Large Synoptic Survey Telescope

LSST DESC
Dark Energy Science Collaboration

Photo-z PDF tests and storage

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Photo-z PDF Tests and Storage

LSST Project will provide. . .

as many point estimates and PDFs as can fit in 200 floats!

(See https://ldm-151.lsst.io/ for more details.)

With input from LSST-DESC, LSST Project must choose. . .

how many and which point estimators

how many and which PDFs

in what parametrizations with how many parameters

Goal: Develop a metric to optimize these choices!

Photo-z PDF Parametrizations

Seek to encapsulate each $p(z)$ in N floats $\vec{d}$ for storage
then reconstruct $\hat{p}(z)$ from $\vec{d}$ for science use later

Formats considered

- Samples $\{\hat{z}_s\}_N \; for \; z_s \sim p(z)$
- Binned (histogram) $\{\hat{P}(z_b)\}_N \; for \; \hat{P}(z_b) = CDF_p[z_b] - CDF_p[z_{b-1}]$
- Quantiles $\{\hat{z}_n\}_N \; for \; \hat{z}_n = CDF_p^{-1}[q_n]$
- Gridded $\{p(z_g)\}_N$
- Functional Parameters $\{\theta_i\}_N \; for \; f_{\{\theta_i\}_N}(z) = p(z)$
  - f may be any specified mixture model, polynomial, spline, etc.

recall $CDF_p[z] = \int^z p(z')dz'$

Photo-z PDF Quantitative $\hat{p}(z)$ Metrics

Root-mean-square error (RMSE)

$$D_{RMSE} = \sqrt{\frac{1}{T}\sum_{t}^{T}(\hat{p}(z_t) - p(z_t))^2}$$

Kullback-Leibler (KL) divergence

$$D_{KL} = \sum_{t}^{T} p(z_t) \log\left[\frac{p(z_t)}{\hat{p}(z_t)}\right]$$

Note asymmetry!

See https://github.com/aimalz/qp/blob/master/docs/notebooks/kld.ipynb

Photo-z PDF Quantitative $CDF_{\hat{p}}(z)$ Metrics

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Kolmogorov-Smirnov (KS) test statistic

$$D_{KS} = \max_{t} \left| CDF_{\hat{p}}[z_t] - CDF_{p}[z_t] \right|$$

Anderson-Darling (AD) test statistic

$$S_{AD} = \sum_{t}^{T} \int_{\infty}^{\infty} \left(CDF_{\hat{p}}[z_t] - CDF_{p}[z_t] \right)^2 w(z_t) dCDF_{p}[z_t]$$

Cramer-von Mises (CvM) test statistic $w_{CvM}(z_t) = 1$

Photo-z PDF Qualitative Metrics

Quantile-quantile (Q-Q) plot

$$\{(CDF_p(z_t), CDF_{\hat{p}}(z_t))\}_T$$

Comparison of moments $\{(\mu_m, \hat{\mu}_m)\}_M$

Recall $\mu_m = \sum_t^T z_t^m p(z_t)$ and $\hat{\mu}_m = \sum_t^T z_t^m \hat{p}(z_t)$

Photo-*z* PDF Tests and Storage: qp

qp
(Malz & Marshall, in prep.)

qp is. . .

a framework for optimizing the choices of
1D PDF parametrization and number of parameters
for storage and distribution

qp is *not*. . .

an "answer" to any question,
particularly how many and which PDF methods
to provide in data releases

Photo-z PDF Tests and Storage: qp

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qp

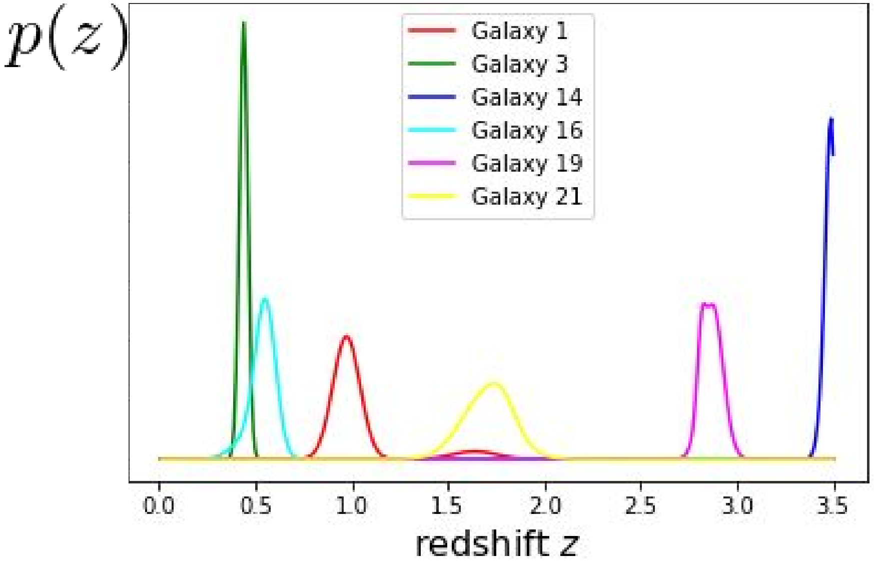
(Malz & Marshall, in prep.)

Test procedure

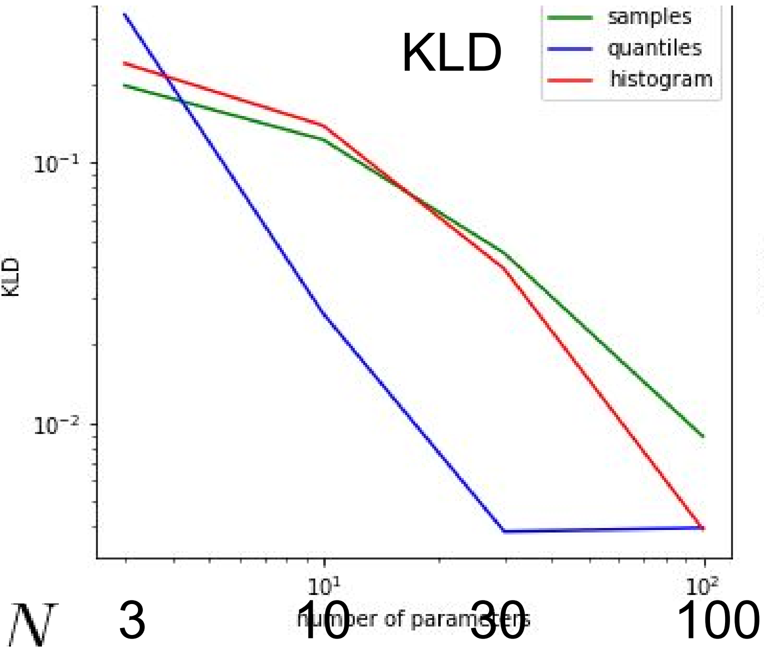
- Obtain realistically complex $\{p_r(z)\}_R$ with $\gg 200$ parameters
- Approximate by samples, binned, quantiles for different N
- Compare science case metrics over parametrizations and N
    - Calculate $\hat{n}_p^{*}(z) = \sum_r^R p_r(z)$ and all $\hat{n}_{\hat{p}}^{*}(z) = \sum_r^R \hat{p}_r(z)$
    - Compute metrics (RMSE & KLD) for all cases

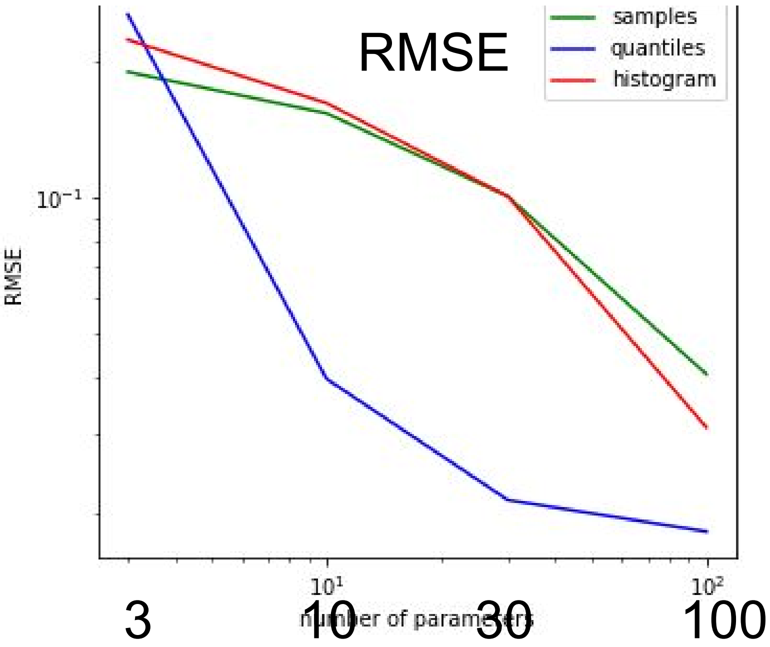
* **Caveat**: The "stacked" $\hat{n}(z)$ is *not* a valid estimator for the redshift distribution $n(z)$!

Photo-*z* PDF Tests: High Precision



Malz & Marshall (in prep.)





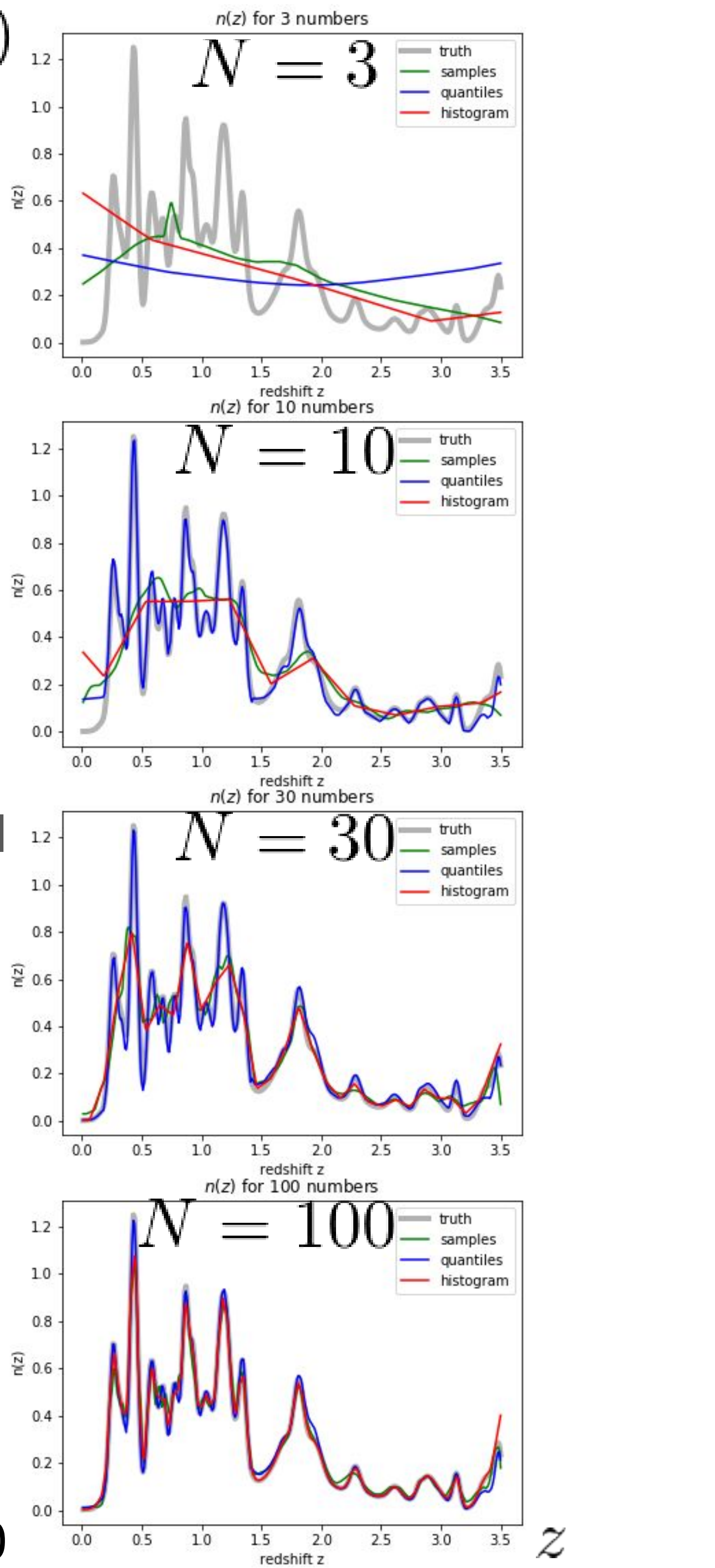
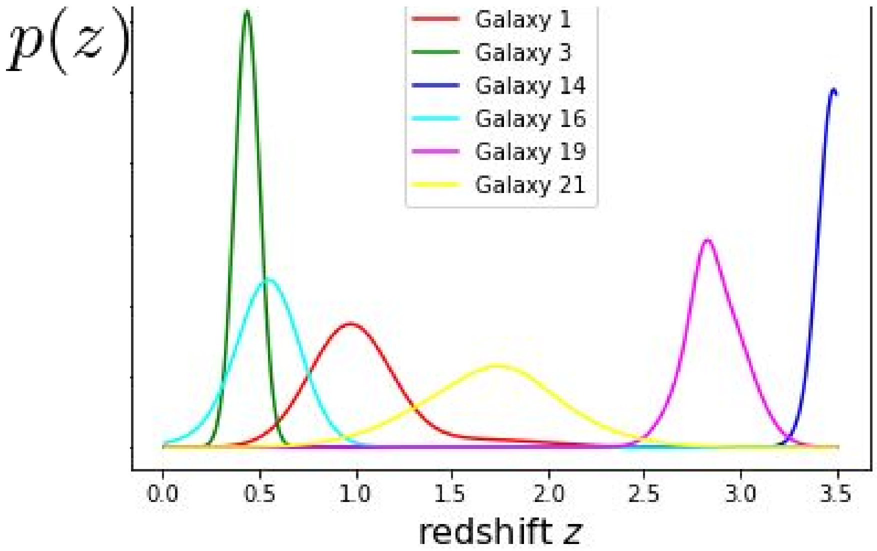
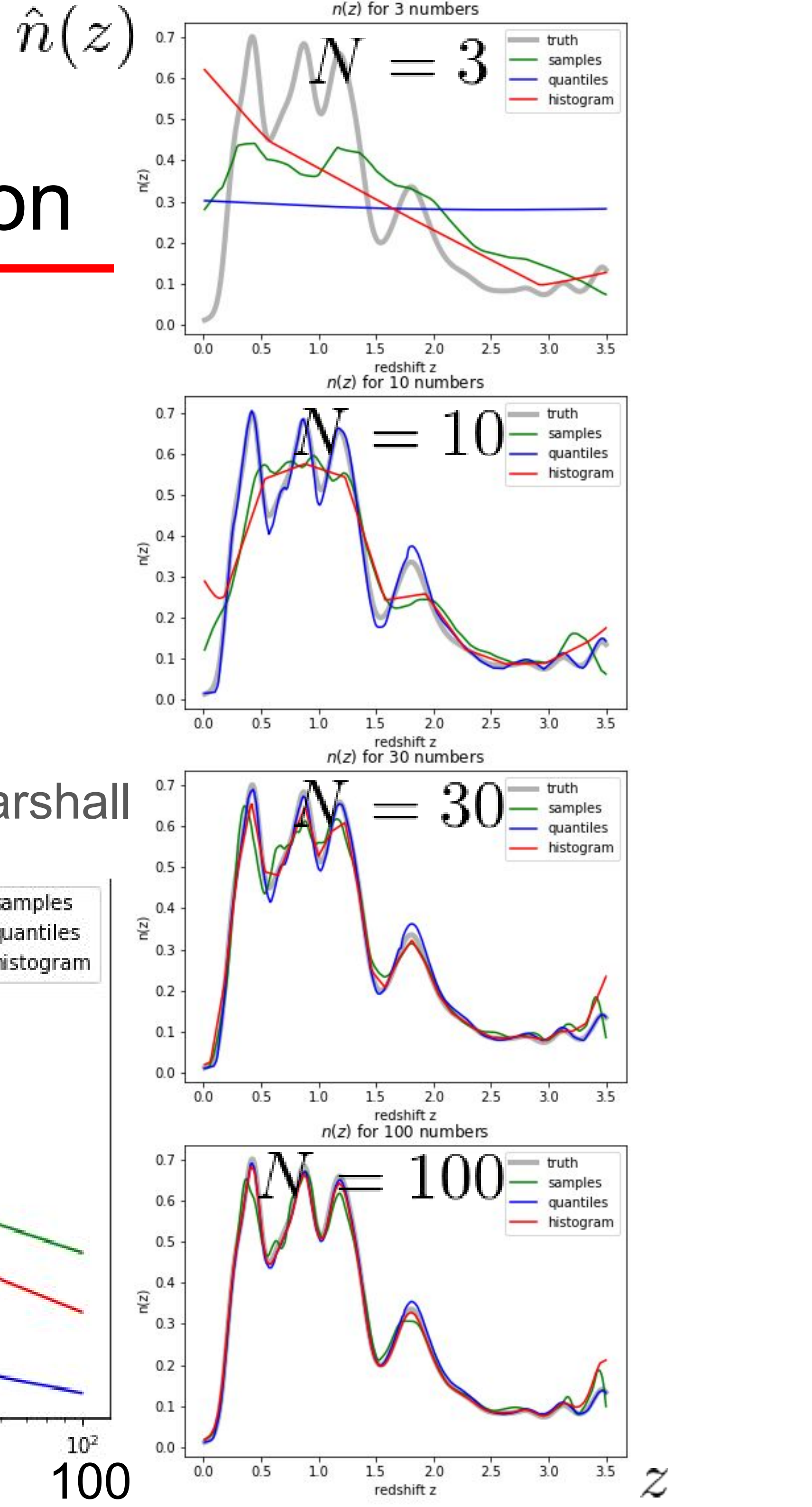
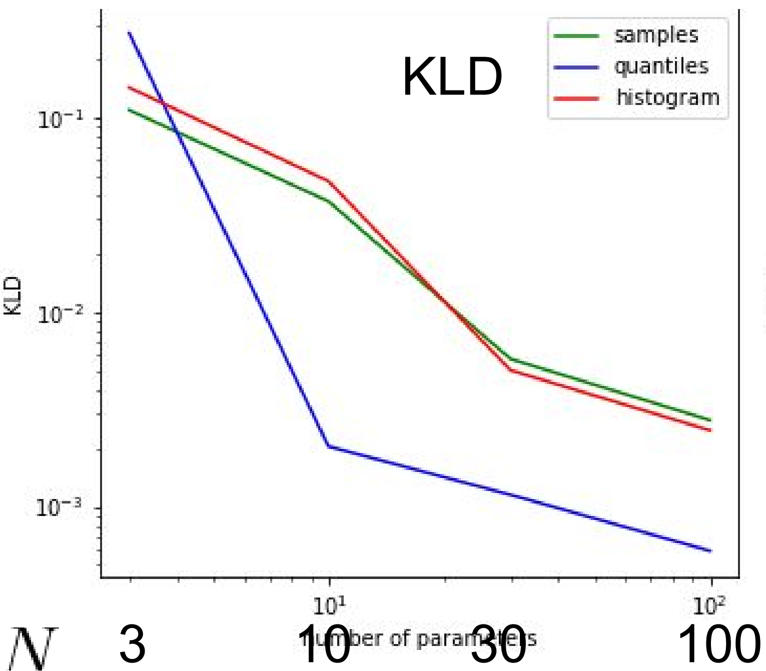


Photo-z PDF Tests: Med. Precision





Malz & Marshall (in prep.)



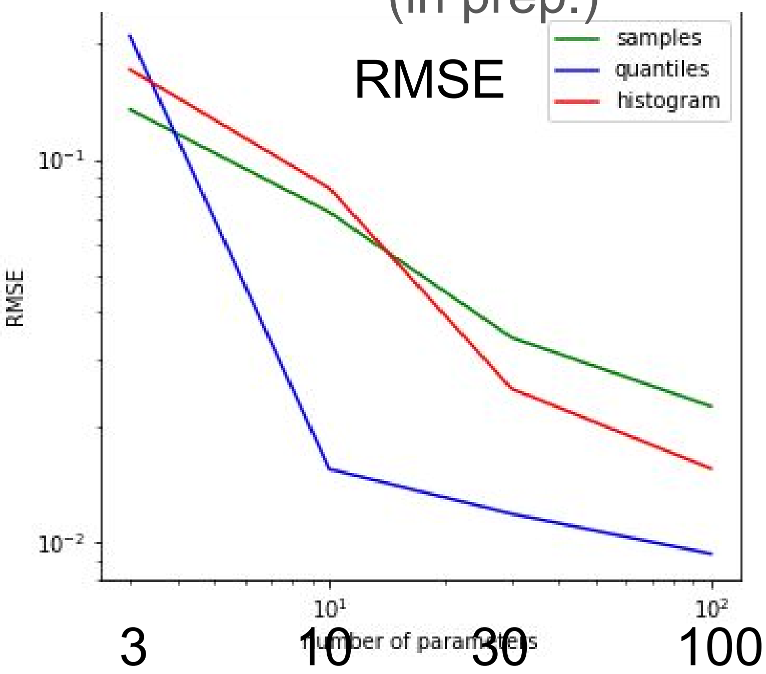
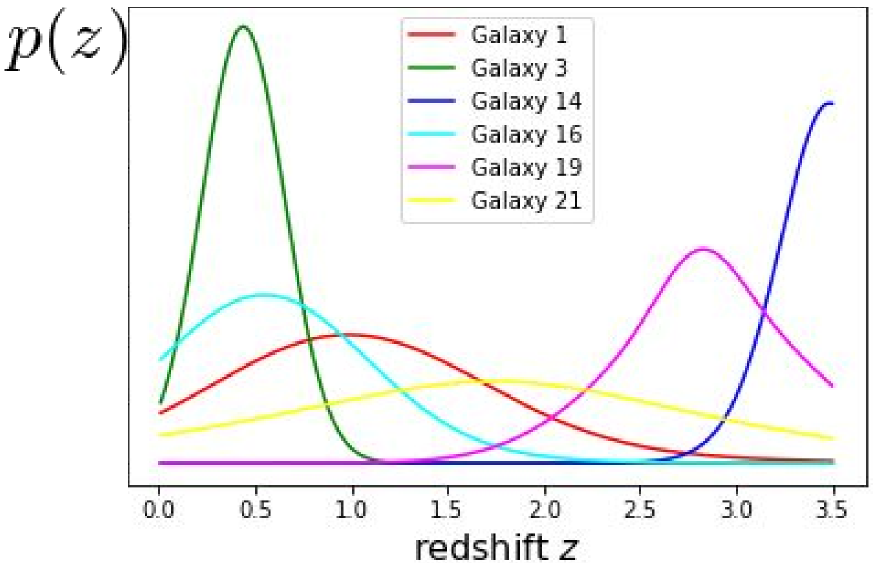
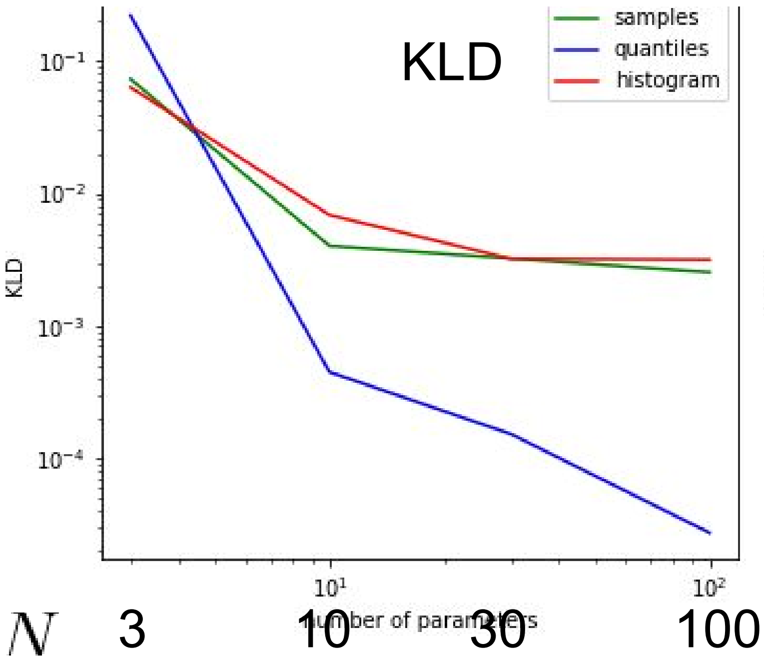
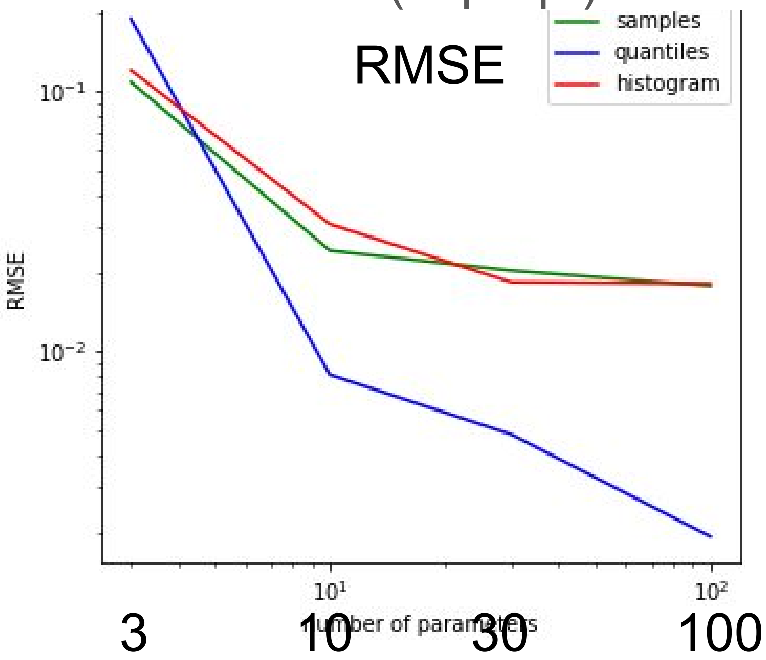


Photo-z PDF Tests: Low Precision



Malz & Marshall
(in prep.)





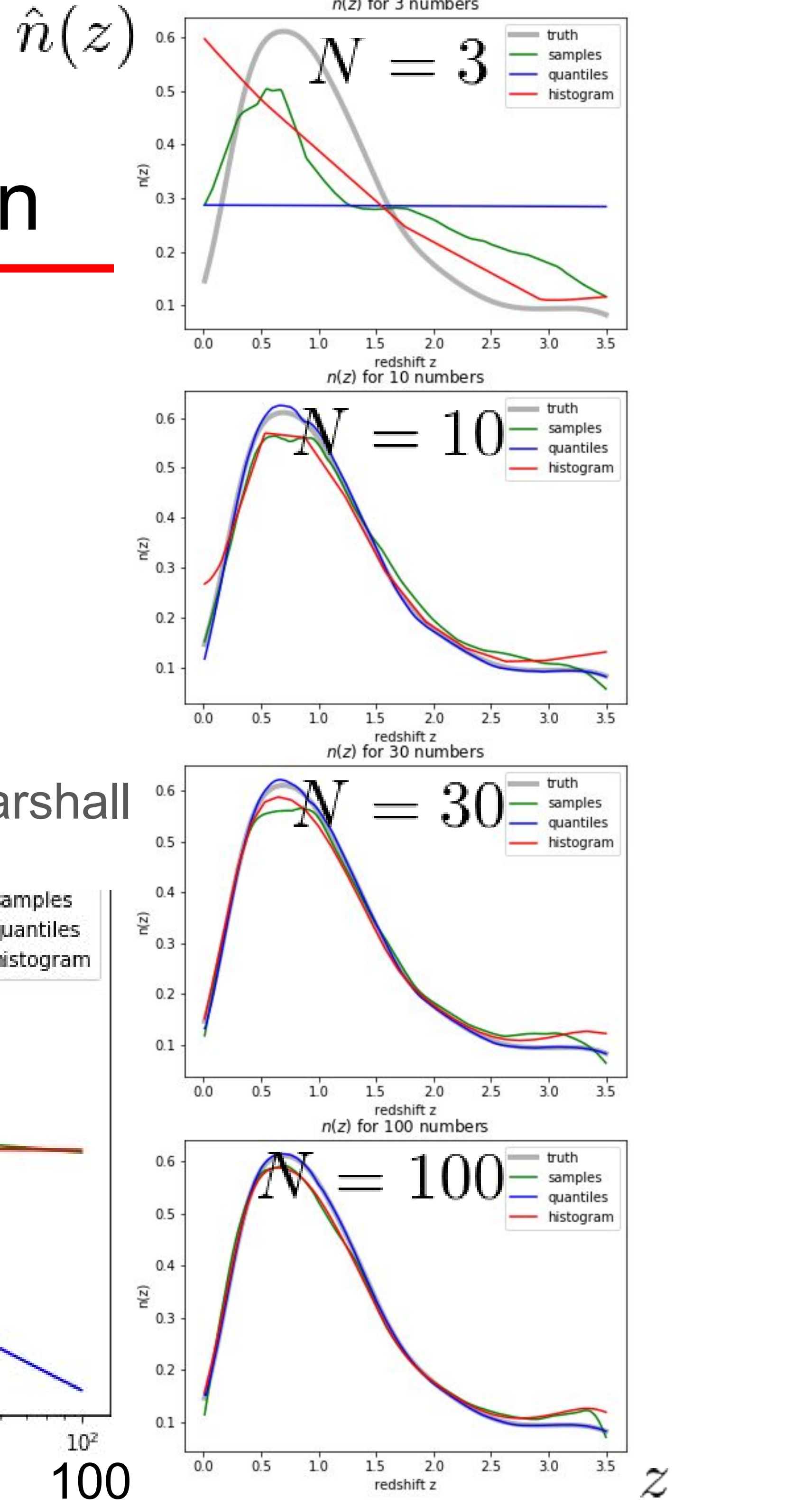


Photo-z PDF Tests and Storage: qp

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qp

(Malz & Marshall, in prep.)

Features (*existing*, *under development*, *planned*)

- Parametrizations: samples, bins, quantiles, grid, GMM, *MM
  - Conversions to quantify effect on science cases
- $\hat{p}(z)$ Metrics: RMSE, KLD, KS, CvM, AD, QQ, moments
  - Tutorials for each metric to provide intuition for interpretation
- Ensembles: metrics applied to science cases
  - stacked $\hat{n}(z)$, other science uses of $\hat{p}(z)$

https://github.com/aimalz/qp