Photometric redshifts estimates and star-galaxy separation using machine learning for the Dark Energy Survey

Ben Hoyle on behalf of
DES photo-z working group
DES star-galaxy separation working group
Markus Rau, Kerstin Peach, Jochen Weller

University Sternwarte Munich
Different photo-z’s biasing correlation functions

Markus Rau, BH et al 2015
Different photo-z’s biasing correlation functions

\[
\text{Rel. Bias} = \frac{C_l(z_{\text{spec}}) - C_l(z_{\text{photo}})}{C_l(z_{\text{specz}})}
\]

Markus Rau, BH et al 2015
Different photo-z’s biasing correlation functions

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Stellar contamination in DES
Crocce et al 2016
Giannantonio et al 2016

Markus Rau, BH et al 2015
Comparison of photo-z codes and their photometric features.

Feature Selection to improve photo-z and other ML problems.

Photo-z’s uncertainties trickling through to cosmological uncertainties.

Star galaxy separation analysis in DES
Comparing Photometric redshift codes

\[ \Delta = \frac{z_{\text{spec}} - z_{\text{phot}}}{1 + z_{\text{spec}}} \]
Comparing Photometric redshift codes

\[ \Delta = \frac{(z_{\text{spec}} - z_{\text{phot}})}{(1 + z_{\text{spec}})} \]

\[ \mu(\Delta) \quad \bar{\Delta z} \quad \text{median, or mean} \]
Comparing Photometric redshift codes

\[ \Delta = \frac{z_{spec} - z_{phot}}{1 + z_{spec}} \]

\[ \mu(\Delta) \quad \Delta z \quad \text{median, or mean} \]

\[ \sigma_{68}(\Delta) \quad \sigma(\Delta) \quad 68\% \text{ spread of data, or standard deviation} \]
## Comparing Photometric redshift codes

<table>
<thead>
<tr>
<th>Code</th>
<th>Type</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>DESDM, Artificial Neural Network</td>
<td>Training-based</td>
<td>Oyakizu et al. (2008b)</td>
</tr>
<tr>
<td>ANNz, Artificial Neural Network</td>
<td>Training-based</td>
<td>Collister &amp; Lahav (2004)</td>
</tr>
<tr>
<td>RVMz, Relevance Vector Machine</td>
<td>Training-based</td>
<td>Tipping (2001)</td>
</tr>
<tr>
<td>NIP-kNNz, Normalized Inner Product Nearest Neighbor</td>
<td>Training-based</td>
<td>de Vicente et al., in preparation</td>
</tr>
<tr>
<td>ANNz2, Machine Learning Methods</td>
<td>Training-based</td>
<td>Sadegh et al., in preparation</td>
</tr>
<tr>
<td>ArborZ, Boosted Decision Trees</td>
<td>Training-based</td>
<td>Gerdes et al. (2010)</td>
</tr>
<tr>
<td>SkyNet, Classification Artificial Neural Network</td>
<td>Training-based</td>
<td>Bonnett (2013); Graff et al. (2013)</td>
</tr>
<tr>
<td>BPZ, Bayesian Photometric Redshifts</td>
<td>Template-based</td>
<td>Brammer, van Dokkum &amp; Coppi (2008)</td>
</tr>
<tr>
<td>EAZY, Easy and Accurate Redshifts from Yule LePhare</td>
<td>Template-based</td>
<td>Arnouts et al. (2002); Ilbert et al. (2006)</td>
</tr>
<tr>
<td>TPZ P(z)</td>
<td>Template-based</td>
<td>Feldmann et al. (2006)</td>
</tr>
<tr>
<td>PhotoZ</td>
<td>Template-based</td>
<td>Bender et al. (2001)</td>
</tr>
<tr>
<td>ZEBRA, Zurich Extragalactic Bayesian Redshift Analyzer Photo-Z</td>
<td>Template-based</td>
<td></td>
</tr>
</tbody>
</table>

### Graphs

- **Adballa et al 2008**
- **Hildebrandt et al 2010**
- **Dahlia 2013**
- **Sanchez et al 2014**
Comparing Photometric redshift features

Which photometric properties (or "features") are used during training?

- grizY DETMODEL
- grizY DETMODEL + colors
- grizY DETMODEL + grizY AUTO
- grizY DETMODEL + grizY AUTO + all colors + all errors

Sanchez at al 2014
Comparing Photometric redshift features

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Sanchez at al 2014

Moriond March 2016
## Choosing features for photo-z

<table>
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| **Magnitudes** | dered_u dered_g dered_r  
dered_i dered_z  
psfMag_u psfMag_g psfMag_r  
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fiberMag_u fiberMag_g fiberMag_r  
fiberMag_i fiberMag_z |
| **Radii** | petroRad_u petroRad_g petroRad_r  
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expRad_u expRad_g expRad_r  
expRad_i expRad_z  
deVRad_u deVRad_g deVRad_r  
deVRad_i deVRad_z |
| **Colors** | dered.z-dered.i  
dered.z-dered.u  
dered.i-dered.r  
dered.i-dered.g  
dered.i-dered.u  
dered.r-dered.u  
dered.g-dered.u  
fiberMag.z-fiberMag.i fiberMag.z-fiberMag.r  
fiberMag.z-fiberMag.g fiberMag.z-fiberMag.u  
fiberMag.i-fiberMag.r fiberMag.i-fiberMag.g  
fiberMag.i-fiberMag.u fiberMag.r-fiberMag.g  
fiberMag.r-fiberMag.u fiberMag.g-fiberMag.u  
psfMag.z-psfMag.i psfMag.z-psfMag.r  
psfMag.z-psfMag.g psfMag.z-psfMag.u  
psfMag.i-psfMag.r psfMag.i-psfMag.g  
psfMag.i-psfMag.u psfMag.r-psfMag.g  
psfMag.r-psfMag.u psfMag.g-psfMag.u |
| **Profile** | fracDeV_u fracDeV_g fracDeV_r  
fracDeV_i fracDeV_z |
| **Ellipticity** | expAB_u expAB_g expAB_r  
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A catalogue of photometric redshifts for the SDSS-DR9 galaxies
(Research Note)
M. Brescia¹, S. Cavauto¹, G. Longo², and V. De Stefano²

ARBORZ: PHOTOMETRIC REDSHIFTS USING BOOSTED DECISION TREES
DAVID W. GERDES, ADAM J. SYPNIEWSKI, TIMOTHY A. MCKAY, JIANGANG HAO¹, MATTHEW R. WEIS Department of Physics, University of Michigan, Ann Arbor, MI 48169

Neural networks and photometric redshifts
R. Tagliaferri¹,², G. Longo³, S. Andreon³, S. Capozziello⁶, C. Donalek⁴, and G. Giordano⁵
¹ DMI - University of Salerno, 84081, Baronissi (SA), Italy

Moriond March 2016
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Department of Physics, University of Michigan, Ann Arbor, MI 48109

Both employ neural networks, where the training variables are the ugriz magnitudes and u-g, g-r, r-i, and i-z colors respectively. The ArborZ algorithm equals or exceeds the performance of these two algorithms over a wide range of training settings.

Neural networks and photometric redshifts
R. Tagliaferri¹ ², G. Longo³, S. Andreon¹, S. Capozziello⁵, C. Donalek¹, and G. Giordano³
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<table>
<thead>
<tr>
<th>Table 2. Column 1: higher accepted spectroscopic redshift for objects in the training set; column 2: input (hence number of input neurons) parameters used in the experiment; column 3: number of neurons in the hidden layer; column 4: interquartile errors evaluated on the test set; column 5: number of objects used in each of the training, validation and test set.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Range parameters</td>
</tr>
<tr>
<td>$z &lt; 0.3$ r, u, g, r, i, z</td>
</tr>
<tr>
<td>$z &lt; 0.5$ r, u, g, r, i, z</td>
</tr>
<tr>
<td>$z &lt; 0.7$ r, u, g, r, i, z</td>
</tr>
<tr>
<td>$z &lt; 0.3$ r, u, g, r, i, z, radius</td>
</tr>
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</tr>
<tr>
<td>$z &lt; 0.3$ r, u, g, r, i, z, radius, petrosian fluxes, surface brightness</td>
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Machine learning techniques determine which more easily measured features (magnitude + colors, radii) provide the most predictive power for ‘target’ feature (spectroscopic redshift / star galaxy separation / star formation rates).
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How can feature importance be calculated?

$$\sigma(target)$$

$$\sigma(target)$$
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How can feature importance be calculated?

\[ \sigma_N \sim \sigma(\text{target}) \]

Gini criteria: Reduce the scatter of the target feature by sub dividing the input feature space. The more slices in a feature dimension, which each time reduce the Gini index, the more that feature dimension has predictive power. In practice this happens in a high dimensional hyper-cube.
# Feature Importance Ranking

## Description

<table>
<thead>
<tr>
<th>Feature name</th>
</tr>
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<tbody>
<tr>
<td>dered_u dered_g dered_r</td>
</tr>
<tr>
<td>dered_i dered_z</td>
</tr>
<tr>
<td>psfMag_u psfMag_g psfMag_r</td>
</tr>
<tr>
<td>psfMag_i psfMag_z</td>
</tr>
<tr>
<td>fiberMag_u fiberMag_g fiberMag_r</td>
</tr>
<tr>
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</tr>
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<td>petroRad_u petroRad_g petroRad_r</td>
</tr>
<tr>
<td>petroRad_i petroRad_z</td>
</tr>
<tr>
<td>expRad_u expRad_g expRad_r</td>
</tr>
<tr>
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</tr>
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</tr>
<tr>
<td>fiberMag_z-fiberMag_i fiberMag_z-fiberMag_r</td>
</tr>
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</tr>
<tr>
<td>fiberMag.i-fiberMag.r fiberMag.i-fiberMag.g</td>
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<tr>
<td>psfMag.r-psfMag.u psfMag.g-psfMag.u</td>
</tr>
<tr>
<td>fracDeV_u fracDeV_g fracDeV_r</td>
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# Feature Importance Ranking

## Magnitudes
- dered_u, dered_g, dered_r, dered_i, dered_z
- psfMag_u, psfMag_g, psfMag_r
- fiberMag_u, fiberMag_g, fiberMag_r
- fiberMag_i, fiberMag_z

## Radii
- petroRad_u, petroRad_g, petroRad_r
- petroRad_i, petroRad_z
- deVRad_u, deVRad_g, deVRad_r
- deVRad_i, deVRad_z

## Colors
- dered_z, dered_i, dered_z-dered_r
- dered_z-dered_g, dered_z-dered_u
- dered_i-dered_r, dered_i-dered_g
- dered_i-dered_u, dered_r-dered_g
- dered_r-dered_u, dered_g-dered_u
- fiberMag_z, fiberMag_i, fiberMag_g

## Profile
- fracDeV_u, fracDeV_g, fracDeV_r
- fracDeV_i, fracDeV_z

## Ellipticity
- expAB_u, expAB_g, expAB_r
- expAB_i, expAB_z
- deVAB_u, deVAB_g, deVAB_r
- deVAB_i, deVAB_z

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<table>
<thead>
<tr>
<th>Input features</th>
<th>Measurement</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original features</td>
<td>( \mu_{\Delta z} \pm \sigma_{\Delta z} )</td>
<td>-0.0001±0.0075</td>
</tr>
<tr>
<td></td>
<td>( \mu_{\Delta z}/(1+z) \pm \sigma_{\Delta z}/(1+z) )</td>
<td>-0.003±0.055</td>
</tr>
<tr>
<td></td>
<td>(</td>
<td>\Delta z/(1+z)</td>
</tr>
<tr>
<td>Using ranked features</td>
<td>( \mu_{\Delta z} \pm \sigma_{\Delta z} )</td>
<td>0.0001±0.0068</td>
</tr>
<tr>
<td></td>
<td>( \mu_{\Delta z}/(1+z) \pm \sigma_{\Delta z}/(1+z) )</td>
<td>-0.002±0.049</td>
</tr>
<tr>
<td></td>
<td>(</td>
<td>\Delta z/(1+z)</td>
</tr>
<tr>
<td>Ranked + standard features</td>
<td>( \mu_{\Delta z} \pm \sigma_{\Delta z} )</td>
<td>-0.0001±0.0066</td>
</tr>
<tr>
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<td>( \mu_{\Delta z}/(1+z) \pm \sigma_{\Delta z}/(1+z) )</td>
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<tr>
<td></td>
<td>(</td>
<td>\Delta z/(1+z)</td>
</tr>
<tr>
<td>Heaps more features</td>
<td>( u_{\Delta z}/(1+z) \pm \sigma_{\Delta z}/(1+z) )</td>
<td>-0.002±0.045</td>
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<tr>
<td></td>
<td>(</td>
<td>\Delta z/(1+z)</td>
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**Feature importance for machine learning redshifts applied to SDSS galaxies**

Ben Hoyle, Markus Michael Rau, Roman Zitlau, Stella Seitz, Jochen Weller

Comments: 10 pages, 4 figures, updated to match version accepted in MNRAS

Subjects: Instrumentation and Methods for Astrophysics (astro-ph.IM); Cosmology and Nongalactic Astrophysics (astro-ph.CO)
Feature Importance Applied to DES

![Graphical representation of feature importance applied to DES with various markers and error bars.]
Feature Importance Applied to DES

Top ranked features
Photo-z propagating to cosmology

\[ W_i(x_i) = \frac{3H_0^2\Omega_m}{2c^2}(1 + z_i)x_i \int_{x_i}^{x_H} dx_s n(x_s) \frac{x_s - x_i}{x_s} \]

\[ C_{ij}(\ell) = \int_0^{x_H} dx \frac{W_i(x)W_j(x)}{x^2} P_\delta \left( \frac{\ell}{x}, x \right) \]

\[ \xi^{+/\cdot,ij}(\theta) = \frac{1}{2\pi} \int d\ell d\ell' C_{ij}(\ell) J_0/4(\ell\theta) \]

Bonnett et al 2015
Photo-z propagating to cosmology

\[ W_i(x_l) = \frac{3H_0^2\Omega_m}{2c^2}(1 + z_i)x_l \int_{x_l}^{x_H} d\chi n(\chi) \frac{X_s - X_l}{X_s} \]

\[ C_{ij}(\ell) = \int_0^{x_H} d\chi \frac{W_i(\chi)W_j(\chi)}{\chi^2} P_\delta(\frac{\ell}{\chi}, \chi) \]

\[ \xi_{+/--}^{ij}(\theta) = \frac{1}{2\pi} \int d\ell \ell C_{ij}(\ell) J_0(\ell\theta) \]

Bonnett et al 2015
Photo-z propagating to cosmology

\[
W_i(x) = \frac{3H_0^2 \Omega_m}{2c^2} (1 + z_l) x_l \int_{x_l}^{x_H} dx_s n(x_s) \frac{x_s - x_l}{x_s}
\]

\[
C_{ij}(\ell) = \int_0^{x_H} d\chi \frac{W_i(\chi)W_j(\chi)}{\chi^2} P_\delta(\frac{\ell}{\chi}, \chi)
\]

\[
\xi_{+/-}^{ij}(\theta) = \frac{1}{2\pi} \int d\ell d\ell' C_{ij}(\ell) J_0(\ell\theta).
\]

Bonnett et al 2015

Normalisation of the power spectrum

100 sq. deg. statistical error
Star Galaxy Separation in DES

Using a PCA method to select features

Soumagnac et al 2015

Soumagnac et al 2015

systematic error $\Delta[w_0]$
statistical error $\sigma[w_0]$
threshold on $f_s$
$\Delta[w_0] \leq \sigma[w_0]$

Fraction of Stellar contamination

$purity at 96\% completeness, for galaxies$

$purity$

$multi\_class$
$\text{new method not including spread\_model}$
$\text{spread\_model (i band)}$
$\text{class\_star (i band)}$

magnitude

$0$ $1$ $2$ $3$ $4$ $5$

$0$ $0.1$ $0.2$

$-0.1$ $-0.2$
Feature Importance Applied to Star-Gal Sep.

DES SV and Y1 blind challenges

Top Ranked Features

True Positive Rate
False Positive Rate (FPR)

Better classifiers worse DES SV data
classifiers worse DES Y1 data
classifiers worse DES Y1 data

color cuts

Nacho Sevilla

Moriond March 2016
I’ve gained some experience working on machine learning problems in cosmology/astrophysics. Things to talk to me about this week at coffee / on the ski-lift / in the bar, which I haven’t had time to cover:

• What happens if the “training” and “testing” sample are not representative of each other?

• Can I just train on simulated data, and keep all my real data back for testing?

• How can I use templates and machine learning methods together?

• What happens if you feed the redshift of one machine into another machine?

• Can I identify anomalous training data (e.g. are the spec-z’s wrong)?

• Can I use ML to help me select a particular objects for follow-up?
Looking ahead + Conclusions

Y1 [Y5] analyses will become systematics limited.

Feature importance analyses improve ML predictions.

Y1 papers planned this summer.

Conversation starters

Things to talk to me about this week at coffee / on the ski-lift / in the bar

- What happens if the “training” and “testing” sample are not representative of each other?
- Can I just train on simulated data, and keep all my real data back for testing?
- How can I use templates and machine learning methods together?
- What happens if you feed the redshift of one machine into another machine?
- Can I identify anomalous training data (e.g. are the spec-z’s wrong) ?
- Can I use ML to help me select a particular objects for follow-up?
Deep learning using the galaxy image

Alpha-z
Using Deep Neural Networks with latest tricks from machine learning computer science applied to SDSS images

Hoyle arXiv:2015
Feature importance vs PCA

Which features produce the most predictive power for the task at hand?

Which (linear) transformations allow you to trade information content for number of features

Extreme example: accidentally include a unique (galaxy) ID in your analysis

Ignore this useless parameter

Wow! What an information rich parameter, let’s us it.