

HOW TO OBTAIN THE REDSHIFT DISTRIBUTION FROM PROBABILISTIC REDSHIFT ESTIMATES

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ABSTRACT

The redshift distribution $n(z)$ is a crucial ingredient for weak lensing cosmology. Spectroscopically confirmed redshifts for the dim and numerous galaxies observed by weak lensing surveys are expected to be inaccessible, making photometric redshifts (photo- z s) the next best alternative. Because of the nontrivial inference involved in their determination, photo- z point estimates are being superseded by photo- z probability distribution functions (PDFs). However, analytic methods for utilizing these new data products in cosmological inference are still evolving. This paper presents a novel approach to estimating the posterior distribution over $n(z)$ from a survey of galaxy photo- z PDFs based upon a probabilistic graphical model of hierarchical inference. We present the Cosmological Hierarchical Inference with Probabilistic Photometric Redshifts (CHIPPR) code implementing this technique, as well as its validation on mock data and testing on the **Buzzard** simulations. CHIPPR yields a more accurate characterization of $n(z)$ containing information beyond the best-fit estimator produced by traditional procedures. The publicly available code is easily extensible to other one-point statistics that depend on redshift.

Keywords: catalogs — cosmology: cosmological parameters — galaxies: statistics — gravitational lensing: weak — methods: analytical — methods: data analysis — methods: statistical — techniques: photometric

1. INTRODUCTION

After a brief literature review addressing how photo- z PDFs are currently used in cosmology, this paper aims to answer the following questions:

- Why should we question existing methods?
- How can we improve the effectiveness of using photo- z PDFs in inference?
- How does the result of CHIPPR compare to established estimators in terms of the accuracy of $n(z)$?
- How significant is the effect of the discrepancy between $n(z)$ estimators on cosmological constraints?

2. METHOD

This paper presents a mathematically consistent method for obtaining the posterior distribution over the redshift density function $n(z)$ using a catalog of photo- z PDFs.

2.1. Model

The directed acyclic graph of Fig. 1 represents a probabilistic graphical model for hierarchical inference of $n(z)$, the mathematical interpretation of which will be presented below.

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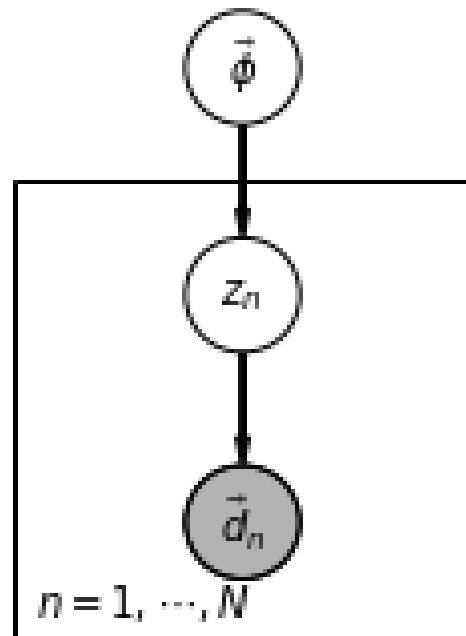


Figure 1. Replace daft version with more polished tikz version.

Math from prob-z version will go here.

This framework entails a number of choices and assumptions that must be addressed explicitly.

1. While we advocate for the approach of hierarchical inference, the probabilistic graphical model presented here is not the only one that could be proposed.

2.2. Alternative Approaches

It is useful to translate some popular existing methods for deriving $n(z)$ from photo- z PDFs into the mathematical framework of Sec. 2.1.

2.3. Implementation

The publicly available CHIPPR code implements the probabilistic graphical model presented in Sec. 2.1.

In addition to the choices and assumptions underlying the probabilistic graphical model, the implementation of CHIPPR makes choices and assumptions of its own.

1. CHIPPR currently only accepts photo- z PDFs and produces $n(z)$ samples of a single format, that of the piecewise constant parametrization, also referred to as a binned histogram parametrization and a sum of top hat functions.

3. VALIDATION ON SIMPLE MOCK DATA

The superiority of CHIPPR over alternative approaches is demonstrated in a number of compelling test cases on mock data. Each experiment is characterized by a single change to a fiducial case in order to isolate the influence of systematic effects known to be relevant to photo- z estimation and propagation in analysis.

3.1. Mock Data & Metrics

The mock data in these tests consists of photo- z interim posteriors rather than photometric data because the various existing methods for deriving photo- z interim posteriors do not in general yield results that are consistent with one another, indicating that their systematics are not well-understood. Because the mock data is independent of any choice of photo- z PDF production method, we not only ensure that our photo- z interim priors are perfectly understood but also deter readers from assuming that CHIPPR has any preference over the method by which photo- z interim posteriors are derived from photometric data.

3.1.1. Mock Data

The mock data used here are produced by the following steps. This method for deriving mock data is referred to as the fiducial case, and variations on it will refer directly to the steps that are altered.

3.1.2. $n(z)$ Accuracy Metric

The Kullback-Leibler divergence will be used as the primary measure of the accuracy of estimators of $n(z)$ in cases of mock data with known true redshifts.

Review precision and bias from kld.ipynb and interpret in terms of a % difference.

3.2. Emulated Data Quality Effects

In the following test cases, the properties of the mock photo- z likelihoods are varied in an effort to emulate known systematics in photo- z estimation.

Figure 2. [plot of z_{phot} vs. z_{spec} with varying intrinsic scatter]

Figure 3. [plot of z_{phot} vs. z_{spec} with template-like catastrophic outliers]

Figure 4. [plot of z_{phot} vs. z_{spec} with training-like catastrophic outliers]

3.2.1. Intrinsic Scatter

One major concern about photo- z s is the intrinsic scatter of point estimators, including those derived from photo- z PDFs, that is observed to varying extents with every existing photo- z algorithm and illustrated in Fig. 2.

To emulate intrinsic scatter, we modify the fiducial case to simply broaden the single Gaussian component of the likelihood. To enforce self-consistency, the mean is drawn from a Gaussian distribution with the newly increased variance.

3.2.2. Template-like Catastrophic Outliers

In addition to intrinsic scatter, photo- z methods employing template fitting tend to produce catastrophic outliers that are distributed to be broad in z_{spec} and narrow in z_{phot} , as in Fig. ???. The systematic behind these catastrophic outliers may be described as an attractor in the space of z_{phot} ; some galaxies at a range of z_{spec} map onto a single z_{phot} (with some scatter) if their true SED does not have sufficiently strong features (as is the case for blue galaxies), leading galaxies of that type at many z_{spec} to have similar colors.

3.2.3. Training-like Catastrophic Outliers

Data driven photo- z methods tend to suffer from a different form of catastrophic outliers that are distributed to be narrow in z_{spec} and broad in z_{phot} , as in Fig. ???. The systematic behind these catastrophic outliers may be described as an attractor in the space of z_{spec} ; some galaxies near a particular z_{spec} map to a range of z_{phot} if their true SED's features fall between photometric filters, leading to many galaxies near that z_{spec} to have similar colors.

3.3. Emulated Interim Prior Effects

The interim prior encapsulates the information about the relationship between observed photometry and redshift upon which a photo- z estimate is based. Interim priors are in general not identical to the true $n(z)$ we wish to estimate; if they were, we would not need any data! For template fitting photo- z methods, the interim prior is usually an input chosen by the researcher. However, for many machine learning methods, the interim prior is some function of the training set data that may be influenced by random numbers and is rarely output with the redshift estimates. Interim priors for template fitting methods tend to have incomplete coverage in the space of true photometry, because they are limited by the choice of the library of SEDs. Interim priors for machine learning methods tend to have incomplete coverage

Figure 5. [plot of template-like interim prior]**Figure 6.** [plot of training-like interim prior]**Figure 7.** [plot of a highly featured true $n(z)$]

in the space of redshifts, because there are fewer galaxies with spectroscopically confirmed redshifts at high redshifts than low redshifts.

Existing $n(z)$ estimation routines will always produce a biased estimator when the interim prior is not equal to the true $n(z)$. We demonstrate here that regardless of the appropriateness of the interim prior as an approximation to the true $n(z)$, CHIPPR is not affected by the choice of the interim prior so long as it has nontrivial coverage.

3.3.1. Template-like Interim Prior

An interim prior based on a template library may be a sum of smooth functions representing $n(z)$ for each SED type in the library. Template libraries do not include every possible galaxy SED, and the $n(z)$ used for each SED type may not be accurate. The interim prior shown in Fig. 5 is an emulation of an interim prior corresponding to a template library of this type.

3.3.2. Training-like Interim Prior

An interim prior based on a training set may be biased toward low redshifts due to the dearth of distant galaxies with spectroscopic redshifts. The interim prior shown in Fig. 6 is an emulation of an interim prior corresponding to a training set biased in this way.

3.4. Underlying $n(z)$ Effects

Existing $n(z)$ estimators are systematically smoother than the true $n(z)$. Here we show that the traditional estimators of $n(z)$ cannot recover a highly featured $n(z)$. The implication of this failure is quite serious; the consistently smooth, unimodal $n(z)$ estimates appearing in the literature could result from much more featured true redshift distributions, and there would be no way to catch this error without using a fully probabilistic method.

3.4.1. Featured $n(z)$

In this test, we choose the true $n(z)$ of Fig. 7, which has nontrivial structure.

4. APPLICATION TO REALISTIC MOCK DATA

To show how the choice of $n(z)$ estimator propagates to cosmological constraints, we apply CHIPPR to a data from a realistic cosmological simulation (probably **Buzzard**).

4.1. Mock Data & Metrics

As in Sec. 3.1, the mock data takes the form of photo- z interim posteriors, but that is where the similarity ends. These photo- z interim posteriors are derived from the photometry resulting from the **Buzzard** simulation by way of [method used to make the interim posteriors]. Because the simulation begins with setting true values of

Figure 8. [moneyplot]

the cosmological parameters, the different estimators of $n(z)$ are propagated through a forecasting code to produce error ellipses on the cosmological parameters.

4.1.1. Mock Data

The details of the **Buzzard** simulation will be summarized here.

4.1.2. Cosmological Constraint Metric

Because the mock data is associated with true values of the cosmological parameters, we may compare the quality of cosmological constraints.

Check Dark Energy Task Force metrics on error ellipses, multi-dimensional KLD, centroid offset, etc.

4.2. Results

5. DISCUSSION

The results of Fig 8 have significant implications for the developing data analysis pipelines of next-generation telescope surveys. However, the method presented here has its own limitations, which are reiterated to discourage the community from applying our work inappropriately.

There are a number of extensions of the work presented in this paper that will be pursued in future work.

6. CONCLUSION

We now summarize answers to the questions posed in the introduction:

- Existing $n(z)$ estimation methods produce biased estimators that propagate to inaccuracies in characterizing the cosmological parameters.
- Photo- z PDFs are probabilistic data products so must be handled in a mathematically consistent manner such as the probabilistic graphical model outlined in this paper.
- In addition to coming with its own error distribution, the $n(z)$ estimator produced by CHIPPR is quantifiably more accurate than established estimators.
- Propagation of the CHIPPR result leads to a quantifiable improvement in the constraints on cosmological parameters.

In conclusion, we discourage the community from continuing to use the stacked estimator and reductions of photo- z PDFs to redshift point estimates in obtaining estimators of $n(z)$. CHIPPR is freely available to the community for incorporation into evolving data analysis pipelines.

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