Image feature extraction and galaxy classification: a novel and efficient approach with automated machine learning

F. Tarsitano, C. Bruderer, K. Schawinski, W. G. Hartley

1 Institute for Particle Physics and Astrophysics, ETH Zürich, Wolfgang-Pauli-Strasse 27, CH-8093 Zürich, Switzerland
2 Modulos AG, Technoparkstrasse 1, 8005 Zürich
3 Department of Astronomy, University of Geneva, ch. d’Écogia 16, CH-1290 Versoix, Switzerland

ABSTRACT

Machine learning methods are extensively used for a broad range of applications, from healthcare to economy and to natural sciences. They are often used in image recognition and are also employed to classify sequences, which represent a simpler and more convenient format to store and organize data. In this work we explore the possibility of applying machine learning methods designed for one-dimensional problems to the task of galaxy image classification. The algorithms used for image classification typically rely on multiple costly steps, such as the Point Spread Function (PSF) deconvolution and the training and application of complex Convolutional Neural Networks (CNN) of thousands or even millions of parameters. In our approach, we extract features from the galaxy images by analysing the elliptical isophotes in their light distribution and collect the information in a sequence. The sequences obtained with this method present definite features allowing a direct distinction between galaxy types, as opposed to smooth Sérsic profiles. Then, we train and classify the sequences with machine learning algorithms, designed through the platform Modulos AutoML, and study how they optimize the classification task. As a demonstration of this method, we use the second public release of the Dark Energy Survey (DES DR2). We show that by applying it to this sample we are able to successfully distinguish between early-type and late-type galaxies, for images with signal-to-noise ratio greater than 300. This yields an accuracy of 86% for the early-type galaxies and 93% for the late-type galaxies, which is on par with most contemporary automated image classification approaches. Our novel method allows for galaxy images to be accurately classified and is faster than other approaches. Data dimensionality reduction also implies a significant lowering in computational cost. In the perspective of future data sets obtained with e.g. Euclid and the Vera Rubin Observatory (VRO), this work represents a path towards using a well-tested and widely used platform from industry in efficiently tackling galaxy classification problems at the peta-byte scale.

Key words: machine learning – galaxies – data patterns

1 INTRODUCTION

Galaxy morphology plays an important role in our studies and understanding of galaxy evolution. Structural components such as bulges, diska, spiral arms and bars formed during galaxies’ aggregated formation histories (Combes & Sanders 1981; de Jong 1996; Elmegreen et al. 1996). As such, morphology is related to other properties that depend on formation and assembly history, such as colour, stellar-mass and recent Star Formation Rate (SFR) (Baldry et al. 2004; Noeske et al. 2007; Cano-Díaz et al. 2019). By looking at the relation between mass and SFR (Schiminovich et al. 2007; Goncalves et al. 2012; Peterken et al. 2021), astronomers have been able to distinguish between three different populations. Most star-forming galaxies belong to the main sequence, and present morphological features typical of spiral or irregular galaxies. Objects in this population are also called Late-Type Galaxies (LTG). We can identify another population with much lower SFR and different shapes, mostly elliptical or bulge-dominated morphologies: we refer to these as Early-Type Galaxies (ETG). The transition between ETG and the main sequence is smoothed by an intermediate and less heavily populated region, called the green valley (Salim 2014; Schawinski et al. 2014).

Historically, galaxies were classified as early or late type by visual inspection, with a modern example of classification in this way provided by Nair & Abraham (2010). Recent citizen science projects like Galaxy Zoo (Lintott et al. 2008; Simmons et al. 2017; Lingard et al. 2020) use the same approach, while benefiting from a huge network of volunteers who are asked to classify galaxies. Quantitative methods for classifying structural properties includes modeling galaxy light profiles with 2D analytic functions, and fitting them to galaxy images. The most commonly used model is the Sérsic profile (Sérsic 1963), a parametric function with parameters describing structural properties such as size, magnitude, ellipticity, inclination and the rate at which light intensity falls off with radius (Sérsic index). The latter quantifies the concentration of light and it is often used to distinguish between ETG and LTG. In fitting galaxy images, the Sérsic model must be convolved with the Point Spread Function (PSF), in order to
We analyse galaxies up to magnitude $m_r < 20$, reaching comparable accuracy: 86% for ETG and 93% for LTG.

Section 2 contains more details about the data set. Our method and details on how we perform the isophotal analysis of galaxy images, extract features from their light distribution and collect those into sequences, is described in Section 3. The sequences are then processed through a neural network designed and run in the framework of Modulos AutoML. More details are given in Section 4. We present the results in Section 5 and discuss further developments in Section 6.

2 DATA

In this work, we use public images from the Dark Energy Survey DR2 release (Abbott et al. 2021; Morganson et al. 2018b; Flaugher et al. 2015a), available through the public DES Data Management. In this section, we provide an overview of the survey, describe the structure of the data set and define the selection function for our sample.

2.1 The Dark Energy Survey

The Dark Energy Survey (DES) is a project aiming to map hundreds of millions of galaxies to measure the effects of dark energy on the expansion history of the Universe and the growth of cosmic structure. The collected data are analysed through different methods: gravitational lensing, galaxy clustering and Baryonic Acoustic Oscillations (BAO). DES used the Dark Energy Camera (DECam) to detect more than 300 million galaxies between the years 2013 and 2019 (Flaugher et al. 2015b). Although conceived for cosmological research, the vast data set assembled by DES represents a powerful survey for the fields of galaxy evolution, stellar populations and Solar System Science too (Abbott et al. 2016). Moreover, in 2017 DECam provided the optical counterpart of the gravitational wave event GW170817 studied by the LIGO-Virgo collaboration of the gravitational wave event GW170817 studied in detail in Palme et al. (2017). The camera has a 2.2 arcsecond diameter field of view and a pixel scale of 0.263 arcsecond (Flaugher 2005). It is mounted on the Victor M. Blanco 4-meter Telescope at the Cerro Tololo Inter-American Observatory (CTIO) located in the Chilean Andes.

2.2 The data set

The DES survey area is covered by images in five photometric bands, $g, r, i, z, Y$. The single exposure images have integration time of 90 seconds in the $g, r, i, z$ and 45 seconds in the $Y$ band. Data are later processed through the DESDM (DES Data Management) pipeline, which first applies calibrations and coadds the images, then detects and catalogues all the objects in those images (Orríca-Wagner et al. 2017; Morganson et al. 2018a). In the image co-addition, the pipeline combines overlapping single-epoch images in one filter and remaps them to artificial tiles on the sky as described in Sevilla et al. (2011), Desai et al. (2012) and Mohr et al. (2012). Object detection is made using a specific software, called SExtractor (Bertin 2011), which extracts structures from the background and distinguishes between point-like (stars) and galaxies. Then, it performs a photometric analysis, where each object is enumerated and assigned to a set of specific properties, collected in a catalogue. For this analysis, properties of the light distribution are measured, namely the object brightness,

1 https://www.modulos.ai/
2 https://des.ncsa.illinois.edu
2.3 Sample selection

We apply cuts to the SExtractor catalogues (see below) to select a final sample of 6525 galaxies. We choose objects which are neither truncated nor corrupted or blended to other objects by setting $\text{FLAGS} = 0, 2$. Additionally, we choose bright objects by applying a cut in magnitude. In Tarsitano et al. (2018), we observe that robust fits are obtained for objects up to a magnitude of 21.5 in the $i$-band. In order to work with optimal isophotal fitting, in this analysis we make a more conservative cut, setting in the same filter $\text{MAG\_AUTO} \leq 20$. For the same reason, we also adopt the cut in signal-to-noise $S/N > 300$. In Tarsitano et al. (2018) we also flagged those galaxies with size smaller than or comparable to the PSF, because in those cases the PSF significantly affects the way the concentration of light is modelled, leading to degeneracies in the estimation of the size and Sérsic index. Therefore our selection function excludes the galaxies with size smaller than 4 $px$ in the $i$-band. We also check that the selected objects have physically meaningful measurements, avoiding galaxies with negative or null radii. In processing the data (see Section 3), we will make use of the Kron radius, which is the radius within which approximately 90% of the galaxy light is included. According to the definition in SExtractor, we consider as Kron radius the product between the KRON_RADIUS and the semi-major axis of the galaxy A_IMAGE. Finally, we exclude from our sample the point-like objects by applying a cut to the MODEST parameter (Drlica-Wagner et al. 2018). The sample selection is summarized in Table 1. Additional information about the MODEST star/galaxy classifier and the SExtractor catalogues can be found here: https://des.ncsa.illinois.edu/releases/y1a1/gold.

### Table 1. Summary of the cuts applied to SExtractor catalogues for the sample selection.

| SELECTION TYPE | SELECTION CUT |
|---------------|---------------|
| Image flags   | $\text{FLAGS} = 0, 2$ |
| Magnitude     | $\text{MAG\_AUTO} < 20$ |
| S/G           | $\text{MODEST} > 0.005$ |
| S/N           | $\text{FLUX\_AUTO}/\text{FLUXERR\_AUTO} > 300$ |

quantified in $\text{MAG\_AUTO}$, and its size, called FLUX_RADIUS, which includes half of the galaxy light. We use these measures to identify and optimise the sample analysed in this work.

3.1 Production of stamps

For each of our selected galaxies (see Section 2.3), we cut square postage-stamp images from the relevant DES tiles, with dimensions equal to four times the Kron radius. This size is chosen to ensure that the image includes the galaxy light distribution entirely and sufficient non-object pixels to be able to determine the background level. For this operation, we use the publicly available CANVAS algorithm $^3$ (Cut ANd VAlidate Stamps), presented and optimized in Tarsitano et al. (2018).

3.1.1 Background

In standard analyses such as parametric fitting, the background needs to occupy at least 60% of the area of the stamp, in order to obtain a correct fit. The fitting algorithm, in fact, needs to distinguish the light signal from the sky, which becomes challenging towards the outskirts and faint wings of a galaxy. Therefore, a clear separation is only possible if the background occupies a larger area of the stamp than the galaxy (Peng et al. 2010). In works that perform image classification with neural networks, the preparation of the sample usually includes data-augmentation with image simulations to artificially place a galaxy with well-known classification at different redshifts. This process requires the PSF to be deconvolved and the reconstruction of images with an appropriate percentage of background. In our work, we do not perform parametric fitting and we extract information solely from the area inside the Kron ellipse of the galaxy. Hence our approach is robust to minor defects or mis-estimations of the background or the image stamp size, and we need not be concerned with multiplying the size of our input images to ensure sufficient background coverage.

3.1.2 Neighbouring objects

A potential source of errors for the galaxy classification is the presence of neighbouring objects. If not taken into account, both standard fitting algorithms and CNNs are prone to imprecise estimations or classification of the galaxy light profile. We consider two cases:

- the neighbour falls outside the Kron ellipse of the galaxy;
- the neighbour is placed inside the Kron ellipse of the galaxy (partially or fully).

The first scenario is negligible for our analysis, since we only consider the pixels inside of the Kron ellipse. However, we cannot ignore the second case. Our aim is to minimize the number of manipulations applied to the images, so we do not apply any algorithm to identify such cases. Moreover, we would need to distinguish cases that are due to chance alignments from more interesting but possibly similar-appearing cases due to, e.g., galaxy-galaxy mergers or star-forming clumps. This latter task is an avenue of future research for our method, but as contaminants do not change the overall trend of the sequences we obtain for elliptical and spiral galaxies, we do not apply corrections for them in the present work.

3.2 Extraction of profiles

The extraction of profiles relies on the elliptical isophote analysis of the galaxy in question. Isophotes are curves connecting locations with the same brightness. We use the algorithm of Elliptical Isophote...
In this section we describe the properties we show in Figure 2 examples of sequences for ETG (upper panel) and LTG (lower panel).

### 4 AI FRAMEWORK AND MODULUS

We run a Modulos AI workflow on a data set randomly split between a test (2175 galaxies) and training+validation sample (4350 galaxies), with all objects visually inspected according to their corresponding 1-D sequences and images. As previously mentioned in Section 3, we show in Figure 2 examples of sequences for ETG (upper panel) and LTG (lower panel). In this section we describe the properties of the workflow in more detail. We use the Modulos AutoML platform (version 0.3.5) to search for suitable models. The platform is designed to perform automated model selection and training for machine learning tasks, and works in the following way:

- **Workflow configuration (ML task):** The user selects the data set to be processed, and sets an objective for which it is optimized.
- **Schema matching:** The platform detects the schema of the desired input and output. It then proposes the feature extraction methods and machine learning models applicable to the data set and target objective.
- **Optimization:** Using a Bayesian optimizer (Srinivas et al. 2009), the platform tries out various combinations of feature extractors, models and their parameters. At each search step, the platform selects a feature engineering method and a model, chooses its architecture and hyperparameters, and trains it. After completing training, the platform uses a validation set to score this particular choice.
- **End point:** There is no clearly defined end point at which the "best model" has been found. However, after a while, the scores for the models begin to converge. As a default, the platform stops if there are no score improvements within 200 steps.
- **Download:** Any trained model can be downloaded and used. We choose the best-performing model.

The key advantages of a platform such as AutoML are that the search for models and configuration is principled and not biased by human intervention. It is also significantly more efficient than optimization searches performed "by hand". During this project, the vast majority of the time was spent on the preparation and the analysis of the data set, with only a few hours required for the automated classification. In our case, we found a suitable solution within 4.30 hours of compute time (14 min 19 sec to train the specific solution).

The objective we set for optimisation is the $F_1$ score. For multi-class classification, the total $F_1$ score is the unweighted arithmetic mean of the $F_{1,i}$ scores of each class $i$ (macro-averaged). These are the harmonic mean of the precision and recall of the classified samples for each respective class, i.e.

$$F_{1,i} = 2 \cdot \frac{\text{precision}_i \cdot \text{recall}_i}{\text{precision}_i + \text{recall}_i} = \frac{2TP_i}{2TP_i + FP_i + FN_i},$$

where $TP_i$ are the true positives for the classified samples for the class $i$ and $FP_i$ and $FN_i$ are the false positives and false negatives respectively.

### 5 RESULTS AND DISCUSSION

The automated machine learning framework returns as best solution an XGBoost model with a PCA decomposition as feature engineering method. XGBoost (Extreme Gradient Boosting) is a decision-tree based Machine Learning algorithm using a gradient boosting framework (Friedman 2001). This model reaches a $F_1$ macro score (see eq. 1) of 90% on training data and 89% on test data, which suggests it is not prone to over or under-fitting. Our best model is publicly available at https://github.com/Federica24/Cosmo and can be applied to any DES data processed as described in the previous sections.

#### 5.1 Information extraction

In order to understand why a combination of an XGBoost model and a PCA feature engineering method is found to be performing...
Automated galaxy classification with Modulos AI

Figure 2. Example of classification between early-type (upper panel) and late-type (lower panel) galaxy, according to their time-series-like profile.

best, we review the key information accessed during classification by our model and compare it to the structure of our data. In Figure 3 we show the collection of sequences classified as ETG (in blue) and LTG (in green). Additionally, we have highlighted 10 arbitrary sequences from each class to illustrate the individual profiles. The human eye is able to distinguish between the two classes by looking at the slopes of the sequences (greater for ETG) and comparing the abundance of spike-like features, which correspond to spiral arms of LTG, and to the smoothness of the sequences representing ETG. If spikes occur in the latter, they are more sparse and might refer to the presence of a neighbour (see Section 3 for reference). The information contained in the slopes and features is enhanced by the PCA analysis, which encodes it into a set of components. Each component brings a unique contribution to the automatic classification, giving the features different weight. By computing the Gini feature importance of the collection of decision trees, we can then understand which features contribute the most in predicting a class for a new data point in our model. We show the three most important nodes picked up by the Gini feature importance with black, vertical lines on Figure 3. We notice that the three nodes refer to points where the two classes of sequences on average start falling at different rates. In other words, these nodes are the ones with the largest discriminatory power for the collection of decision trees, which perform classifications by sequentially dividing up the sequences. We find that the most important node for our best model (numbered 139) is 15 times more important than the others. This may be because it provides the highest signal-to-noise estimate of the light intensity fall-off. The next few most important nodes provide supporting information to effectively distinguish objects’ effective radii. This sequential split becomes especially important to distinguish sequences in the smooth transition region where a few sequences from different classes show similar slopes. This sequential splitting as a qualitative measure of the slopes is physically meaningful: in fact, as commented already in Section 3.2, we expect LTG sequences to fall off slower than ETG, due to their lower Sérsic index. As mentioned in Section 2.3 the PSF can change the rate of fall off from one isophote to the next, leading to a global rescaling of first steps of each sequence. This effect can be particularly significant for galaxies with size smaller than the PSF, but we did not include those in our sample.

The scores of all trained solutions provided by the AutoML platform are summarized in Figure 4. Looking at these offers insights into which combinations of machine learning models and feature engineering methods are optimal for our task. The models shown are both decision trees-based and are either XGBoost (solid lines) or Random Forest models (dashed lines) and are color-coded by the feature engineering method. We observe that the PCA decomposition performs the best and is more important to the success of the overall model than the choice of XGBoost versus random forest. PCA rotates
the feature space in order to successfully emphasize the slopes of the profiles. On the lower end we find the Random and the t-test feature selection methods: since they only select a subset of nodes (either random selection or by applying the Student’s t-test), they seem to be less likely to pick up the most important information to distinguish the profiles and their slopes.

Finally, we use the aforementioned best model to make predictions on our test sample. We quantify the distance between the predictions and the true values by computing the confusion matrix (Figure 5), normalized over the number of predictions, for which we used the Python sklearn library. The main diagonal shows the amount of objects correctly classified, while the off-diagonal elements quantify incorrect classifications. The majority of mis-classified galaxies have low S/N ratios and tend to have small sizes and ellipticity, as shown in Figure 6.

5.2 Model failures and future perspective

Although there is by no means a simple cut we can perform to identify wrongly classified cases, inspecting examples of the isophotal fittings of both successful and unsuccessful classifications, we notice that objects with bad isophotal fitting tend to be mis-classified more often. This is compatible with the outcome shown in the confusion matrix, where it yields more incorrect classifications for ETG: a poor isophotal fit introduces perturbations into a 1D-sequence which would show a regular pattern typical of such galaxies. A few examples of galaxies with poor isophotal measurements are shown in Figure 7. Due to the small apparent size or low image resolution, the fitting does not model the light distribution well, resulting in an incorrect fit of the wings. As can be seen in the middle and right-hand panels, this manifests as a sudden change in the angular orientation of some isophotes with respect to the central regions of the galaxy. This issue can be corrected by applying sigma clipping to the recovered set of isophotes, identifying those that have parameters that are discrepant with the majority of fitted isophotes. However, the appropriate level of clipping varies from object to object and, at present, is not straightforward to determine in an automated way. As our aim is to describe a fully-automated method that can be run efficiently on large survey data, we thus quote our results without this fix. We will return to the issue of mis-aligned isophotes in future work, where we develop a routine to perform flexible isophotal fitting automatically, combining the structural information on the isophotes (e.g. position angle, ellipticity) with new feature engineering solutions, and apply our method to more contextual outputs, such as the presence of clumps or spiral arms.

6 CONCLUSIONS

In this work, we describe a novel approach to galaxy morphological classification. It consists of first analysing the main features of the two-dimensional light distribution in a galaxy image with isophotal fitting. This then allows to unravel it to a one-dimensional sequence. The advantage of such an approach is the low complexity of one-dimensional data, which makes both data storage and processing easier and faster compared to classification methods directly analysing images (e.g. parametric fitting). The selection, calibration, and train-
Automated galaxy classification with Modulos AI

Figure 4. Summary of the results provided by the Modulos AutoML platform. The solutions are Decision Tree models, either XGBoost (solid lines) or Random Forest (dashed lines), which are able to sequentially capture and combine information from the sequences in the data set. The lines are color-coded by the feature engineering method. PCA decomposition is associated to the solutions maximizing the F1 score (in the y-axis), given their ability in rotating the feature space so to emphasize the most important nodes in the sequences.

Figure 5. Confusion matrix representing the accuracy achieved in classifying galaxy profiles. The x-axis shows the true values, while the y-axis are the predicted categories. The main diagonal shows the correct classifications. The model seems quite robust in classifying the early-type galaxies of the sample.

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This research made use of Photutils, an Astropy package for detection and photometry of astronomical sources (Bradley et al. 2020). The authors thanks Modulos for the usage of their platform to perform image training and classification.

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It can be used to predict the galaxy type of other galaxies in the DES DR2 data set. We obtain an overall F1 score of 90% and 89% on training and test data, respectively, which proves that the dimensionality reduction of the data, even though it implies information loss, still contains enough information to successfully classify galaxies. Our accuracy is comparable to the results found by (Vega-Ferrero et al. 2020) for image-based classification using DES images. In the future, we will expand upon our promising results by developing a more robust isophotal measurement approach to focus on performance at low S/N, and target higher context features, such as bars, spiral arms and clumps.

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Figure 6. Properties of the classified sample in terms of signal-to-noise ratio (left panel), size (central panel) and ellipticity (right panel), distinguishing between objects with and without successful classification. This diagnostic plot alone cannot trace all the mis-classifications. A clearer test is shown in Figure 7.

Figure 7. Examples of isophotal fitting for mis-classified galaxies. If compared to Fig. 2, here we notice that the fitting fails at modelling galaxy wings and introduces rotations in the isophotal ellipses.

DATA AVAILABILITY

The best automated classification model presented in this paper and discussed in Section 5 is publicly available at https://github.com/Federica24/Cosmo and can be used to classify any DES data from the public release DR2 processed with isophotal fitting, as described in this work.

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