The VIMOS Public Extragalactic Redshift Survey (VIPERS).
Unsupervised classification with photometric redshifts: a method to accurately classify large galaxy samples without spectroscopic information*

M. Siudek1,2, K. Malek2, A. Pollo2,3, B. R. Granett4,5, M. Scodeggio6, T. Moutard7,8, A. Iovino4, L. Guzzo5,4, B. Garilli6, M. Bolzonella9, S. de laTorre8, U. Abbas10, C. Adami8, D. Bottini8, A. Cappi11, O. Cucciati9, I. Davidzon8,9, P. Franzetti6, A. Fritz6, J. Krywult13, V. Le Brun8, O. Le Fèvre8, D. Maccagni6, F. Marulli2,14,9, M. Polletta6,15,16, L.A.M. Tasca8, R. Tojeiro17, D. Vergani9, A. Zanichelli18, S. Arnouts8,9, J. Beu20, E. Branchini21,22,23, J. Coupon24, G. De Lucia25, O. Ilbert8, L. Moscardini12,14,9, G. Zamorani8, and T. T. Takeuchi26

(Affiliations can be found after the references)

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ABSTRACT

Aims. Techniques to classify galaxies and estimate their properties based on the photometric observations solely will be necessary for future large cosmology missions, such as Euclid or LSST. However, the classification accuracy is always lower in photometric surveys and can be systematically biased with respect to classifications based upon spectroscopic data. Our aim is to test how precisely the detailed classification scheme introduced by (Siudek et. al. accepted, hereafter: S1) for galaxies at z ~ 0.7 could be reproduced if only photometric data were available.

Methods. We applied the Fisher Expectation-Maximization (FEM) unsupervised clustering algorithm to 54,293 VIPERS galaxies. To construct the parameter space, we used reliable photometric redshifts and 12 rest-frame magnitudes obtained by the SED-fitting with the photo-z scatter σ ∼ 0.03, and the outlier rate η ∼ 2%. Subsequently, we compared the results to the analogous classification based on spectroscopic redshifts and corresponding absolute magnitudes.

Results. The FEM algorithm divided the VIPERS data into four main groups: (1) red, (2) green, (3) blue, and (4) outliers. Each group was further divided into 3, 3, 4, and 2 subclasses, respectively. The accuracy of reproducing galaxy classes using spectroscopic data is high: 92%, 84%, 96% for red, green, and blue classes, respectively. Our method was able to efficiently separate outliers (stars and broad-line AGNs), but failed to distinguish a class of star-forming galaxies with redder r − K colours and higher SFR than remaining star-forming classes. The presented verification of the photometric classification demonstrates that large photometric samples can be used to distinguish different galaxy classes at z > 0.5 with an accuracy provided so far only by spectroscopic data except for particular galaxy classes. Confirming the synergy between classifications based on spectroscopic and photometric data demonstrates the usefulness of our approach in future large surveys.

Key words. Galaxies: groups - general - galaxies: evolution - galaxies: star formation - galaxies: stellar content - Galaxy: fundamental parameters - Galaxies: statistics

1. Introduction

Nowadays, applying effective classification tools to process large datasets becomes imperative. Forthcoming surveys, such as the European Space Agency’s Euclid mission (Laureijs et al. 2011), the Large Synoptic Survey Telescope (Ivezic et al. 2008; LSST Science Collaboration et al. 2009) will undoubtedly open the era of unprecedentedly big astronomical observations requiring machine learning and deep learning techniques to handle the data (see Fraix-Burnet et al. 2015 for a review).

Among the machine learning tools, of particular interest are clustering algorithms. Broadly speaking, they can be separated into two main classes: supervised (when the classifier is trained with a representative sample) and unsupervised methods (without any training process). Machine learning algorithms have already been applied to galaxy classification (e.g. Sánchez Almeida et al. 2010; Marchetti et al. 2012; Malek et al. 2013; Krakowski et al. 2016, S1). The ability to distinguish between galaxy classes is a starting point to study galaxy formation and evolution (e.g., Buda 2011; Buda & Zhang 2011). While supervised algorithms have demonstrated reasonable efficiency in automatic classification of unknown sources if a good training sample was provided (e.g. Solarz et al. 2012; Malek et al. 2013; Krakowski et al. 2016; Kurcz et al. 2016; Solarz et al. 2017), application of unsupervised machine learning techniques to galaxy classification is arguably yet to be proven. Unsupervised techniques applied to classify galaxies usually are not able to converge to an optimal number of galaxy classes (mostly because of
the problem with initial seeding) or fail in following the continuous and physical nature of galaxy types (e.g. Sánchez Almeida et al. 2010; Hocking et al. 2018).

Unsupervised machine learning algorithms were so far mostly applied to classify galaxy spectra mainly based on Principal Component Analysis (PCA) and k-means analysis (e.g. Sánchez Almeida et al. 2010; Marchetti et al. 2012; Peth et al. 2016). Using data based on photometric redshifts (hereafter $z_{\text{phot}}$) for classification purposes is obviously coarser than with spectroscopic data (hereafter $z_{\text{spec}}$) due to larger errors. Unfortunately, obtaining full spectroscopic information in wide-field imaging surveys is not achievable due to the large number of galaxies and high costs in observing time, especially for high-redshift sources. The next generation of extragalactic surveys will be dominated by multi-band photometry data. Therefore, there is strong necessity to develop clustering tools able to provide galaxy classification using $z_{\text{phot}}$ on a comparable accuracy level as when using $z_{\text{spec}}$.

Standard approaches to classify galaxies use methods based mainly on the bimodality in their colour distribution (e.g. Fritz et al. 2014; Haines et al. 2017; Krywult et al. 2017; Siudek et al. 2017). However, this does not allow for very precise classification and may lead to differences in the observed properties depending on the adopted criteria (e.g. Renzini 2006; Moresco et al. 2013). In S1 we introduced a new approach to the galaxy classification based on the unsupervised FisherEM (hereafter FEM; Hudelot et al. 2011) algorithm, which works in the multidimensional space of absolute magnitudes (in 12 different filters) and $z_{\text{spec}}$. The classification is thus based on a large parameter space, rather than just on the standard colour-colour plane, and therefore is more sensitive to the galaxy properties. The classification based upon broadband magnitudes allows detailed evolution studies of the red sequence, blue cloud and green valley. The FEM algorithm separated different galaxy classes and determined the optimal number of homogeneous classes automatically, yielding 11 galaxy classes from the earliest to the latest types with an additional group of outliers (mainly normal stars, as such sources are expected to contaminate photometrically selected samples. The remaining 32 sources are high-redshift objects ($z_{\text{spec}} > 1.5$) which were excluded from the spectroscopic sample defined in S1 as they are SED-fitting failures. Our sources cover the redshift range $0.3 < z_{\text{phot}} < 1.2$, with the first percentile reaching down to $z_{\text{phot}} = 0$ and up to $z_{\text{phot}} = 4.8$.

In this paper we present the photometric classification (hereafter PHOT classification) of VIPERS galaxies and its comparison to the $z_{\text{spec}}$-based classification (hereafter SPEC classification; S1). The aim of the paper is to verify how precisely the SPEC classification can be reproduced, thus testing the usefulness of this large photometric dataset.

The paper is organized in the following way: In Sect. 2 we present the VIPERS data sample. Sect. 3 presents results and discusses their physical interpretation. The summary is presented in Sect. 4. Throughout this paper the cosmological framework assumes $\Omega_m = 0.30$, $\Omega_{\Lambda} = 0.70$, and $H_0 = 70$ kms$^{-1}$Mpc$^{-1}$.

2. Data and sample selection

The analysis presented in this paper is based on the final galaxy sample from the VIMOS Public Extragalactic Redshift Survey (VIPERS; Scodelligo et al. 2018) performed with the VIMOS spectrograph mounted on the Very Large Telescope at ESO (VIMOS, Le Fèvre et al. 2003). VIPERS was designed to map the large-scale distribution over an unprecedented volume of $5 \times 10^{3}h^3$Mpc$^{-3}$ in the redshift range $0.5 < z < 1.2$. A simple and robust pre-selection in the $(u-g)$ and $(r-i)$ colour-colour plane was used to remove galaxies with $z < 0.5$ (Guzzo et al. 2014). VIPERS provided spectroscopic redshifts of 86,775 galaxies limited to $z_{\text{phot}} \leq 22.5$ mag over an area of $\sim 23.5$ deg$^2$ and corresponding full photometrically-selected parent catalogue. The associated photometric catalogue consists of magnitudes based on $u$-, $g$-, $r$-, $i$- and $z$-band imaging from the CFHTLS T0007 release (Hudelot et al. 2012), FUV and NUV observations from GALEX (Martin et al. 2005), and new $K_s$-band observations conducted as part of the VIPERS Multi-Lambda Survey (VIPERS-MLS; Moutard et al. 2016a), complemented by $K_s$-band measurements from VIDEO (Jarvis et al. 2013). A detailed description of the VIPERS survey can be found in Guzzo et al. (2014) and Scodelligo et al. (2018).

In this paper we present the classification based on the absolute magnitudes and $z_{\text{phot}}$. Similarly as in the SPEC classification (S1) the absolute magnitudes were derived by spectral energy distribution (SED) fitting described in Moutard et al. (2016b), except that now the computation was based on the $z_{\text{phot}}$ from the VIPERS-MLS (for full description of $z_{\text{phot}}$ measurements, please refer to Moutard et al. 2016a).

Our photometric sample includes the whole sample (52,113 objects) classified with the SPEC classification (sample selection is discussed by S1) completed by additional 2,180 sources. 2,148 sources of those 2,180 are spectroscopically confirmed stars, as such sources are expected to contaminate photometrically selected samples. The remaining 32 sources are high-redshift objects ($z_{\text{spec}} > 1.5$) which were excluded from the spectroscopic sample defined in S1 as they are SED-fitting failures. Our sources cover the redshift range $0.3 < z_{\text{phot}} < 1.2$, with the first percentile reaching down to $z_{\text{phot}} = 0$ and up to $z_{\text{phot}} = 4.8$.

The comparison between $z_{\text{phot}}$ and $z_{\text{spec}}$ for the VIPERS sample is shown in Fig. 1. The measured scatter is $\sigma_{\text{d}(z+/z-)} \sim 0.03$ and the outlier rate$^1$ is $\eta \sim 2\%$.

3. Results

3.1. The optimal class number

We ran the FEM algorithm on the PHOT sample based on the multidimensional space, and the optimal number of classes (12) and the best discriminative latent mixture (DBk) were established using the same approach as for SPEC classification (S1). We note that the optimal number of classes was the same as for SPEC classification; although a new class of stars appeared, at the same time we were not able to distinguish between

$^1$ Following Ilbert et al. (2006) and Moutard et al. (2016b) the scatter is defined as $\sigma_{\text{d}(z+/z-)} = 1.48 \cdot \text{median}(z_{\text{spec}} - z_{\text{phot}})/(1 + z_{\text{spec}})$, and the photo-z outlier rate, $\eta$ as the percentage of galaxies with $|\Delta z|/(1+z) > 0.15$. 

Fig. 1: The comparison between $z_{\text{phot}}$ and the corresponding $z_{\text{spec}}$ of 54,293 VIPERS sources used in the following analysis. The blue dashed line corresponds to $z_{\text{phot}} = z_{\text{spec}}$. The red dotted lines show the threshold for defining outliers.
dusty star-forming galaxies and less dusty star-forming class (galaxies from SPEC class 8 were assigned to PHOT class 9; see Fig. 2). Therefore, the number of classes was preserved. VIPERS sources were not strictly assigned to one class, but the probability of being a member of each class was given. However, 94% of sources have their assignment well defined, i.e. have a high probability (> 75%) of belonging to one class. In the following discussion we used only class members with a high probability of belonging to a given class, rejecting 3,007 objects with low class membership probability (< 50%) or with a high (> 45%) probability of belonging to the second group (see S1 for details).

### 3.2. The colour-colour diagram

The 12 different photometric classes (hereafter PHOT class) within VIPERS sample follow the trend from red, passive, through green, intermediate, to blue, star-forming galaxy types, plus additional groups of outliers (stars and AGNs). Even if such a detailed classification is possible only in the full multidimensional parameter space, it is well reflected by the positions of groups on the \((\text{NUV} - r)\) vs. \((r - K)\) diagram (hereafter \(\text{NUV}rK\); Arnouts et al. 2013) diagram\footnote{Note, however, that the \(\text{NUV}, r, K\) parameter space would not be sufficient to create such a fine division}. Fig. 2 presents a comparison of the distribution of the FEM classes in the \(\text{NUV}rK\) diagram, when \(z_{\text{phot}}\) and \(z_{\text{spec}}\) were used in the classification procedure.

The galaxy sequence obtained from the PHOT classification almost exactly mirrors the spectroscopic classes (hereafter SPEC classes). Fig. 2 shows that the median \(\text{NUV} - r\) and \(r - K\) colours of red galaxies (classes 1–3) are similar in both classifications. Green galaxies (classes 4–6) are also located in the same area in the \(\text{NUV}rK\) diagram in SPEC and PHOT classifications. The main difference is displayed by the group of star-forming galaxies. In the PHOT classification four star-forming groups were found (7–11 classes). The SPEC classification distinguished one additional class of dusty star-forming galaxies (SPEC class 8) characterized by redder \(rK\) colours \((r - K_{\text{median}} = 1.00^{+0.12}_{-0.14})\). and higher \(SFR\) \((SFR = 1.41^{+0.28}_{-0.30})\) than remaining star-forming classes. These galaxies were mostly assigned to the PHOT class 9 of star-forming galaxies (~ 75%; see also Fig. 3). This might be a consequence of a discrete nature of SED templates, which resulted in the lowest \(z_{\text{phot}}\) accuracy \((\sigma_{z_{\text{spec}}} / (1 + z) \sim 0.037)\) for galaxies within SPEC class 8 among all classes (except class 12), which yields the inability of distinguishing more dusty star-forming galaxies. We note that also in SPEC classification those galaxies were not straightforwardly distinguished. Galaxies in SPEC class 8 are characterized by lower membership probability than other SPEC classes (see Fig. C.1 in S1). Moreover, the SPEC class 8 was distinguished on the last cycle of the FEM algorithm, i.e. the class is absent if we consider a SPEC classification with only 11 classes (Fig. B.2 and B.3 in S1). Extremely dusty green galaxies (class 6) are, however, properly identified in the PHOT classification.

Furthermore, in the PHOT classification an additional group of outliers (marked with green in Fig. 2) was separated. The class of outliers with red \(\text{NUV} - r\) and blue \(r - K\) colours is mainly (96%) composed of stars (not included in the original SPEC sample). More than half of the stars present in the photometric dataset (1,234 out of 2,148; 57%) were assigned to this class. The remaining 914 stars were distributed in different groups. However, they constitute just a small fraction of all members of the other classes except for class 12 (42%; 55 stars). Class 12, besides stars, consists of broad-line AGNs (50%). In the case of the SPEC classification it was a pure sample of broad-line AGNs (95%).

![Fig. 2: The NUVrK diagram of the VIPERS galaxies classified into 12 classes according to the FEM algorithm using \(z_{\text{phot}}\) (points with error bars) and \(z_{\text{spec}}\) (rectangles). The error bars and size of squares correspond to the 25th, and 75th percentile range of the galaxy colour distribution. The median colours are marked with points.](image-url)

![Fig. 3: The distribution of 52,113 VIPERS galaxies and 2,180 additional sources (mainly stars) within 12 SPEC (left side) and PHOT classes (right side). Colours represent objects flow from each SPEC class to PHOT class.](image-url)
Table 1: The accuracy (A [%]) of the PHOT classification given as the percentage of the number of galaxies in each SPEC class ($N_{\text{spectro}}$) to the subsample of $N_{\text{photo}}$ galaxies which are found in the same PHOT class ($N_{\text{photo}}$).

| Cls | $N_{\text{spectro}}$ | $N_{\text{photo}}$ | A [%] | Cls | $N_{\text{spectro}}$ | $N_{\text{photo}}$ | A [%] |
|-----|---------------------|------------------|-------|-----|---------------------|------------------|-------|
| 1-3 | 10,849              | 9,985            | 92    | 7   | 5,708              | 4,432            | 78    |
| 1   | 4,515               | 3,838            | 85    | 9   | 6,331              | 5,773            | 91    |
| 2   | 2,552               | 1,884            | 74    | 10  | 14,595             | 12,781           | 88    |
| 3   | 3,782               | 2,279            | 60    | 11  | 2,893              | 2,036            | 70    |
| 4   | 4,576               | 3,100            | 68    | 7-11| 31,896             | 30,552           | 96    |
| 5   | 3,512               | 2,673            | 76    | 12  | 174                | 52              | 30    |
| 6   | 1,107               | 661              | 60    | 4-6 | 9,195              | 7,662            | 84    |

3.3. Statistical differences between spectroscopic and photometric classifications

Fig. 3 presents the distribution of VIPERS sources within SPEC classes (S1) and their migration to PHOT classes. The majority of objects (> 70%) were assigned to the same class independently of the fact that $z_{\text{spec}}$ or $z_{\text{phot}}$ was used. However, a small "exchange" between classes occurred, mainly between classes located close to each other. For example PHOT class 2 (marked with dark red in Fig. 3) is built mainly from galaxies assigned to SPEC class 2 (∼56%; dark red), but also includes objects from SPEC class 1 (∼17%; brown), and 3 (∼20%; red). There are also more extreme "jumping-objects" where sources assigned to e.g., red and passive SPEC classes were classified as intermediate or star-forming PHOT classes, and this is seen as thin flows between distant groups in Fig. 3. However, jumps over more than 2 classes are very rare (∼2%). Less secure assignment of these sources is also mirrored by their lower membership probability (mean probability for "jumping-objects" is lower by ∼7% than those for members of "main" streams). Therefore, some objects with a low PHOT membership probability did not migrate from the SPEC class to the corresponding PHOT class, but drastically changed their classification. These galaxies are also characterized by lower $z_{\text{phot}}$ accuracy ($\sigma_{\Delta z_2/(1+z_2)}$ ∼ 0.05), what may explain the difficulties in the assignation of the proper class.

Fig. 4 presents the comparison between the spectroscopic and morphological class properties: the strength of the 4000Å break ($D4000_n$, as defined by Balogh et al. 1999), the equivalent widths for [OII]λ3727, and the Sérsic index when $z_{\text{phot}}$ and $z_{\text{spec}}$ were used in the classification procedure are shown as a function of the class number. Except for SPEC class 12 (composed by broad-line AGNs) and SPEC class 8 (blue, dusty star-forming galaxies not distinguishable in the PHOT classification), the median properties of each class agree well in the two classifications and do not show any significant differences. PHOT class 12 is strongly contaminated by stars which results in a difference between their properties.

4. Summary

We presented an unsupervised classification of VIPERS sources observed at $z$ ∼ 0.7 based on the $z_{\text{phot}}$ and corresponding absolute magnitudes. The unsupervised photometric classification does not require additional training with spectroscopic samples, after photometric redshifts have been estimated.

Three classes of red passive galaxies (classes 1–3) did not change if no spectroscopy information was provided (with an accuracy of 92%; see Tab. 1). Also green, intermediate galaxies (classes 4–6) were accurately (84%) separated when only $z_{\text{phot}}$ was provided. Spectroscopy is also not necessary to separate blue, star-forming galaxies as a whole class, as the algorithm using $z_{\text{phot}}$ was able to almost perfectly identify the same group as SPEC classification (96%). However, spectroscopic information is needed to obtain a more detailed picture of some of the blue subclasses. In particular, the PHOT classification was not able to separate dusty star-forming galaxies (SPEC class 8) from less dusty star-forming galaxies (class 9). This might be a consequence of the SED fitting procedure adapted to the VIPERS dataset (Moutard et al. 2016a), which was not able to describe properly dusty star-forming galaxies. Possibly, a better set of templates might improve the outcome. A detailed efficiency of the PHOT classification is given in Tab. 1. In the PHOT sample, which includes stars, the algorithm, in some cases, is not able to distinguish stars and AGNs and, therefore, assigned them to the same class. This resulted in (expected) differences between PHOT class 12 and SPEC class 12.

We conclude that quite reliable $z_{\text{phot}}$ ($\sigma ∼ 0.03, \eta ∼ 2%$) allow for a highly effective identification of different galaxy classes at $z > 0.5$ by the FEM unsupervised algorithm. The resultant classification is almost identical with the classification based on $z_{\text{spec}}$, confirming that the FEM algorithm is a new robust tool, which can provide a detailed picture of galaxy types at $z ∼ 1$ also without spectroscopic information. In general, it would imply that for division into basic blue/green/red classes at our redshift range the observed colours are sufficient and even wrongly assumed redshifts do not affect much the results (especially the selection of red galaxies). For a finer division into subclasses, a correct redshift is necessary. However, to reproduce most subclasses the photometric accuracy as provided by our data is sufficient, except for blue dusty star-forming galaxies (class 8), where spectroscopic accuracy becomes crucial. The
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1 Center for Theoretical Physics, Al. Lotnikow 32/46, 02-668 Warsaw, Poland
2 National Centre for Nuclear Research, ul. Hoza 69, 00-681 Warszawa, Poland
3 Astronomical Observatory of the Jagiellonian University, Orla 171, 30-001 Cracow, Poland
4 INAF - Osservatorio Astronomico di Brera, Via Brera 28, 20122 Milano – via E. Bianchi 46, 23807 Merate, Italy
5 Università degli Studi di Milano, via G. Celoria 16, 20133 Milano, Italy
6 INAF - Istituto di Astrofisica Spaziale e Fisica Cosmica Milano, via Bassini 15, 20133 Milano, Italy
7 Department of Astronomy & Physics, Saint Mary’s University, 923 Robie Street, Halifax, Nova Scotia, B3H 3C3, Canada
8 Aix Marseille Univ, CNRS, LAM, Laboratoire d’Astrophysique de Marseille, Marseille, France
9 INAF - Osservatorio di Astrofisica e Scienza dello Spazio di Bologna, via Gobetti 93/3, 40129 Bologna – Italy
10 INAF - Osservatorio Astrofisico di Torino, 10025 Pino Torinese, Italy
11 Laboratoire Lagrange, UMR7293, Université de Nice Sophia Antipolis, CNRS, Observatoire de la Côte d’Azur, 06300 Nice, France
12 Dipartimento di Fisica e Astronomia - Alma Mater Studiorum Università di Bologna, via Gobetti 93/2, I-40129, Bologna, Italy
13 Institute of Physics, Jan Kochanowski University, ul. Sztwotrzyna 15, 25-460 Kielce, Poland
14 INFN, Sezione di Bologna, viale Bert Pichat 6/2, I-40127, Bologna, Italy
15 IRAP, Université de Toulouse, CNRS, UPS, Toulouse, France
16 IRAP, 9 av. du colonel Roche, BP 44346, F-31028 Toulouse cedex 04, France
17 School of Physics and Astronomy, University of St Andrews, St Andrews KY16 9SS, UK
18 INAF - Istituto di Radioastronomia, via Gobetti 101, I-40129, Bologna, Italy
19 Canada-France-Hawaii Telescope, 65–1238 Mamalahoa Highway, Kamuela, HI 96743, USA
20 Aix Marseille Univ, Univ Toulon, CNRS, CPT, Marseille, France
21 Dipartimento di Matematica e Fisica, Università degli Studi Romo Tre, via della Vasca Navale 84, 00146 Roma, Italy
22 INFN, Sezione di Roma Tre, via della Vasca Navale 84, I-00146 Roma, Italy
23 INAF - Osservatorio Astronomico di Roma, via Frascati 33, I-00040 Monte Porzio Catone (RM), Italy
24 Department of Astronomy, University of Geneva, ch. d’Ecogia 16, 1290 Versoix, Switzerland
25 INAF - Osservatorio Astronomico di Trieste, via G. B. Tiepolo 11, 34143 Trieste, Italy Observatory, Blackford Hill, Edinburgh EH9 3HJ, UK
26 Division of Particle and Astrophysical Science, Nagoya University, Furo-cho, Chikusa-ku, 464-8602 Nagoya, Japan

Article number, page 5 of 5