Estimating the redshift of galaxies from their photometric colors using machine learning methods

Estimación del corrimiento al rojo para galaxias a partir de sus colores fotométricos usando métodos de aprendizaje automático

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Keywords

Universe; expansion; redshift; galaxies; svm; decision trees; ada boost; random forest.

Abstract

The determination of the redshift, a factor also known as *z*, is obtained from variations in the wavelength's spectrum of galaxies or distant objects, such variation is basically the difference between the wavelength measure on Earth of the element present in the galaxy and the direct measure of the same element on the object by the use of spectroscopy. From the value *z*, it's possible to obtain the values of the object's distance and the speed at which it moves away from us. Obtaining spectroscopic data directly from astronomical objects, is not always an easy task to run and the use of color index become a more accessible alternative for many researchers. In this work we present the preliminary results of several machine learning methods, using regression based algorithms. The goal will be to obtain the value of *z*, from the photometric colors.

Palabras clave

Universo; expansión; desplazamiento al rojo; galaxias svm; árboles de decisión; bosque al azar.

Resumen

La determinación del corrimiento al rojo, factor conocido como *z*, se obtiene a partir de las variaciones en la longitud de onda del espectro de la galaxia u objeto lejano, dicha variación se da entre la medición en la Tierra del elemento presente en la galaxia y la medición directamente en el objeto mediante espectroscopia. A partir del valor *z*, es posible obtener los valores de la distancia del objeto y la velocidad a la que se aleja de nosotros. La obtención de datos espectroscópicos en el objeto, no siempre resultan fáciles de obtener y los índices de color se convierten en una alternativa más accesible para muchos investigadores, en este trabajo se muestran los resultados preliminares de diversos métodos de aprendizaje automático, donde como un problema de regresión y a partir de los índices fotométricos podemos estimar el valor de *z*.

Introduction

Since the beginning of our universe 14 billions of years ago, the space around it has been expanding, for this reason, the galaxies and other objects seem to be moving away from us at specific rates. Due to the uniformity of such expansion, a direct relationship is present between the speed of expansion of those galaxies and the distance from us. The resulting movement of the expansion, as shown if figure 1, causes a shift in the frequency of photons that can be visualized in the spectrum of the distant galaxies, since the universe is expanding away from us, the shift is towards lower frequencies i.e red side of the spectrum, the effect is called redshift.

Spectral analysis consists in the measurement of the emission of photons at certain wavelengths that can be represented as spectral lines in specific positions in the resulting spectrum, from those lines one can determine the elements present in the object [2]. When astronomers measure spectral lines in distant objects such as galaxies, lines appear to be shifted toward the red side of the spectrum due to the difference between the wavelength measured on earth and the one observed, the redshift is then defined by a value called *z*:

$$z = \frac{\lambda_{obs} - \lambda_{emit}}{\lambda_{emit}}$$

From the redshift value z, it's possible to obtain the velocity v at which the galaxy is moving away from us using the relation $v = c \times z$, where c is the speed of light. Finally, with the value of v it's also possible to estimate the distance of the galaxy using the Hubble Constant (H_o=72 Km/s/Mpc) and the following relation $d=v/H_o$

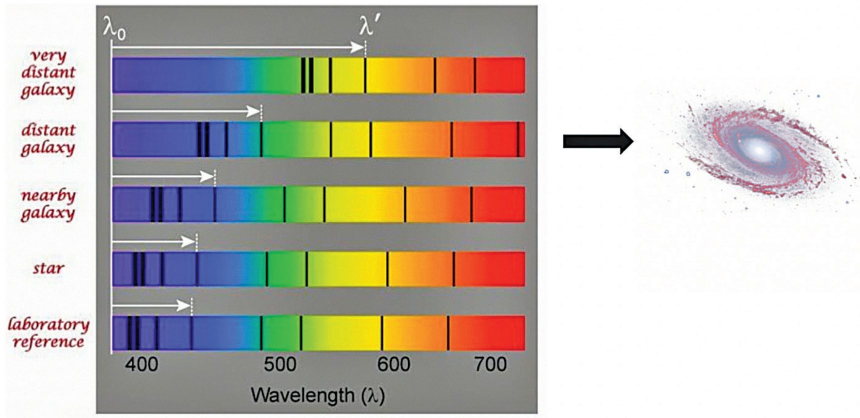


Figure 1. Comparison of different redshifts (Source: https://www.universetoday.com/)

The conventional way to do this analysis is by the observation of the samples one by one of the resulting lines in the spectrums and calculate the observed shift, however with large amounts of data this process can be very time consuming and subjected to errors. On the other hand, not all the galaxies have all the spectral values related to the shift, for those reasons the use of machine learning results in a powerful and convenient option to estimate the values of z, from photometric colors.

Machine Learning (ML) Algorithms

We've chosen four basic supervised methods to estimate the value of z from the photometrics filters [3], which results in a very convenient way to estimate z since the observational data i.e color index is generally more available and easier to be obtained than the spectral data for such galaxies. The methods selected are briefly described [1], [5]:

- *Support Vector Machines (SVM):* In this case is called Support Vector Regression (SVR), essentially a support vector (SV) is generated to follow the data trend and create the regression model.
- *Decision Trees (DT):* This method maps a set of inputs features to their corresponding output targets, thanks to a series of individual decisions where each decision is represented by a node of the tree. Each decision node involves specific values, such values are determined from the training data in the learning algorithm based on the principle of "the most effective way to fit the data".
- *Random Forest (RF):* The goal is to have several random DT, each tree is created from random sets of samples from the data and each node is also created by selecting randomly the features to generate the best data fit.
- *AdaBoost (AB):* Adaptive Boosting is based on the idea of having several weak classifiers or regressors to form together a much stronger and effective classifier or as in this case, a regressor.

Methodology and data

We use the spectrums from Sloan Digital Sky Survey catalogue (SDSS) [4], it's of particular interest the magnitude of the flux received in five bands (u, g, r, i and z). In astrophysics the color index is the result of the difference between the magnitude of two filters i.e u-g, g-r, r-i and i-z, those values will be our features. The u filter is near the blue side of the spectrum and the *z* filter near the red side of the spectrum, if the spectrum is shifted to the red side then the value of *z* will be larger, meaning that the galaxy is moving away from us. In figure 2 the blue spectrum corresponds to the measurement at *z=0* in other words our reference, however as the galaxy is moving away the z value will be increased towards the red side, resulting in a speed *v* and a distance *d* of the galaxy from our perspective. Our database was made up of samples with values of flux in the u, g, r, i and z bands and is composed of 50000 galaxies; table 1 shows the first and last three values of our dataset.

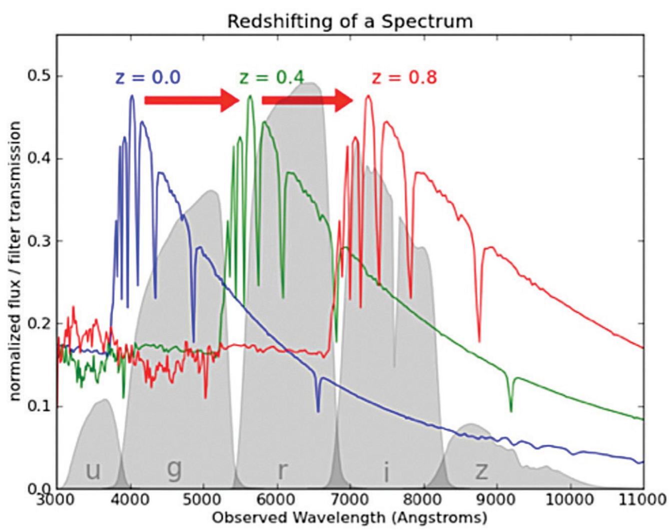


Figure 2. Redshifting of a spectrum (Source: https://scikit-learn.org/)

With the goal of making use of conventional ML algorithms to solve this regression problem, we based our analysis in the measurement of the mean error as our metric:

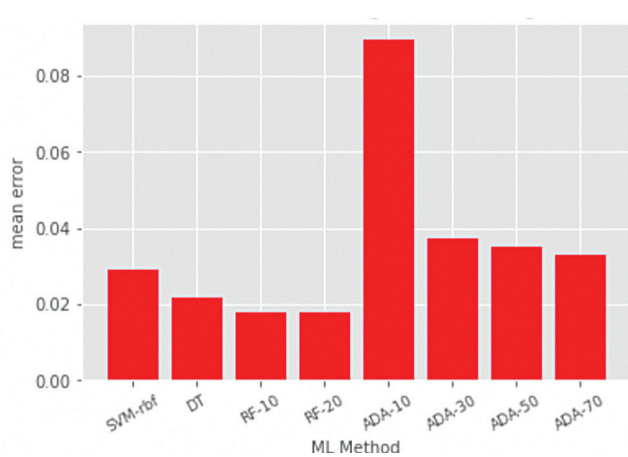
$$med_{diff} = median(|Y_{i,predicted} - Y_{i,target}|)$$

Table 1. Samples from the database (Source: original dataset from SDSS)

ID	u	g	r	i	z	redshift
0	19.84132	19.52656	19.46946	19.17955	19.10763	0.539301
1	19.86318	18.66298	17.84272	17.38978	17.14313	0.164570
2	19.97362	18.31421	17.47922	17.07440	16.76174	0.041900
49997	19.82667	18.10038	17.16133	16.57960	16.19755	0.078459
49998	19.98672	19.75385	19.57130	19.27739	19.25895	1.567295
49999	18.00024	17.80957	17.77302	17.72663	17.72640	0.474945

Results

In the experiments, we used scikit-learn framework to run a comparison between the four proposed methods. In the case of SVM, the kernel used was rbf (SVM-rbf), with decision trees (DT) we used the depth as our hyperparameter, even with the use of several depth values the results remain almost the same. With Random Forrest we used two references values for the n_ estimators hyperparameter, 20 and 100 (RF-20 and RF-100), beyond the value of 200 the results seems to have no major variations, finally with Ada Boost we did the same setting as with RF to create two models (ADA-20 and ADA-100). Considering that the value of *z* is mostly in a range between 0 and 1 in our database, the mean error obtained for the all the methods varied from 0.001 to 0.003, in the order of 10^{-3} a variation between 10 and 30, that represent a good result considering this as our first approach, however RF algorithm was the one that delivered the best result of 0.001, for this reason is considered the best result. In the case of ada boost method, one particular experiment using the hyperparameter n_estimators with a value of 10, resulted in the poorest mean error in the margin of 0.008, not bad at all but the lowest obtained from the experiments. As expected SVM reached the highest computational cost, due to the nature of the algorithm. The results obtained in regards to the mean error are shown in figure 3. In terms of the time consumed per algorithm, all the measurements were taken using the same computer: Apple MacBook Pro 2015 with processor 2.5 GHz Intel Core i7 and 16 GB 1600 MHz DDR3 memory, as expected SVM-rbf was the highest in terms of computational cost and RF was not just the best in terms of the mean error but also one of the most effective (RF-20) in terms of computational cost.



ML Method	Mean Error
SVM-rbf	0.0291
DT	0.0217
RF-10	0.0178
RF-20	0.0177
ADA-10	0.0895
ADA-30	0.0373
ADA-50	0.0350
ADA-70	0.0330

Figure 3. Mean error of the redshift in the galaxies, using the ML proposed methods.

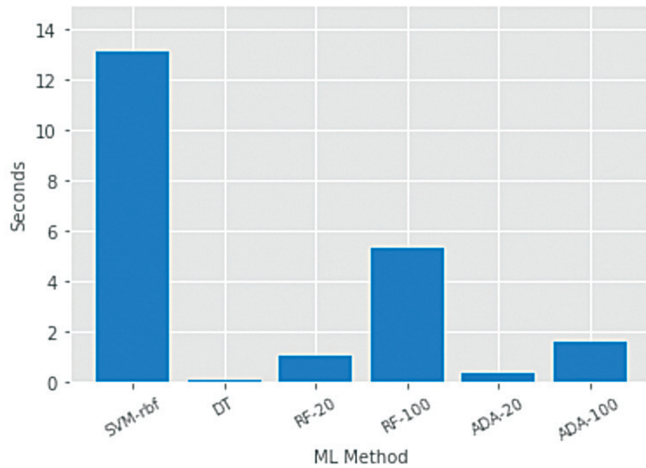


Figure 4. Time consumed per each ML method.

Conclusions and future work

The regression methods selected for the series of experiments resulted in a good approach to estimate the redshift value *z*, the use of mean error represented also a good metric due to the nature of the regression model. Even with the good results obtained with the proposed methods, actual analysis is concentrated in the minimization of the mean error through the use of artificial neural networks, another potential improvement to the model consist in the inclusion of more data to the current dataset as it become available. Other tasks are concentrated in the analysis of variations in the splitting of the dataset in order to validate and measure any overfitting effects on the results.

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