Communications of BAO, Vol. 67, Issue 2, 2020, pp. 354-358

Deep Convolutional Neural Networks models for the binary morphological classification of SDSS-galaxies

Vasylenko M.*[1,2], Dobrycheva D.†[1], Khramtsov V.‡[3], and Vavilova I.§[1]

[1]Main Astronomical Observatory the National Academy of Sciences of Ukraine, Kyiv, Ukraine
[2]Institute of Physics of the National Academy of Sciences of Ukraine, Kyiv, Ukraine
[3]Institute of Astronomy, V. N. Karazin Kharkiv National University, Kharkiv, Ukraine

Abstract

We present the deep learning approach for the determination of morphological types of galaxies. We demonstrate the method's performance with the redshift-limited ($z < 0.1$) training sample of 6 163 galaxies from the SDSS DR9. We exploited the deep convolutional neural network classifiers such as InceptionV3, DenseNet121, and MobileNetV2 to process images of SDSS-galaxies (100x100 pixels, 25 arcsec in each axis in size) using g, r, i filters as $R - G - B$ channels to create images. We provided the data augmentation (horizontal and vertical flips, random shifts on ± 10 pixels, and rotations) randomly applied to the set of images during learning, which helped increase the classifier's generalization ability. Also, two different loss functions, MAE and Lovasz-Softmax, were applied to each classifier. The target sample galaxies were classified into two morphological types (late and early) trained on the images of galaxies from the sample. It turned out that the deep convolutional neural networks InceptionV3 and DenseNet121 with MAE-loss function show the best result attaining 93.3% accuracy.

Keywords: *Galaxies, galaxy morphology, machine learning methods*

1. Introduction

The morphological classification of galaxies is one of the critical elements in studying the evolution of the Universe for astrophysics and observational cosmology. The most accurate method of classifying galaxies used so far by astronomers is visual classification. In 1654, Giovanni Battista Hodierna published the work "On the taxonomy of the world of comets and magnificent objects in the sky", in which one of the parts was devoted to the classification of nebulae into three classes: "Luminosae", "Nebulosae" and "Occultae" (Fodera-Serio et al. (1985)). A century later, Charles Messier compiled a larger list of nebulae, star clusters, and galaxies without classifying them. After confirming that some nebulae are "outer" galaxies, Edwin Hubble proposed his famous morphological classification of galaxies into three classes: elliptical, spiral, and irregular (Hubble (1926)). This classification is still used with many refinements made by Gerard Henri de Vaucouleurs and other scientists. However, a main drawback of visual classification (human labeling) is an involvement of many labor from highly qualified specialists or, in some cases, amateur astronomers (for example, the Galaxy Zoo project[1]). Current or future galaxy surveys such as SDSS (Blanton et al., 2017, Eisenstein et al., 2011), LSST (Ivezić et al., 2017), DES (Dark Energy Survey Collaboration et al., 2016), KiDS (de Jong et al., 2017), etc. can detect hundreds of millions of galaxies that cannot be manually classified. This increases interest in the alternative approach in artificial intelligence, such as various recently developed machine learning methods for automated morphological classification of galaxies in optical, radio, and other

*vasmax@mao.kiev.ua, Corresponding author
†daria@mao.kiev.ua
‡vld.khramtsov@gmail.com
§irivav@mao.kiev.ua
[1]http://data.galaxyzoo.org

DOI: 10.52526/25792776-2020.67.2-354

spectral ranges. There is probably not a day without an article about machine learning techniques for different astrophysical tasks.

In previous our research with traditional machine learning methods, we have discovered relationships between the photometric parameters of galaxies and their morphological types, which give the opportunity to classify galaxies without preliminary visual inspection (Dobrycheva & Melnyk, 2012, Dobrycheva et al., 2015, Melnyk et al., 2012). As a result, we conducted ternary and binary morphological classification of the low-redshift SDSS galaxies. We demonstrated (Dobrycheva et al., 2017, 2018, Vasylenko et al., 2019, Vavilova et al., 2020) that the Random Forest (RF) and Support Vector Machine (SVM) with Scikit-learn machine learning in Python provide the highest accuracy for the binary galaxy morphological classification: 96.4% correctly classified (96.1% early E and 96.9% late L types) and 95.5% correctly classified (96.7% early E and 92.8% late L types), respectively. We had a good experience with such methods as the decision-tree-based classifiers likely CatBoost for searching new gravitationally lensed quasars (Khramtsov et al., 2019b), generative adversarial networks (GAN) for restoring the Zone of Avoidance (Vavilova et al., 2018), machine-learning regression techniques (linear, polynomial, k-nearest neighbors, gradient boosting, and artificial neural network regression) for inference of moduli distances to galaxies (Elyiv et al., 2020), Xception Convolutional Neural Network (CNN) model to classify morphological galaxy inner features (**?**).

It allowed us to reveal problem points of methods, to build the prediction model, and to surely apply the supervised learning technique as deep convolutional neural networks for the automated morphological galaxy classification, which will be described in this article.

2. Sample

Target sample. We emphasize that, unlike most other authors, we paid attention to the visual cleaning of the dataset (see details (Dobrycheva, 2013)). Our target dataset contains of N = 316 031[2] SDSS-galaxies from DR9 (Ahn et al., 2012) with unknown morphological types at redshift $z < 0.1$ with the absolute stellar magnitudes $-24^m < M_r < -13^m$ limits $m_r < 17.7$ by visual stellar magnitude in r-band to avoid typical statistical errors in spectroscopic flux.

Training sample. Any supervised machine learning method (SMLM) needs a representative training sample because SMLM is searching for a relationship between input and output data. The accuracy of SMLM strictly depends on the training sample's quality. Our first step before applying the machine learning methods was to compose a training sample (Fig.1)

With this aim, we made visual binary morphological classification of 6 163 galaxies ($\sim 2\,\%$ of the target sample), which were randomly selected at different redshifts and with different luminosity: early type galaxies E – from ellipticals to lenticulars ($N = 4\,147$); late type galaxies L – from $S0a - Sdm$ to irregular Im/BCG galaxies ($N = 2\,016$) in slightly modified de Vaucouleurs classification.

Parameters for Deep Learning (DL) methods. We processed the SDSS-galaxy's images that are 100x100 pixels, or 25 arcsec in each axis in size. We used g, r, i filters with SDSS as $R - G - B$ channels to create images.

3. Methods and Results

We analyzed the classification quality of different Deep Convolutional Neural Networks models for the binary morphological classification of galaxies (spiral and elliptical) to reveal their problems. The non-triviality and relevance of this task is that for the training of models, we use a relatively small sample of images (6 163 images of SDSS-galaxies), which imposes restrictions on the assessment of the quality of models and their further operation. This challenge provoked us to use several well-known techniques: image augmentation (horizontal and vertical flips, random shifts on ±10 pixels, and rotations within 180 degrees), splitting training data into training and test samples. As the neural network models, we used InceptionV3, DenseNet121, and MobileNetV2. To train the models, we divided the input sample of 6 163 objects into two parts: $\sim 90\,\%$ (5 545 images) as a training and

[2] http://leda.univ-lyon1.fr/fG.cgi?n=hlstatistics&a=htab&z=d&sql= iref=52204

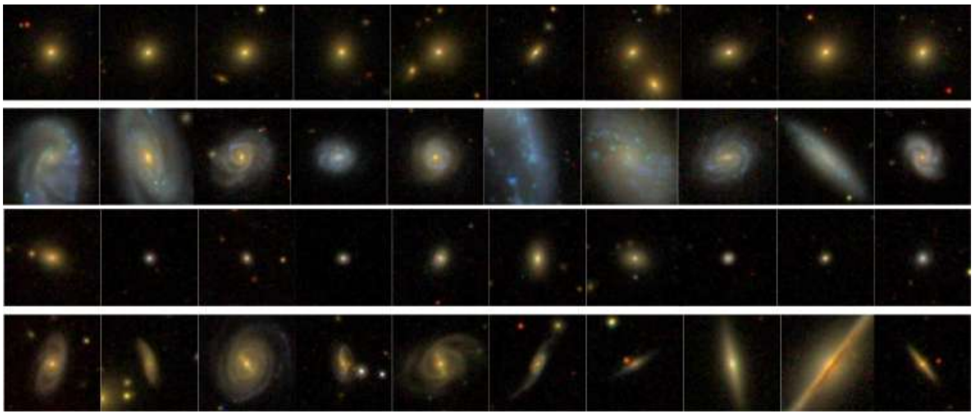

Figure 1. (Top figure) Representative galaxy sample with rival probabilities; top row: Ellipticals with DL, Spirals with SVM; bottom row: Ellipticals with SVM, Spirals with DL. (Bottom figure) Representative galaxy sample with reliable DL classification; top row: Ellipticals; bottom row: Spirals (Khramtsov et al., 2019a)

$\sim 10\,\%$ (618 images) as a validation. However, to better control the models' generalizing capabilities, we conducted a 5-fold cross-validation, in which a sample of 5 545 images were divided into 5 parts. We drove five exercises of each of the models on 4/5 of all 5 545 images (4 436 images) and tested on 1/5 of all 5 545 images (1 109 images), where different test samples were used during each training. As a result, we obtained five implementations trained on different subsets of 5 545 images for each of the models. The resulting classification algorithm for each model is the averaged one of the predicted classes by all five implementations.

We showed that the highest accuracy in the validation sample was attained with InceptionV3 ($> 92.0\,\%$) and DenseNet model ($> 93.0\,\%$), where the accuracy depends on the loss function. Table 1 shows that Mean Absolute Error (MAE) is the best for the InceptionV3 and DenseNet models as a loss function. One can see that, in this case, the accuracy of the test and training samples is practically coincided, and we can say that our models are not overfitted. We also tried to develop an unsupervised learning neural network representing each image as only a few dozen numbers. We hoped that galaxies of different types would be in different areas of the created space, but this method was not implemented with such high classification accuracy as the conventional Deep Convolutional Neural Networks.

DenseNet121. This neural network's feature is that each layer is connected to each subsequent layer, which allows to learn deeper and more accurate models. Before transmission, the features are not summed but combined into one tensor (channel-wise concatenation). Also, the number of parameters of this network is much smaller than that of networks with the same accuracy, which increases the classifier's accuracy on small data sets relative to other networks (Huang et al. (2017)).

InceptionV3. The fundamental difference from other networks lies in several features. Neighboring pixels are often correlated so you can reduce the dimension before the convolution without losing information, so the 5x5 convolution is replaced by two consecutive non-linearly connected 3x3, which in turn are collapsed into a vector 1xn. Besides, a hybrid scheme is used, namely, the pool operation is applied to half of the parameters and the convolution to the other. This operation will compress the previous layer without reducing the number of features, some convolutions will be processed with half the resolution but with fewer features. The network will learn to share, which requires maintaining the resolution, and for which the pool is enough. Also, this network feature is that the last layers become wider after reducing the dimension, which allows the network to increase the effectiveness of training in the place where training is the most effective (Szegedy et al. (2015)).

MobileNetV2. The peculiarity of this network is that it does not use max pooling-layers. Instead, it uses a convolution with a coke equal to two. Hyperparameters for MobileNet are the width factor and the depth factor. The width factor is responsible for the number of channels in each layer, and the depth factor is responsible for the size of the tensors fed to the input. Varying these parameters, we choose the optimal network size and image processing depth to optimize the ratio of execution

Table 1. Accuracy of the classification depending on the type of neural network and loss function

Model	**Loss function**	**Accuracy on the validation sample (618 images)**	**Accuracy of 5-fold cross-validation on the training sample (6 163 images)**	**Accuracy on the training sample (6 163 images)**
InceptionV3	MAE	93.3 %	94.2 %	94.3 %
InceptionV3	$Lovasz-Softmax$	92.2 %	93.9 %	94.2 %
MobileNetV2	MAE	89.7 %	89.9 %	89.2 %
MobileNetV2	$Lovasz-Softmax$	89.9 %	90.4 %	90.8 %
DenseNet121	MAE	93.3 %	94.2 %	94.3 %
DenseNet121	$Lovasz-Softmax$	93.0 %	94.1 %	94.0 %

time, resources spent, and the classifier's obtained accuracy (Howard et al. (2017)).

Loss function determines the model's ability to predict and quantifies the difference between the calculated and true values for a data sample. This function is used to maximize the quality of the classifier by minimizing the value of this function. We have anticipated that our model may contain emissions (damaged images). By this reason we chosen the mean absolute error (MAE) as one of the variants of the loss function. We remind that MAE is the sum of the absolute differences between our target and predicted values. It copes well with the averaging of results and is less sensitive to emissions. Its disadvantage is that this function's gradient remains constant even for its small values and it does not differentiate at zero. Additionally, we used the Lovasz-Softmax loss function, which showed good results for classifying segmented images (Berman et al. (2018)).

4. Conclusion

In this way, we determined the data classification algorithm, the model training strategy, and the models themselves that should be used to attain the highest accuracy. Also, for other models (DenseNet, Inception), we used several other image pre-processing methods (image shift by several pixels, logarithm of pixel intensity, etc.), which improve the resulting accuracy. With a given dataset, we also used the state-of-art deep neural networks such as CapsNet, InceptionResNetV2, VGG16, and VGG19, but they don't give a good result.

We conclude that Convolutional neural networks InceptionV3 and DenseNet121 with the MAE-loss function show the best result providing 93.3% accuracy for the binary morphological classification of the low-redshift SDSS-galaxies based on their images.

Acknowledgements

This work was conducted in the frame of the budgetary program "Support for the development of priority fields of scientific research" (CPCEL 6541230) and the Youth Scientific Project (2019-2020, Dobrycheva D.V., Vasylenko M.Yu.) of the National Academy of Sciences of Ukraine.

HyperLeda (Makarov et al., 2014) and SDSS-IV (Blanton et al., 2017) were helpful to our research. This study has also used the NASA/IPAC Extragalactic Database (NED), which is operated by the Jet Propulsion Laboratory, California Institute of Technology, under contract with the National Aeronautics and Space Administration.

References

Ahn C. P., Alexandroff R., Allende Prieto C., et al. 2012, ApJS, 203, 21

Berman M., Triki A. R., Blaschko M. B., 2018, arXiv e-prints, p. 1705.08790v2

Blanton M. R., Bershady M. A., Abolfathi B., et al. 2017, AJ, 154, 28

Dark Energy Survey Collaboration Abbott T., Abdalla F. B., Aleksić J., et al. 2016, MNRAS, 460, 1270

Dobrycheva D. V., 2013, Odessa Astron. Publ., 26, 187

Dobrycheva D., Melnyk O., 2012, Advances in Astronomy and Space Physics, 2, 42

Dobrycheva D. V., Melnyk O. V., Vavilova I. B., et al. 2015, Astrophysics, 58, 168

Dobrycheva D. V., Vavilova I. B., Melnyk O. V., et al. 2017, arXiv:1712.08955,

Dobrycheva D. V., Vavilova I. B., Melnyk O. V., et al. 2018, Kin.Phys.Cel.Bod., 34, 290

Eisenstein D. J., Weinberg D. H., Agol E., Aihara H., et al. 2011, AJ, 142, 72

Elyiv A. A., Melnyk O. V., Vavilova I. B., et al. 2020, A&A, 635, A124

Fodera-Serio G., Indorato L., Nastasi P., 1985, Journal for the History of Astronomy, 16, 1

Howard A. G., Zhu M., Chen B., Kalenichenko D., et al. 2017, arXiv e-prints, p. 1704.04861v1

Huang G., Liu Z., et al. 2017, arXiv e-prints, p. 1608.06993v5

Hubble E. P., 1926, ApJ, 64, 321

Ivezić Ž., Connolly A. J., Jurić M., 2017, in Brescia M., Djorgovski S. G., Feigelson E. D., Longo G., Cavuoti S., eds, Vol. 325, Astroinformatics. pp 93–102 (arXiv:1612.04772), doi:10.1017/S1743921316013156

Khramtsov V., Dobrycheva D. V., Vasylenko M. Y., et al. 2019a, Odessa Astron. Publ., 32, 21

Khramtsov V., Sergeyev A., Spiniello C., et al. 2019b, A&A, 632, A56

Makarov D., Prugniel P., Terekhova N., Courtois H., Vauglin I., 2014, A&A, 570, A13

Melnyk O. V., Dobrycheva D. V., Vavilova I. B., 2012, Astrophysics, 55, 293

Szegedy C., Vanhoucke V., Ioffe S., Shlens J., Wojna Z., et al. 2015, arXiv e-prints, p. 1512.00567v3

Vasylenko M. Y., Dobrycheva D. V., Vavilova I. B., et al. 2019, Odessa Astron. Publ., 32, 46

Vavilova I. B., Elyiv A. A., Vasylenko M. Y., 2018, Rus.Rad.Phys.Rad.Astr., 23, 244

Vavilova I., Dobrycheva D., Vasylenko M., et al. 2020, Multiwavelength Extragalactic Surveys: Examples of Data Mining. Elsevier, doi:10.1016/B978-0-12-819154-5.00028-X

de Jong J. T. A., Verdoes Kleijn G. A., Erben T., et al. 2017, A&A, 604, A134