COLOR–MAGNITUDE DISTRIBUTION OF FACE-ON NEARBY GALAXIES IN SLOAN DIGITAL SKY SURVEY DR7

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Abstract

We have analyzed the distributions in the color–magnitude diagram (CMD) of a large sample of face-on galaxies to minimize the effect of dust extinctions on galaxy color. About 300,000 galaxies with log(a/b) < 0.2 and redshift z < 0.2 are selected from the Sloan Digital Sky Survey DR7 catalog. Two methods are employed to investigate the distributions of galaxies in the CMD, including one-dimensional (1D) Gaussian fitting to the distributions in individual magnitude bins and two-dimensional (2D) Gaussian mixture model (GMM) fitting to galaxies as a whole. We find that in the 1D fitting, two Gaussians are not enough to fit galaxies with the excess present between the blue cloud and the red sequence. The fitting to this excess defines the center of the green valley in the local universe to be (u − r)0.1 = −0.12M0.1 − 0.061. The fraction of blue cloud and red sequence galaxies turns over around M0.1 ∼ −20.1 mag, corresponding to stellar mass of 3 × 10^{10} M\odot. For the 2D GMM fitting, a total of four Gaussians are required, one for the blue cloud, one for the red sequence, and the additional two for the green valley. The fact that two Gaussians are needed to describe the distributions of galaxies in the green valley is consistent with some models that argue for two different evolutionary paths from the blue cloud to the red sequence.

Key words: galaxies: evolution – galaxies: fundamental parameters – galaxies: spiral – galaxies: statistics – methods: data analysis

Online-only material: color figures

1. INTRODUCTION

The distribution of galaxies in the color–magnitude diagram (CMD) provides a powerful tool to investigate the evolution of galaxy populations. A remarkable feature of the CMD is a robust bimodality, which divides the galaxy population into a “blue cloud” (or blue sequence) and a “red sequence.” The bimodality is seen in the optical colors (Strateva et al. 2001; Blanton et al. 2003c), UV–optical colors (Wyder et al. 2007), the 4000 Å break (D$_\text{4000}$; Kauffmann et al. 2003), and spectral type (Madgwick et al. 2002). Galaxies in “red sequence” are quiescent, bulge-dominated galaxies (Blanton & Moustakas 2009), while the “blue cloud” is characterized by star-forming (SF), disk-dominated galaxies. Between these two sequences, there is a region called the “green valley.”

Baldry et al. (2004) explored the distribution of galaxies in the (u − r) versus $M_r$ diagram for low-redshift Sloan Digital Sky Survey (SDSS) samples. Their galaxies separate into “blue cloud” and “red sequence,” and the distribution of (u − r) color at each absolute magnitude bin is well fitted by the sum of two Gaussians. However, Wyder et al. (2007) showed that the (NUV − r) color distribution at each $M_r$ cannot be well fitted by the sum of two Gaussians due to an excess of galaxies between the blue and red sequences. They utilized Balmer decrements and the dust–star formation history (SFH)–color relation (Johnson et al. 2006) to correct the extinction of each galaxy, there still remain galaxies in the green valley region between two sequences. Thus, galaxies in the green valley region may not be a simple mixture of blue and red galaxies.

The understanding of the CMD color bimodality is also complicated by galaxy dust extinction. Salim et al. (2009) found that many green valley galaxies are simply dust-obscured actively SF galaxies. However, there still exist 24 μm detected galaxies, some with LIRG-like luminosities, which have little current SF. They belong to the green valley or even the red sequence due to their SFH, not just dust reddening.

The CMD bimodality is already in place at z ~ 1 (Cooper et al. 2006), with color becoming bluer at higher redshift (Blanton et al. 2006; Willmer et al. 2006). Based on the DEEP2 and COMBO-17 surveys, Faber et al. (2007) argued that the number density of blue galaxies is more or less constant from z ~ 1 to 0, while the number density of red galaxies has increased. This work supports that the red sequence has grown in mass by a factor of three since z ~ 1. A plausible scenario is that the growth of red galaxies was triggered by quenching star formation in blue galaxies, which caused them to migrate into the red sequence (Bell et al. 2004). In addition, galaxies may also be moving from the lower end of the red sequence to the blue cloud through accreting gas-rich dwarf galaxies (Faber et al. 2007).

Studies of galaxy morphologies show that red sequence is dominated by spheroidal galaxies with Sérsic index $n = 4$, while the blue cloud is occupied by disk-dominated galaxies with Sérsic index $n = 1$ (Driver et al. 2006). Mendez et al. (2011) investigated the morphologies of green valley galaxies from the AEGIS survey and found that most green valley galaxies are not classified as mergers and that the merger fraction in the green valley is lower than that in the blue cloud. Lackner & Gunn (2012) presented a set of bulge–disk decompositions for a sample of 71,825 SDSS main-sample galaxies and found that the majority of green valley galaxies are bulge+disk galaxies, and that the integrated galaxy color is driven by the color of galaxy disks.

In general, blue galaxies with star formation being quenched will evolve from the blue cloud to the red sequence, passing through the green valley that thus represents an intermediate phase of this quench process. Different mechanisms have been proposed to cease star formation in blue galaxies, such as...
mergers (Bell et al. 2004; Hopkins et al. 2010), active galactic nucleus (AGN) feedback (Croton et al. 2006; Martin et al. 2007; Schawinski et al. 2010), morphological quenching (Martig et al. 2006, 2009), cold flows accretion, and shock heating (Dekel & Birnboim 2006; Cattaneo et al. 2006; see Peng et al. 2010 for a recent review).

Peng et al. (2010, 2012) investigated the quenched fraction of galaxies as a function of local density, stellar mass, and redshift. They parameterized galaxy quenching as fully separable “environment quenching” and “mass quenching,” which are directly associated with the quenching processes of satellite and central galaxies in groups. This model is successful at predicting the mass function of passive and SF galaxies. These effects may also be reflected in the color–magnitude distribution of galaxies, we will try to find some evidence of these effects in our analysis.

In this paper, we focus on fitting CMD using different methods. Our study aims at a better understanding of the “green valley” and may answer the question whether the “green valley” is dominated by one component. Since different quenching mechanisms will produce different distributions of galaxies in color–magnitude space, the fine structure of CMDs may also provide valuable clues about galaxy quenching mechanisms. Previous works always focus on the whole galaxy population without identification, which may conceal the fine structure of CMDs due to dust extinction, therefore, we selected a nearly face-on galaxy sample to minimize the effect of dust.

This paper is organized as follows. Section 2 describes the sample selection in this work. In Section 3, we investigate the color–magnitude distribution and show one-dimensional (1D) and two-dimensional (2D) Gaussian fitting results. Section 4 discuss the implications of the results. Section 5 is the conclusion. Throughout this paper, we assume a flat $\Lambda$CDM cosmology with a matter density $\Omega_m = 0.3$, cosmological constant $\Lambda = 0.7$, and Hubble’s constant $H_0 = 100$ km s$^{-1}$ Mpc$^{-1}$ (i.e., $h = 1$).

2. THE SAMPLE

The photometric and spectroscopic data used in this paper are taken from the main galaxy sample in SDSS DR7 (York et al. 2000; Strauss et al. 2002; Abazajian et al. 2009). The sample selection criteria are as follows.

1. $r$-band apparent magnitude $m_r < 17.77$ mag with $ugriz$ flux signal-to-noise ratio ($S/N > 5$. The criterion of $S/N$ can reduce outliers. By comparing the color distribution of bright galaxies and the overall population, this criterion does not generate significant selection effects.

2. $log(a/b) < 0.2$, $a/b$ is the ratio of the major axis to minor axis of de Vaucouleurs’ profile. Gas and dust tend to reside in the disk of spirals and the colors of spirals are seriously reddened by dust attenuation. For example, the total extinction from face-on to edge-on is about $0.7, 0.6, 0.5$, and $0.4$ mag for the $ugriz$ passbands (Masters et al. 2010), therefore, we choose the nearly face-on galaxies to minimize the dust reddening effect.

In total, our sample consists of 329,384 galaxies. To ensure a broader span of luminosity and the completeness of color in each magnitude bin, we divide galaxies into 12 bins from $M_{r,0.1} = −18.50$ to $−21.5$ mag and $0.02 < z < 0.18$ with bin size of 0.25 mag, as shown in Figure 1 ($M_{r,0.1}$ is the absolute magnitude in $r$ band $k$ corrected to $z = 0.1$). The galaxy number and median redshift in each bin are shown in Table 1. We will analyze the color distribution of galaxies in each bin.

Using the New York University Value-Added Catalog (Blanton et al. 2005) and the MPA-JHU catalog, we obtain the physical parameters for our sample, such as $u, g, r, i, z$ absolute magnitudes $k$ corrected to $z = 0.1$ (Blanton et al. 2003a), stellar mass, and $D_n 4000$ (Kauffmann et al. 2003; Salim et al. 2007). We use MODELMAGs for galaxy magnitude and color in this paper, which are derived from the best-fitting exponential or de Vaucouleurs galaxy profile. MODELMAGs have occasional problems recovering accurate magnitudes for galaxies with mixed morphologies, and petro magnitude (Petrosian 1976) provides a better measure for flux (Taylor et al. 2011; Simard et al. 2011), but the uses of MODELMAGs do not change any of the results that we present in Section 3.

Although galaxies in each magnitude bin cover certain redshift ranges, the effect of redshift evolution in color should be negligible given the overall redshift range of the whole sample from 0.0 to 0.2.

3. RESULTS

3.1. Color Distribution Fitting

As shown in Figure 2, the distributions of galaxies in each magnitude bin show apparent two peaks except for the two brightest bins where the distribution profile is characterized by a red peak plus a blue tail. We fit a single Gaussian to blue and red peaks. Respectively, we select the left 0.15 mag of red peaks as the red boundaries and select the right 0.25 mag of blue
Figure 2. \((u - r)\) color distribution in 0.25 mag absolute magnitude bins. The magnitude range is labeled in the upper left of each figure from \(-21.50\) to \(-18.50\) mag. The black histogram is the \((u - r)\) distribution in each magnitude bin, the color histogram’s bin is 0.02 mag. The blue and red dashed lines mark the color boundaries when fitting Gaussian distribution to blue cloud and red sequence. The solid blue and red lines are the Gaussian fitting results for blue cloud and red sequence, and the solid purple line is the sum of two Gaussians. Finally, the solid green marks the residual distribution between actual color distribution and the sum of two Gaussians. (A color version of this figure is available in the online journal.)
peaks as the blue boundaries. For the two brightest bins, due to a very small blue fraction, we artificially adjust the boundaries until these two peaks are well fitted, the color boundaries are plotted as the dashed blue and red lines in each magnitude bin in Figure 2.

As shown in Figure 2, two Gaussians accurately fit the blue cloud and red sequence, but the color distribution apparently cannot be fitted well by the sum of the two Gaussians in each magnitude bin because of the obvious excess between the two sequences. We define the excess between two sequences as the “green valley galaxy” population.

The parameters of the best fits are shown in Figure 3. In the top panel, the contours illustrate the nearly face-on galaxies distribution in CMD, the blue boxes mark the median color of blue sequence, the red diamonds mark the red sequence, and the error bar of each point gives the 1σ width of the Gaussian fitting.

To quantify each sequence, the fraction of blue cloud (red sequence) is defined as the ratio of the blue cloud (red sequence) galaxies number to the total number in each magnitude bin.

\[ \text{fraction} = \frac{\text{blue cloud galaxies}}{\text{total galaxies}} \]

The discontinuity of the volume-limited samples in Section 2 makes them inappropriate for GMM fitting, therefore, we select a subsample from our main sample with criteria 0.04 < z < 0.08, galactic extinction in the u band less than 0.3 mag and in the r band less than 0.5 mag, which are used to reduce outliers. As shown in Figure 5, this subsample contains 67,499 galaxies and is complete to \( M_r < -19.2 \) mag.
The mixture model provides a method of describing more complex probability distributions, by combining several probability distributions. GMM is a parametric probability density function represented as a weighted sum of Gaussian component densities. GMM is among the most statistically mature methods used for clustering (Xu & Jordan 1996; Dasgupta 1999; Verbeek et al. 2003).

When fitting models, it is possible to increase the likelihood by adding more free parameters, however, which may result in overfitting. To minimize the number of redundant parameters, we make use of Akaike information criterion (AIC) and Bayesian information criterion (BIC) for model selection. As shown in Figure 6, the AIC and BIC have the same trend, but BIC converges faster than AIC, therefore, we prefer BIC as our criterion and treat the minimum value of BIC as the best models for fitting.

The outlier data in each diagram may affect the distribution of AIC and BIC and produce extra components that occupy very little fraction and spread distribution, it will generate one or two ellipses that have a tiny center and large radius, like a “background” in each diagram. This is the intrinsic problem of BIC, and we can minimize this effect by removing outliers.

The results of GMM fitting are shown in Figure 6. For $(u-r)$ versus $M_r$, the GMM exactly detects the blue cloud and red sequence. Between these two sequences, the green valley region contains two Gaussian components: one located in the faint end of the red sequence and extending to the faint end of the blue cloud, and the other in the bright end of blue cloud stretching toward the bright end of red sequence. For the $(u-g)$ CMD, the red sequence is decomposed into two components and the faint component in the green valley is bluer than the corresponding component in the $(u-r)$ CMD. Whether the number of components is $N = 4$ or $N = 5$, there are always two Gaussian components in the green valley region. In the fourth subgraph of Figure 6, the values of BIC are almost equal when $N = 4$ and $N = 5$, it suggests there is not much improvement for fitting when we chose five components, therefore, we prefer the four components result as our finding.

Figure 7 shows the GMM results for color–mass space. The distribution of Gaussians is the same as that in Figure 6. As shown in Figure 7, the mean stellar mass of the bright component in the green valley region is close to the characteristic mass, $M^*$ ($10^{10.5} M_\odot$).

Given that galaxies fainter than $M_{r,0.1} = -19.2$ mag are not complete in this subsample, we check the results by only fitting the complete ($M_{r,0.1} < -19.2$ mag) sample only, and find that the AIC and BIC converge at very large values. However, if we set the same number of Gaussian components as in Figure 6, the ellipses’ center almost do not change while the size of ellipses are somewhat different. The completeness thus does not change the GMM fitting results.

Essentially, the work in Section 3.1 is a 1D fitting and GMM fitting is a 2D fitting. The 1D color fitting shows that the color distribution of galaxies cannot be fitted by two Gaussians, which may suggest some potential components in the green valley region, and the GMM fitting successfully decomposes the color–magnitude distribution.

As small residuals shown in Figure 6, GMM fit the data very well. We also show the GMM results in terms of 1D color...
distribution in Figure 8, the solid colored lines mark the models generated from GMM fitting; the red and blue lines represent the red sequence and blue cloud, and the green and cyan lines mark the faint and bright components of green valley, respectively. The sum of models (black dashed line) also fit the data (plus signs) very well too. Distinct from fitting in Section 3.1, the component number in Figure 8 is selected by BIC and the model distribution (solid colored line) in each magnitude bin is not a Gaussian, but a skew Gaussian because it is a 1D projection of an incomplete 2D Gaussian. These are advantages of GMM fitting, which make its results reasonable.

4. DISCUSSION

In this study, we carried out Gaussian profile fittings to the CMD through two methods, i.e., the fitting to distributions in individual magnitude bins and to distributions in 2D as a whole. The two Gaussian components in the CMD green valley are homologous to the excess in color distribution fitting and explain why we cannot fit the color histogram well only two Gaussians. The green valley region is not dominated by a single Gaussian, but at least two Gaussian components. Galaxies in the green valley are composed of these two components plus the Gaussian tails of blue and red galaxies.

By fitting the \((u - r)\) color distribution in each magnitude bin, our results are different from those of Baldry et al. (2004), but agree with the (NUV – r) results of Wyder et al. (2007). As we select only nearly face-on galaxies that are not considered by Baldry et al. (2004), we attribute the difference to dust extinction, which seriously reddens the color of blue cloud galaxies and covers the excess in the green valley region.

Kauffmann et al. (2003) showed that galaxies tend to divide into two distinct groups below and above a stellar mass of \(3 \times 10^{10} M_\odot\). Galaxies below this mass limit tend to have younger stellar populations, while more massive galaxies tend to be older. We find that the fraction of blue cloud and red sequence are equal to each other around \(M_{f,0.1} \sim 20.1\) mag, corresponding to stellar mass about \(M^* \ (10^{10.5} M_\odot)\). As shown in Figure 3, our result is very consistent with their conclusion.

If we assume that the density of galaxies represents their evolution time scale in color–magnitude space, the GMM results would intuitively show us the evolutionary paths of different galaxies: the components in Figure 6 would represent galaxies in different evolving phases, and the inclination of ellipses’ major axes may suggest the galaxy evolving direction in color–magnitude space. The faint component in the green valley may be the early-quenching population, which quenched while galaxies are still small and grow mass along red sequence via “dry” mergers (Faber et al. 2007). In the faint end of the red sequence, these red low-luminosity galaxies tend to be in overdense regions (Blanton et al. 2006), environment possibly plays a very important role in their evolution.

If the two components in the green valley are dominated by two independent quenching processes, this scene would agree with Peng et al. (2010) very well. According to the model of Peng et al. (2010), galaxies in the faint component are dominated by “environment quenching” and galaxies in the bright one are dominated by “mass quenching,” which are both associated with the quenching processes of satellite and central galaxies in groups (Peng et al. 2012). Since these two effects are fully independent of each other, they may produce the two independent Gaussian components we found in the CMD.

As shown in Figure 7, the mean stellar mass of the bright component in the green valley region is about the characteristic mass, \(M^*\). \(M^*\) also corresponds to a dark halo mass, \(M_{\text{halo}} \sim 10^{12} M_\odot\), based on the model of Dekel & Birnboim (2006). In their model, galaxies with \(M_{\text{halo}} \gtrsim 10^{12} M_\odot\) will generate a steady shock in the gas accreting onto the dark matter halo, the shock heats the gas and absolutely quenches star formation when AGNs begin to work. This process is strongly related to the mass of the galaxy, which may dominate the evolution of the bright galaxy component in the green valley.

Wong et al. (2012) selected a local post-starburst galaxies (PSGs) sample from SDSS. Those PSGs occupy the low-mass end of the “green valley” below the transition mass within the color–stellar mass diagram (the same position as the faint component of the green valley in Figure 7). They proposed that those PSGs represent a population of galaxies that is rapidly transitioning between the SF and the passively evolving phases. Mendel et al. (2013) select a sample of young passive galaxies from SDSS, which is identified based on the contribution of A-type stars to spectra and the relative lack
of ongoing star formation. Most of these recently quenched galaxies have a stellar mass $>10^{9.5} \, M_\odot$ and are predominantly early-type systems. McIntosh et al. (2013) studied the recently quenched ellipticals (RQEs) with stellar mass $>10^{10} \, M_\odot$ and found a number of RQE properties that are consistent with these galaxies being new remnants from a gaseous major merger. Their studies show that the low- and high-mass galaxies in the green valley are very different, and suggest that the green valley
is dominated by different quenching processes, supporting our GMM fitting results.

In Figure 8, it is notable that the blue peak of color bimodality is dominated by the bright component of the green valley (the cyan line) for galaxies $M_r < -20.25$ mag, which implies that the blue galaxy population with $M_r > 10^{10.5} M_\odot$ is distinct from galaxies that were traditionally thought to be blue clouds. This case is consistent with Schawinski et al. (2014), which proposed that the early- and late-type galaxies in the green valley have two different evolutionary pathways. The evolving early-type galaxies generally have stellar mass, $M_\star > 10^{10.5} M_\odot$, rapidly quenching star formation, moving out of the blue cloud into the green valley, and to the red sequence as fast as stellar evolution allows (Schawinski et al. 2014).

It is still unclear about the quenching mechanisms of galaxies, differentiating such mechanisms requires more evidences which are beyond the scope of this work.

5. SUMMARY

In this paper, we have analyzed the color–magnitude distribution of a sample of nearly face-on galaxies, selected from the SDSS DR7 main galaxy sample. We fit $(u - g)$ and $(u - r)$ color distribution in each magnitude bin and apply GMM to fit the CMDs. The results are as follows.

1. The color distributions of galaxies cannot be fitted by two Gaussians and there is an obvious excess in the green valley region.

2. With rising luminosity, red galaxies increase while blue galaxies decrease, the fraction of the blue cloud and the red sequence cross at $M_{r,0.1} \sim -20.1$ mag. At this magnitude, the mean stellar mass of galaxies is about the characteristic mass, $M^*$.

3. By fitting the excess between the blue cloud and the red sequence, we find that the center of the green valley for face-on galaxies in the local universe is $(u - r)_{0.1} = -0.121M_{r,0.1} - 0.061$.

4. The GMMs of CMDs accurately illustrate the red sequence and the blue cloud, and yields two Gaussian components for the green valley region, which might suggest two different evolutionary paths from the blue cloud to the red sequence.

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REFERENCES

Abazajian, K. N., Adelman-McCarthy, J. K., Agüeros, M. A., et al. 2009, ApJS, 182, 543
Balder, I. K., Glazebrook, K., Brinkmann, J., et al. 2004, ApJ, 600, 681
Bell, E. F., Wolf, C., Meisenheimer, K., et al. 2004, ApJ, 608, 752
Blanton, M. R., Brinkmann, J., Csabai, I., et al. 2003a, AJ, 125, 2348
Blanton, M. R., Eisenstein, D., Doug, D. W., & Zehavi, I. 2006, ApJ, 645, 977
Blanton, M. R., Hogg, D. W., Bahcall, N. A., et al. 2003b, ApJ, 592, 819
Blanton, M. R., Hogg, D. W., Bahcall, N. A., et al. 2003c, ApJ, 594, 186
Blanton, M. R., & Moustakas, J. 2009, ARA&A, 47, 159
Blanton, M. R., Schlegel, D. J., Strauss, M. A., et al. 2005, AJ, 129, 2562
Cattaneo, A., Dekel, A., Devriendt, J., Guiderdoni, B., & Blaizot, J. 2006, MNRAS, 370, 1651
Cooper, M. C., Newman, J. A., Croton, D. J., et al. 2006, MNRAS, 370, 198
Croton, D. J., Springel, V., White, S. D. M., et al. 2006, MNRAS, 365, 11
Dasgupta, S. 1999, Learning Mixtures of Gaussians, Proc. IEEE Symp., Foundations of Computer Science, 634
Dekel, A., & Birnboim, Y. 2006, MNRAS, 368, 2
Driver, S. P., Allen, P. D., Graham, A. W., et al. 2006, MNRAS, 368, 414
Faber, S. M., Willmer, C. N. A., Wolf, C., et al. 2007, ApJ, 665, 265
Hopkins, P. F., Bundy, K., Croton, D., et al. 2010, ApJ, 715, 202
Johnson, B. D., Schiminovich, D., Seibert, M., et al. 2006, ApJ, 644, L109
Kauffmann, G., Heckman, T. M., White, S. D. M., et al. 2003, MNRAS, 341, 33
Lackner, C. N., & Gunn, J. E. 2012, MNRAS, 421, 2277
Madgwick, D. S., Lahav, O., Baldry, I. K., et al. 2002, MNRAS, 333, 133
Martig, M., Bournaud, F., Teyssier, R., & Dekel, A. 2009, ApJ, 707, 250
Martin, D. C., Wyder, T. K., Schiminovich, D., et al. 2007, ApJS, 173, 342
Masters, K. L., Nichol, R., Bamford, S., et al. 2010, MNRAS, 404, 792
McIntosh, D. H., Wagner, C., Cooper, A., et al. 2013, arXiv:1308.0054
Mendel, J. T., Simard, L., Ellison, S. L., & Patton, D. R. 2013, MNRAS, 429, 2212
Mendez, A. J., Coil, A. L., Lotz, J., et al. 2011, ApJ, 736, 110
Peng, Y.-j., Liley, S. J., Kováč, K., et al. 2010, ApJ, 721, 193
Peng, Y.-j., Liley, S. J., Renzini, A., & Carollo, M. 2012, ApJ, 757, 4
Petrosian, V. 1976, ApJ, 209, L1
Salim, S., Dickinson, M., Michael Rich, R., et al. 2009, ApJ, 700, 161
Salim, S., Rich, R. M., Charlot, S., et al. 2007, ApJS, 173, 267
Schawinski, K., Urry, C. M., Simmons, B. D., et al. 2014, MNRAS, 440, 889
Schawinski, K., Urry, C. M., Virani, S., et al. 2010, ApJ, 711, 284
Simard, L., Mendel, J. T., Patton, D. R., Ellison, S. L., & McConnachie, A. W. 2011, ApJ, 196, 11
Strateva, I., Ivezic, Ž., Knapp, G. R., et al. 2001, AJ, 122, 1861
Strauss, M. A., Weinberg, D. H., Lupton, R. H., et al. 2002, AJ, 124, 1810
Taylor, E. N., Hopkins, A. M., Baldry, I. K., et al. 2011, MNRAS, 418, 1587
VanderPlas, J., Connolly, A. J., Ivezic, Z., & Gray, A. 2012, Introduction to astroML: Machine Learning for Astrophysics (CIDU), IEEE Conf., 47
Verbeek, J. J., Vlassis, N., & Kröse, B. J. A. 2003, Neural Comput., 15, 469
Willmer, C. N. A., Faber, S. M., Koo, D. C., et al. 2006, ApJ, 645, 853
Wong, O. I., Schawinski, K., Kaviraj, S., et al. 2012, MNRAS, 420, 1684
Wyder, T. K., Martin, D. C., Schiminovich, D., et al. 2007, ApJS, 173, 293
Xu, L., & Jordan, M. I. 1996, Neural Comput., 8, 129
York, D. G., Adelman, J., Anderson, J. E., Jr., et al. 2000, AJ, 120, 1579
