual known (spectroscopic) redshifts as the output. With the weights set in this way, the network can be used to estimate the redshift of other galaxies in an evaluation set, and the results can be compared with the known redshifts of the evaluation set to determine the quality of photo-$z$ estimation. A comprehensive discussion of artificial neural networks is presented in Haykin (1999), and a specialized discussion for the context of photo-$z$ estimation is presented in, e.g., Vanzella et al. (2004).

The artificial neural network package used in this analysis is a multilayer perceptron developed for the IDL environment by one of the authors (J.S.). Perceptrons are standard artificial neural network architectures for pattern recognition, consisting of input, hidden, and output neurons, as described previously. The primary motivation for the development of this code was to treat additional available galaxy information beyond photometric data (for example, shape parameters) on an equal footing with the photometric data. The IDL code can be relatively easily modified and could, in principle, be configured for a wide variety of input data situations. As training convergence is relatively slow in this network, it is most useful in situations where a robust training set is available from the outset.

As implemented here, the network has an input layer of neurons, five of which accept the observed magnitudes in each

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TABLE 1

| CONTENTS OF MORPHOLOGICAL PRINCIPAL COMPONENT VECTORS |
|---------------------------------------------|
| PC1 | PC2 | PC3 | PC4 | PC5 | PC6 | PC7 | PC8 |
|-----|-----|-----|-----|-----|-----|-----|-----|
| $C$ | $-0.52$ | $+0.13$ | $+0.01$ | $-0.17$ | $-0.03$ | $+0.19$ | $+0.09$ | $-0.8$ |
| $A$ | $+0.10$ | $-0.41$ | $+0.62$ | $-0.18$ | $-0.61$ | $+0.15$ | $+0.07$ | $-0.007$ |
| $S$ | $+0.06$ | $+0.29$ | $+0.72$ | $-0.18$ | $+0.60$ | $-0.02$ | $+0.04$ | $+0.03$ |
| $G$ | $-0.47$ | $-0.07$ | $+0.09$ | $-0.19$ | $-0.09$ | $-0.67$ | $-0.51$ | $+0.12$ |
| $M_{20}$ | $+0.49$ | $+0.05$ | $+0.004$ | $+0.03$ | $-0.09$ | $-0.67$ | $+0.32$ | $-0.44$ |
| $\varepsilon$ | $+0.07$ | $+0.62$ | $-0.14$ | $-0.63$ | $-0.34$ | $+0.03$ | $+0.13$ | $-0.23$ |
| $n$ | $-0.50$ | $-0.006$ | $+0.07$ | $+0.21$ | $-0.04$ | $-0.20$ | $+0.74$ | $+0.32$ |
| $r_e$ | $-0.02$ | $+0.58$ | $+0.24$ | $+0.65$ | $-0.36$ | $+0.01$ | $-0.22$ | $-0.03$ |

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Available from http://www.slac.stanford.edu/~jacks.
optical band, and an additional variable number of input neurons that accept values of as many morphological parameters as desired. The input layer treats all input information on an equal footing, normalizing each input parameter across all objects in the training set so that the inputs for each neuron on the input layer are distributed between 0 and 1. There are two hidden layers of 30 neurons each and an output layer with a single neuron obtaining a value between 0 and 1, which is a proxy for the estimated redshift, with the linear conversion defined during the training when the known redshifts of the training set are supplied subject to the conversion.

The network uses a hyperbolic tangent activation function for the neurons beyond the input later, and the weights are adjusted during training via the back-propagation technique (e.g., Haykin 1999), where in each training iteration the weights are altered in a way to move downhill in the high-dimensional surface of summed training set redshift errors in the space of weights. Each iteration during training consists of the network evaluating the entire training set and adjusting the weights. In addition to standard back propagation, this network features an algorithm to “kick” the weights away from possible local minima in the summed error. The top panel of Figure 2 shows the estimated photo-z versus spectroscopic redshift for the galaxies in the evaluation set of a particular determination with no morphological information included. This determination features 350,000 training iterations, 700 galaxies in the training set, and 1912 galaxies in the evaluation set, which is the standard used in all determinations here. The bottom panel of Figure 2 also shows photo-z estimations for the same galaxies with the Lephare template-fitting method as reported in Ilbert et al. (2006). The custom neural network determination apparently leads to fewer catastrophic outliers (i.e., those where \( |z_{\text{phot}} - z_{\text{spec}}| / (1 + z_{\text{spec}}) \gg 0.15 \)) than with the Lephare template-fitting method, although it has a larger scatter for those galaxies in which the photo-z estimate is close to the actual redshift.

5. RESULTS ON INCLUSION OF SHAPE PARAMETER INFORMATION

To determine the effect of including a single or multiple principal components in addition to the band magnitudes, we complete six realizations of the training and evaluation process for every case, with a training set of 700 galaxies with 350,000 training iterations and an evaluation set of the remaining 1912 galaxies, and we record the number of outliers and the rms error in the evaluation set. In this work we follow convention (e.g., Ilbert et al. 2006) and define outliers in a given realization as those galaxies where

\[
\text{Outliers: } \frac{|z_{\text{phot}} - z_{\text{spec}}|}{1 + z_{\text{spec}}} > 0.15,
\]

where \( z_{\text{phot}} \) and \( z_{\text{spec}} \) are the estimated photo-z and actual (spectroscopically determined) redshift of the object, respectively. The rms photo-z error in a realization is given by a standard definition:

\[
\sigma_{\Delta z / (1+z)} = \sqrt{\frac{1}{n_{\text{gals}}} \sum_{\text{gals}} \left( \frac{z_{\text{phot}} - z_{\text{spec}}}{1 + z_{\text{spec}}} \right)^2},
\]

where \( n_{\text{gals}} \) is the number of galaxies in the evaluation set and \( \sum_{\text{gals}} \) represents a sum over those galaxies. Note that we do not
exclude outliers from the calculation of the rms photo-z error. Because the membership of the training set varies in each realization, and because the training process contains kicks to knock the weights away from local minima in the summed error (see § 4), each realization for a given input parameter set produces a slightly different number of galaxies in the evaluation set with outlier level errors and a slightly different average error. For comparison, the template-fitting results reported by Ilbert et al. (2006) give 5% outliers and an rms error of $\sigma_{\Delta z/(1+z)} = 0.1881$ for this sample. This error is dominated by the catastrophic outliers (Fig. 2) and drops substantially to below that of the custom neural network method if outliers are excluded.

Figure 3 shows the number of outliers and rms error for the inclusion of the seven different principal components individually. Figure 4 shows the number of outliers and rms error for the inclusion of multiple principal components, starting with none, then adding in the first, then adding in the first and second, then adding in the first through third, and so on. In each figure, the error bars correspond to the standard deviation of the number of outliers or rms scatter in the different realizations. We note that with six realizations per case, the standard deviations in the number of outliers and rms photo-z error are not particularly robust; however, we include them to provide a sense of the scatter of results from different realizations. We note that the last principal component (PC8) should, by definition, contain minimal significant variation in the morphological parameters, so we do not include it in the analysis.

It is apparent that adding in any one of the principal components of the morphological parameters may provide a small decrease in the average number of outliers or the rms error or both, but the differences are not statistically significant compared with the inclusion of no morphological information. As seen

![Figure 2](image_url)

**Fig. 2.** Top: The estimated photo-z vs. the actual redshift, as determined by the custom artificial neural network used in this work, for the case of no morphological parameters included. This determination is of the type used in this analysis, with 350,000 training iterations, where the training set is formed from 700 galaxies and the evaluation set, for which the results are plotted, consists of the remaining 1912 galaxies. Outliers in a determination are defined as those where $|z_{\text{phot}} - z_{\text{spec}}|/(1 + z_{\text{spec}}) > 0.15$, shown as the two diagonal lines. Bottom: The photo-z estimations for the same galaxies as in the top plot, as estimated with the Lephare template-fitting code as reported in Ilbert et al. (2006). The template-fitting method has a lower scatter for nonoutliers but a larger number of catastrophic outliers (i.e., those where $|z_{\text{phot}} - z_{\text{spec}}|/(1 + z_{\text{spec}}) \gg 0.15$) than the custom neural network for these galaxies.

![Figure 3](image_url)

**Fig. 3.** Number of outliers (top) and rms error $\sigma_{\Delta z/(1+z)}$ (bottom) in the photo-z estimation with the inclusion of different individual principal components of the morphological parameters. The uncertainties represent the standard deviation of the values obtained from different realizations, as discussed in § 5.
6. DISCUSSION

We have used a custom artificial neural network for photometric redshift estimation to evaluate the effects of including galaxy shape information, in the form of principal components of morphological parameters, on the photo-z estimation. The data set we use consists of 2612 galaxies with five optical band magnitudes, reliable spectroscopic redshifts, and eight morphological parameters each. We note that a neural network is, in a sense, an unbiased way of determining the relative strength of the correlations of a set of input parameters with the output parameter and that this network is designed to treat all input parameters on an equal footing.

In order to more effectively include the morphological information, we form principal components of the morphological parameters. An analysis of the principal components and galaxy types shows that the value of the first few principal components and galaxy type are correlated.

However, we find that the inclusion of morphological information does not significantly decrease the number of outliers or rms error in photo-z estimation for this data set with the neural network technique used. When only one principal component of the morphological parameters is included, there can be a slight, but not significant, decrease. When multiple principal components of the morphological parameters are included, the number of outliers and the rms error increases. We conclude that any gain that may arise in a neural network photo-z determination from correlations between morphology and redshift in this data set is overwhelmed by the additional noise introduced. It may be that any correlations between principal components of the morphological parameters and the galaxy type are degenerate to some extent with the correlations between galaxy type and galaxy colors.

This analysis is applicable to artificial neural network photo-z estimations, and possibly other training set methods, with similar data. It is possible, however, that morphological parameters could yield improvements for other algorithms, especially template-fitting methods with relatively large outlier fractions. This is because such outliers usually occur when a particular spectral break is confused for another break in a different galaxy type at a different redshift (e.g., an elliptical galaxy at low redshift mistaken for a spiral at high redshift). Having additional information to guide the template selection might therefore be helpful in reducing the outlier fraction. A preliminary analysis using Figure 1 to build prior probability distributions on the template selection in the Lepheare package produced a few percent reduction in the number of outliers. A more thorough analysis of the effects of shape parameters in photometric redshift estimation with a template-fitting method will be presented in a forthcoming work.

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Fig. 4.—Number of outliers (top) and rms error $\sigma_{\Delta z/(1+z)}$ (bottom) in the photo-z estimation with the inclusion of multiple principal components of the morphological parameters, starting with none, adding the first morphological principal component, then the first and the second principal components, and so on. The uncertainties represent the standard deviation of the values obtained from different realizations, as discussed in § 5.
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