Morpho-Photometric Redshifts

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ABSTRACT

Machine learning (ML) is a standard approach for estimating the redshifts of galaxies when only photometric information is available. ML photo-z solutions have traditionally ignored the morphological information available in galaxy images or partly included it in the form of hand-crafted features, with mixed results. We train a morphology-aware photometric redshift machine using modern deep learning tools. It uses a custom architecture that jointly trains on galaxy fluxes, colors and images. Galaxy-integrated quantities are fed to a Multi-Layer Perceptron (MLP) branch while images are fed to a convolutional (convnet) branch that can learn relevant morphological features. This split MLP-convnet architecture, which aims to disentangle strong photometric features from comparatively weak morphological ones, proves important for strong performance: a regular convnet-only architecture, while exposed to all available photometric information in images, delivers comparatively poor performance. We present a cross-validated MLP-convnet model trained on 130,000 SDSS-DR12 galaxies that outperforms a hyperoptimized Gradient Boosting solution (hyperopt+XGBoost), as well as the equivalent MLP-only architecture, on the redshift bias metric. The 4-fold cross-validated MLP-convnet model achieves a bias $\Delta z/(1 + z) = -0.70 \pm 1 \times 10^{-3}$, approaching the performance of a reference ANNZ2 ensemble of 100 distinct models trained on a comparable dataset. The relative performance of the morphology-aware and morphology-blind models indicates that galaxy morphology does improve photometric redshift estimation.

Key words: keyword1 – keyword2 – keyword3

1 INTRODUCTION

Spectroscopic redshifts of galaxies are used as distance measures to study large-scale structure in the Universe. It has always been challenging to obtain the spectra, and thus reliably measure the redshifts, of the numerous galaxies imaged on the sky by astronomers, because of practical limitations in the resources that can be allocated to spectroscopic follow-up surveys. As an example, SDSS has imaged roughly 200 million galaxies while it obtained the spectra of about 2 million of those (Beck et al. 2016). As we approach the era of the Large Synoptic Sky Survey (LSST), with vast dedicated imaging capabilities but limited systematic spectroscopic follow-up, the challenge of measuring the redshift of imaged galaxies has only become more acute (Graham et al. 2018; Salvato et al. 2018).

Machines trained to estimate galaxy redshifts based on their integrated fluxes/colors are one of the two main approaches being considered to tackle the challenge of photometric redshift ("photo-z") estimations. A variety of algorithms have been applied and trained on this problem in the supervised learning framework, whereby the subset of imaged galaxies for which spectroscopic redshifts have been measured are used as a training set. Post-training, the redshifts of the vast majority of galaxies, without spectra, are estimated by the trained machine, based on photometric data only.

In an attempt to improve photo-z estimations, various studies have considered adding morphological information, beyond the usual galaxy-integrated colors, as training input for the machine. Results have been somewhat inconclusive, in the sense that performance gains are not systematic when morphological data is added: performance gains/losses from morphological data depend on details of the task/dataset/method adopted (see Soo et al. 2018, and references therein for a detailed account). While the magnitude any gain from adding morphological data is a priori unclear, reports of gains or losses depending on which combination of morphological features are included are not entirely surprising: feature engineering is a notoriously 'non-linear'
process\(^1\) and optimizing over the feature space for best performance is a generally complex enterprise (e.g., D’Isanto et al. 2018).

Here, we present a machine learning (ML) focused study of photo-z estimation that attempts to clarify the role that morphology has in promoting better redshift estimations. Our approach is to use the modern tools of deep learning, in the form of a deep convolutional network (convnet). One of the key achievements in computer vision over the past few years has been the demonstration that properly trained convnets can automatically learn powerful and generizable features for a variety of tasks on image data (see Chapter 9, Goodfellow et al. 2016). Therefore, the promise of deep learning in the photo-z context is an ability to build a machine that automatically learns strong morphological features for photo-z estimation. While convnets have been applied to the photo-z estimation task before (Hoyle 2016; D’Isanto & Polsterber 2018), no clear improvements over traditional ML approaches have been reported (Salvato et al. 2018). By contrast, we report in this work clear improvements in photo-z estimation performance with the inclusion of morphological data but only when a custom network architecture is adopted that treats separately galaxy-integrated features and the image data containing morphological information.

In Section 2, we describe our dataset acquisition and preparation pipeline. In Section 3, we detail our machine learning approach. Results can be found in Section 4, before we conclude in Section 5.

2 DATASET ASSEMBLY AND PREPARATION

2.1 Data Acquisition

To assemble the dataset, we closely follow the methodology detailed in Hoyle (2016). A catalog of SDSS-DR10 galaxies with spectroscopically-measured redshifts is obtained by executing the same SQL command on the SDSS CasJob server as described in the Appendix of Hoyle (2016). One additional variable request is made for the u-band extinction data. This results in a spectroscopic catalog of approximately 1.92M galaxies with ugriz photometric information and measured spectroscopic redshifts.

To build a training/validation set, 5-band images are downloaded for about 136,000 galaxies listed in our spectroscopic catalog. A distinct test set is built by downloading an additional 26,000 images (making sure there is no overlap with the training set). All image downloads are from SDSS-DR12 data. When multiple objects/spectra exist for a given catalog entry, only coordinates for the first listed entry is used to avoid duplicates. The astropy SDSS query module is used for plate downloads. After download, cut-outs of 72x72 pixels centered on the galaxy catalog coordinates of interest are extracted in 5 bands and stored for training/validation/testing (larger 144x144 cut-outs were also experimented with and eventually discarded). Small cut-outs are computationally efficient at training time and they guarantee that the vast majority of images collected are images of galaxies in isolation, with only limited information on the larger scale galactic environment.

All fluxes and images are corrected for extinction. We follow the method of Kim & Brunner (2017) for SDSS images, by first converting images from fluxes to luptitudes, applying extinction corrections then transforming back to fluxes.\(^2\)

2.2 Data Preparation

We experimented with various transformations of the input data, since it is not a priori clear which input format yields the best training performance. Performance on the validation set was used to settle on the adopted input format. Color cuts were applied to improve sample quality, following the suggested color cuts of Beck et al. (2016):

\[
\begin{align*}
-0.911 < (u - g) < 5.597 \\
0.167 < (g - r) < 2.483 \\
0.029 < (r - i) < 1.369 \\
-0.452 < (i - z) < 0.790
\end{align*}
\]

No photometric error cut was applied however (unlike Beck et al. 2016).

Scalar input data is composed of 10 features: the 5 SDSS magnitudes, 4 SDSS colors and the r-band Petrosian radius. All these permutation-invariant\(^3\) features are normalized to have zero-mean and unit-variance using the scikit-learn StandardScaler built-in function. The scaler is fit on the training set and then applied to the test set. Image data is prepared in flux units, rather than magnitudes, over 5 channels: 4 flux difference channels \((F_u - F_g, F_g - F_r, F_r - F_i, F_i - F_z)\), and a ‘stacked’ flux which is the sum of the all the ugriz flux images. Note that the flux difference images differ from the colors traditionally used by astronomers (which are logarithmic flux ratio). The flux images are then simply normalized, per galaxy, to the max pixel value across all channels for that galaxy. This normalization guarantees that galaxy-specific spectral information remains encoded in the four flux-difference channels.

3 MODEL ARCHITECTURE AND TRAINING

3.1 Mixed MLP-Convnet Architecture

The main idea leading to the network architecture presented in this paper originates from the well-documented astrophysical knowledge that photometric (galaxy-integrated) colors are the primary variables correlating with the spectroscopic redshifts of galaxies, while galaxy morphology is typically of secondary importance (Soo et al. 2018). This means that a convnet presented with images (only) will first need to learn to integrate the fluxes of galaxy over their spatial extent to perform well on the redshift regression task before it can focus on secondary morphological details. Conversely, a

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\(^1\) For example, two features that are found to beneficial in isolation have no guarantee to remain beneficial if used together.

\(^2\) https://github.com/EdwardJKim/dl4astro

\(^3\) The specific order in which these features are fed to the MLP branch is unimportant (as long as it remains fixed). By contrast, pixel features in images are fed to the convnet in a way that guarantees spatial continuity.
MLP (or any other standard ML algorithm) can do well on the photo-z estimation task, once presented with the most meaningful galaxy-integrated colors as input features.

Given this, one way to help a network use colors effectively and still learn additional/secondary features from morphological details in images is to feed both types of information to the network through two separate branches. Optimizing such a split network on the full redshift regression task should permit the complementarity of photometric and morphological information to be used optimally as back-propagating gradients flow through each network branch using all input features as best as it can (see Chapter 6, Goodfellow et al. 2016).

This observation naturally leads to the concept of a mixed MLP-convnet architecture with concatenated features, since the MLP branch should perform well on photometric quantities and the convnet should do well on complementary morphological information. Ideally, the convnet will learn the best complementary features to the photometric quantities, and in so could outperform the hand-crafted morphological features that have been traditionally used by astronomers (Soo et al. 2018, and references therein).

The final architecture adopted in this work is composed of two separate branches: an MLP branch with 10-feature input and a convnet branch with 5-channel 72x72 image input. Details of the architectures are provided in Table 1. Our models were built with Keras on top of a TensorFlow backend and we use keras-specific terminology to describe our network. The MLP branch has two hidden layers with 4 fully-connected (dense) neurons each. PReLU activations are used in the MLP branch. The convnet branch has 4 convolutional blocks (with 2 convolutional layers each), concluded with a maxpooling operation at the end of the first three blocks. The convolutional features are collected at the end of the convnet branch via a global average-pooling operation and subsequently concatenated with the MLP branch features through a Merge layer, before the final regression layer. Note that we pose the problem as a regression task, rather than a 100-bin multi-class classification task like Hoyle (2016).

All convolutional layers use 3x3 kernels, followed by ReLU activations. Filter sizes are doubled at the end of each convolutional block (16->32->64->128). MaxPooling2D operates with (2,2) strides. All layers are initialized with an ‘he-normal’ weight distribution. This convnet architecture is inspired by the seminal VGG network architecture designed for Imagenet (Simonyan & Zisserman 2014). No extra regularization, batch-normalization or drop-out layers were used, for simplicity. Note that we use a relatively small number of filters relative to standard ImageNet-scale architectures (Simonyan & Zisserman 2014).

Some degree of architecture optimization (monitoring the validation performance) was performed on the convnet branch, specifically in terms of filter size, kernel size and number of convolutional blocks, but there is likely still room for improvement using more modern architectures/blocks than the simple VGG scheme. The MLP architecture was not optimized, with the exception of activations (PReLU seems to perform somewhat better than ReLU).

With the mixed MLP-convnet architecture adopted here, the model has the potential to learn all there is to learn in the galaxy-integrated quantities fed to the MLP branch, leaving the convnet branch free to learn the best complementary features that might exist in images, in particular all relevant morphological features (beyond the r-band Petrosian radius that is explicitly fed to the MLP branch). The split network architecture also allows us to test our main hypothesis on the role of morphological features, by selectively zeroing the input of the convnet branch (or the MLP branch) in order to compare the contribution of each branch in isolation vs together. In what follows, we refer to these modified models as MLP-only and convnet-only, respectively. One of the main goals of our work is to find out whether a mixed MLP-convnet model can indeed outperform the equivalent MLP-only model, which would indicate that morphological features can indeed be efficiently learned to provide beneficial returns to photo-z estimation.

### 3.2 Training Procedure

A simple data augmentation procedure is adopted at training time (only), whereby all images fed to the network are randomly flipped left-right and up-down (independently). The custom data generator built for this augmented training makes sure that the photometric features are propagated unchanged to the MLP branch, while only images fed to the convnet branch are augmented.

We have experimented with training on a reduced subset of the full training data set, to characterize model performance as a function of dataset size. Our full data set comprises 136000 galaxy samples but we have also built models with only 50%, 25% and 12.5% of all samples, randomly selected. For convenience, we refer to these various datasets as the 128K (full), 64K, 32K and 16K datasets.

To compare validation vs. test performance with some confidence, we performed 4-fold cross-validation. This involves the compute-intensive task of training 4 times the same architecture on a different 3/4 of the training data each time, validating on the remaining 1/4 of the data. We report
validation performance as the average validation score over the 4 folds. We report test set performance as the average of the test scores produced by the 4 distinct CV-trained models on the full test dataset. The rms variations on our CV performance scores are often less than the amount of overfitting revealed by the difference between test performance and validation performance. CV and test set performance rms variations are typically at the few % level, rarely exceeding 5%.

Training was performed with an Adam optimizer, a batch size of 32 samples (fed through a custom data generator), for 200 epochs. For each CV-fold, the model with the best validation performance over 200 epochs was retained for test set performance evaluation. All model optimization choices were driven by cross-validation performance.

We have optimized on two distinct regression objectives. In MSE-trained models, the model was optimized against the mean-squared error of predictions vs ground truth. In MAE-trained models, the model was optimized against the mean-absolute error of predictions vs ground truth. MAE is an L1-norm while MSE is an L2-norm. As such, MAE is known to regularize against outliers, relative to MSE (large squared errors are weighted more with MSE).

### 3.3 Performance metrics

We adopt standard performance metrics for our redshift estimation models. The normalized redshift bias is

\[
\delta z = \left\langle \frac{z_{\text{pred}} - z_{\text{true}}}{1 + z_{\text{true}}} \right\rangle,
\]

where \(<\cdots>\) denotes the mean over data samples, \(z_{\text{true}}\) is the measured spectroscopic redshift and \(z_{\text{pred}}\) is the predicted redshift. We also use the \((1 + z_{\text{true}})\)-normalized dispersion measures \(\sigma\) and \(\sigma_{68}\), where

\[
\sigma = \sqrt{\langle \delta z^2 \rangle}, \quad (3)
\]

is the standard deviation of the redshift bias \(\delta z\) and \(\sigma_{68}\) is the sample-mean 68% percentile spread of the absolute error on the redshift \(z\) (see, e.g. Soo et al. 2018, for similar implementations). Finally, we report the outlier fraction beyond 3\(\sigma_{68}\), referenced as \(f(3\sigma_{68})\). For comparison, ANNZ2 reports errors \(\delta z \approx 0.2 - 0.4 \times 10^{-3}, \sigma_{68} \approx 0.03 - 0.05\) and \(f(3\sigma_{68}) \approx 0.04\), for their ensemble solution made of 100 distinct models built on a dataset of 180,000 SDSS DR10 galaxies (Sadeh et al. 2016).

### 4 RESULTS

The validation set and test set performances of our deep learning solutions are presented in Figures 1 and 2 for the dispersion metrics \(\sigma\) and \(\sigma_{68}\) and in Table 2 for the bias \(\delta z\) and outlier fraction \(f(3\sigma_{68})\) metrics.

In Figures 1 and 2, the 4-Fold CV performance (dashed lines) and test set performance (solid lines) are presented for three separate models, for various dataset sizes (16K-32K-64K-128K). The mixed MLP-convnet is shown in red, the equivalent MLP-only model is shown in green and the equivalent convnet-only model is shown in black. Figure 1 shows results on the \(\sigma_{68}\) metric for training with the MAE objective (left panel) and the MSE objective (right panel).

![Figure 1](image.png)

**Figure 1.** Performance on the \(\sigma_{68}\) metric as a function of training dataset size (16K-32K-64K-128K). Models shown in the left panel are trained with an MAE (L1-norm) objective, while models in the right panel are trained with an MSE (L2-norm) objective. In each panel, solid lines show test-set performance while dashed lines show cross-validation performance. Results for the mixed MLP-convnet, MLP-only and convnet-only architectures are shown in red, green and black, respectively. The best test performance is achieved by the MLP-convnet model with MAE-training.

![Figure 2](image.png)

**Figure 2.** Same as above on the the \(\sigma\) metric. The best test performance is achieved by the MLP-convnet with MAE-training again, indicating that regularization against outliers is beneficial.

Figure 2 shows the same for the \(\sigma\) metric performances. Note that the vertical scales differ in each panel of each figure.

It is worth emphasizing that the trained networks, optimized on validation performance only, are found to appreciably overfit on the validation set, which makes the test set performance crucial in being unbiased. Overfitting is particularly acute for the convnet-only model (compare the black solid and dashed lines in Figures 1 and 2). While the CV performance of the convnet-only model is decent, its test set performance is quite poor. We have not investigated the origin of this result in detail but note that it could be caused by our choice of feeding non-standard flux images (as opposed to colors) to the convnet branch of all our models. Given the generalized overfitting behavior of these models, we focus our discussion of model performance exclusively on the test set performance in what follows.

On the dispersion metrics, Figures 1 and 2 show that the best performance is obtained when training on an MAE-objective, which regularizes against outliers. This is true on both the \(\sigma_{68}\) and \(\sigma\) metrics. Focusing on the MAE-trained solutions, we find that the MLP-convnet model exceeds the
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Table 2. Convnet/MLP Test Performance: Bias and Outlier Fraction

| Dataset | Model+Objective | Bias (4 Folds) | Outlier % |
|---------|----------------|----------------|-----------|
| 128K    | MLP-convnet+MAE | $-0.70 \times 10^{-3} \pm 0.001$ | 6.03      |
| 64K     | MLP-convnet+MAE | $-0.24 \times 10^{-3} \pm 0.001$ | 5.80      |
| 32K     | MLP-convnet+MAE | $4.26 \times 10^{-3} \pm 0.003$ | 5.94      |
| 16K     | MLP-convnet+MAE | $5.77 \times 10^{-3} \pm 0.005$ | 6.44      |
| 128K    | MLP-convnet+MSE | $1.42 \times 10^{-3} \pm 0.002$ | 6.10      |
| 64K     | MLP-convnet+MSE | $0.68 \times 10^{-3} \pm 0.001$ | 5.99      |
| 32K     | MLP-convnet+MSE | $6.01 \times 10^{-3} \pm 0.003$ | 6.41      |
| 16K     | MLP-convnet+MSE | $6.39 \times 10^{-3} \pm 0.002$ | 6.66      |
| 128K    | MLP-only+MAE    | $50.1 \times 10^{-3} \pm 0.04$  | 2.80      |
| 64K     | MLP-only+MAE    | $14.5 \times 10^{-3} \pm 0.02$  | 4.43      |
| 32K     | MLP-only+MAE    | $3.97 \times 10^{-3} \pm 0.008$ | 4.72      |
| 16K     | MLP-only+MAE    | $9.16 \times 10^{-3} \pm 0.05$  | 3.03      |
| 128K    | MLP-only+MSE    | $47.2 \times 10^{-3} \pm 0.04$  | 2.55      |
| 64K     | MLP-only+MSE    | $16.1 \times 10^{-3} \pm 0.02$  | 4.80      |
| 32K     | MLP-only+MSE    | $6.84 \times 10^{-3} \pm 0.01$  | 4.96      |
| 16K     | MLP-only+MSE    | $12.1 \times 10^{-3} \pm 0.05$  | 3.45      |
| 128K    | convnet-only+MAE| $-5.48 \times 10^{-3} \pm 0.008$| 4.37      |
| 64K     | convnet-only+MAE| $18.2 \times 10^{-3} \pm 0.04$  | 4.43      |
| 32K     | convnet-only+MAE| $27.8 \times 10^{-3} \pm 0.03$  | 3.85      |
| 16K     | convnet-only+MAE| $-4.27 \times 10^{-3} \pm 0.008$| 4.58      |
| 128K    | convnet-only+MSE| $11.1 \times 10^{-3} \pm 0.006$ | 3.97      |
| 64K     | convnet-only+MSE| $18.1 \times 10^{-3} \pm 0.03$  | 2.60      |
| 32K     | convnet-only+MSE| $36.4 \times 10^{-3} \pm 0.03$  | 3.08      |
| 16K     | convnet-only+MSE| $-8.76 \times 10^{-3} \pm 0.008$| 4.10      |

The performance of the MLP-only model. This indicates that automatically learned morphological features, once disentangled from the galaxy-integrated features fed to a separate MLP branch, do indeed improve the performance on dispersion. However, the largest gains achieved with morphology-MLP branch, do indeed improve the performance on dispersed from the galaxy-integrated features fed to a separate automatically learned morphological features, once disentangled from the galaxy-integrated features fed to a separate MLP branch. This indicates that autonomous learning of morphological features, once disentangled from them, has proven very effective.

Table 3. XGBoost Hyperparameter Range Explored

| Parameter                | Range          |
|--------------------------|----------------|
| Depth                    | 4–7            |
| N_estimators             | 500–1750       |
| Colsample_bytree         | 0.5–1          |
| Subsample                | 0.5–1          |
| Learning rate            | 0.01–0.2       |

4.1 Comparison to a strong baseline

In this section, we present a strong baseline model based on well-tested machine learning algorithms and optimization strategies that do not involve deep learning, nor morphological features. Our motivation for doing so is that it is difficult to evaluate the performance of ML algorithms in isolation. Globally optimal solutions to specific ML problems are generally not known. As a result, performance comparisons, e.g., through competitions among computer scientists and machine learning practitioners, are common practice.

By providing a way to rank algorithm performance consistently: the relative performances on a well-defined task can be evaluated in a controlled experiment (same dataset, same evaluation metric, etc...). We are left with the option to present a separate baseline model, if possible with a ML methodology that differs significantly from the deep learning approach presented above. One such reference point can be obtained by building a strong baseline model with a hyperoptimized Gradient Boosting solution. Indeed, over the past few years, a specific implementation of the gradient boosting algorithm, XGBoost, has proven very effective on numerous data science competition datasets on platforms such as Kaggle (Chen & Guestrin 2016). Together with the TPE-hyperoptimization algorithm provided in the hyperopt module, this should constitute a strong baseline solution to the redshift estimation problem for permutation-invariant features (as opposed to image features).

We build our baseline model with the open-source automated modeling tool MLBox, which conveniently integrates key features of the scikit-learn package, together with XGBoost and hyperopt built-in implementations. The model is trained on the same 10 scalar features as the MLP-branch above, described in §2. We optimize the 4-fold cross-validation performance of an XGBoost model over the range of hyperparameter values listed in Table 2, performing 40 hyper-optimization steps. Other XGBoost parameters are left to their default values.

As test set results show, the performance of our mixed MLP-convnet solution is comparable to the hyperoptimized XGB solution, which achieves best values of $\sigma_{68} \simeq 0.22$ and $\sigma \simeq 0.056$. Hyperoptimized XGB does somewhat better on the $\sigma_{68}$ metric but somewhat worse on the $\sigma$ metric. Note that MSE training appears generally better

4 https://mlbox.readthedocs.io/en/latest/
Figure 3. Representative test set performance shown as a scatter plot and marginal distributions of 192,000 spectroscopic vs. photometric redshifts predicted by a hyper-optimized XGBoost model. This specific model one was trained on the full 128K dataset with an MSE objective. The bias and dispersion are small but outliers are also easily spotted.

than MAE training for hyperoptimized XGBoost (contrary to what is found for our deep learning solution).\(^5\) On the redshift bias metric \(\delta z\), XGBoost hyperoptimized offers a consistently strong performance that is only slowly improving with dataset size (\(\delta z \approx 2.5 - 3.0 \times 10^{-3}\), see Table 5). Our convnet-MLP solution, once trained on the largest dataset available, outperforms the XGBoost results with \(\delta z \leq 10^{-3}\) (Table 2).

Outlier fractions are fairly consistent across all the models we have built, with typical values \(\sim 4 - 6\%\) (Tables 2 & 5).

Figure 3 illustrates our results with a scatter plot and marginal distributions of spectroscopic redshifts (ground truth) vs. predicted photometric redshifts from a representative XGBoost model. Specifically, Figure 3 shows 192,000 test set predictions from the hyper-optimized XGBoost model trained on the full 128K dataset with an MSE objective. This model achieves a bias \(\delta z \approx 2.73 \times 10^{-3}\) and dispersion \(\sigma = 0.056\). While bias and dispersion are small, outliers occur at a rate of a few \%, including some obvious catastrophic errors.

\(^5\) Another difference is that XGBoost exhibits rather minor over-fit to the validation set relative to the deep learning solutions we have presented.

| Dataset | Objective | \(\sigma_{68}\) | \(\sigma\) |
|---------|-----------|--------------|-------------|
| 128K    | MAE       | 0.022        | 0.056       |
| 64K     | MAE       | 0.025        | 0.059       |
| 32K     | MAE       | 0.025        | 0.059       |
| 16K     | MAE       | 0.025        | 0.059       |
| 128K    | MSE       | 0.022        | 0.056       |
| 64K     | MSE       | 0.023        | 0.057       |
| 32K     | MSE       | 0.024        | 0.057       |
| 16K     | MSE       | 0.024        | 0.057       |

| Dataset | Objective | Bias (1 model) | Outlier % |
|---------|-----------|---------------|-----------|
| 128K    | MAE       | \(2.49 \times 10^{-3}\) | 5.63      |
| 64K     | MAE       | \(2.52 \times 10^{-3}\) | 5.96      |
| 32K     | MAE       | \(2.37 \times 10^{-3}\) | 6.14      |
| 16K     | MAE       | \(2.55 \times 10^{-3}\) | 6.00      |
| 128K    | MSE       | \(2.73 \times 10^{-3}\) | 5.54      |
| 64K     | MSE       | \(2.74 \times 10^{-3}\) | 5.79      |
| 32K     | MSE       | \(3.00 \times 10^{-3}\) | 5.93      |
| 16K     | MSE       | \(3.33 \times 10^{-3}\) | 5.59      |

5 CONCLUSIONS

We have presented a split MLP-convnet architecture aimed at helping a deep neural network disentangle strong photometric and weak morphological features. This network outperforms other ML solutions, including the equivalent MLP-only network, which do not include morphological features. As a result, this work establishes that morphological features indeed do help the task of photometric redshift estimation. While the gain is small on dispersion metrics such as \(\sigma\) or \(\sigma_{68}\) and unimportant on the outlier fraction metric, it is significant on the astrophysically important redshift bias metric, \(\delta z\). Our results exploring split morpho-photometric architectures may also explain why pure convolutional approaches to redshift estimation do not necessarily outperform standard morphology-blind approaches based on color features.

Our work has is no way exhausted the full potential of morpho-photometric redshift estimation. In particular, further gains in performance could be expected from various extensions of this work, such as the use of larger training sets, architecture improvements (e.g., Resnets, Densenets, etc.), additional MLP-branch optimization, additional attempts at model regularization (e.g., batch-normalization), extensions of the training process (e.g. further image augmentation such as shifts, rotations) or even model ensembling. In terms of applications, it would be interesting to explore whether morpho-photometric redshifts can be useful to address strong degeneracies in color space, or blending issues more frequently encountered at high redshifts, which are potentially lifted in the presence of morphological information.
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