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Preliminary Target Selection for the DESI Quasar (QSO) Sample

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ABSTRACT

The DESI survey will measure large-scale structure using quasars as direct tracers of dark matter in the redshift range $0.9 < z < 2.1$ and using quasar Ly-α forests at $z > 2.1$. We present two methods to select candidate quasars for DESI based on imaging in three optical (g, r, z) and two infrared $(W1, W2)$ bands. The first method uses traditional color cuts and the second utilizes a machine-learning algorithm.

Keywords: quasars, surveys, large-scale structure, machine-learning

INTRODUCTION

DESI (DESI Collaboration et al. 2016) will precisely measure the baryon acoustic feature imprinted on large-scale structure, as well as the effect of redshift-space distortions on galaxy clustering. The most distant large-scale structures will be measured using quasars (or QSOs). In the redshift range $0.9 < z < 2.1$, QSOs will be used as direct tracers of dark matter. At higher redshifts, DESI will analyze the foreground neutral-hydrogen absorption systems at $\lambda = 1216$ Å (rest frame) that comprise the Ly-α forest.

DESI will primarily target QSOs using optical imaging in the grz bands combined with *WISE* infrared photometry in $W1$ and $W2$. Results presented here use such imaging from the DR8 release[1] of the DESI Legacy Imaging Surveys (Dey et al. 2019). DESI will allocate 260 fibers deg^{-2} (i.e. fibers/deg^2) to QSO targets, requiring at least 120 (50) of those to be QSOs at redshift $z < 2.1$ ($z > 2.1$).

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[1] http://legacysurvey.org/dr8/

QUASAR TARGET SELECTION

QSOs are powered by accretion onto supermassive black holes at the centers of galaxies. The resulting emission can greatly outshine that of the host galaxy, and the "nuclear" emitting regions of even the nearest QSOs are too small to resolve. QSO selection is challenging at optical wavelengths, because the colors and point-like morphologies of QSOs mimic faint blue stars. Without u-band imaging, selections based on the "UV excess of QSOs compared to stars cannot be implemented (as for, e.g., BOSS and eBOSS; Ross et al. 2012; Myers et al. 2015). Crucially, though, QSOs are ~ 2 magnitudes brighter in the near-infrared at all redshifts compared to stars of similar optical magnitude and color, thus providing a powerful method to discriminate QSOs from contaminating stars.

For DESI, we have investigated two methods to select QSOs, one based on color cuts and the other on a machine-learning algorithm. We will finalize a method during DESI Survey Validation, a four-month period prior to the start of the main survey. We restrict both selections to objects with stellar morphology, to avoid an almost 10-fold contamination by galaxies, and we impose a depth limit of $r = 22.7\,(AB)$. We also require that the targets are not in corrupted imaging pixels, nor pixels that are in the vicinity of bright stars, globular clusters, or nearby galaxies. Such "masked" sources have `MASKBITS` of 1, 5, 6, 7, 10, 12 or 13 set in Legacy Surveys catalogs.

Our color-cut selection uses $W1 - W2$ to select redder sources, and $r-W$ vs. $g - z$ (where W is a weighted average of $W1$ and $W2$ fluxes with flux(W)=0.75$\times$flux$(W1)$+0.25$\times$flux$(W2)$) to reject stars based on the "infrared excess" of QSOs (see Figure 1). We impose $g - r < 1.3$ and $-0.4 < r - z < 1.1$ to avoid regions in color space almost solely populated by stars. We also restrict the magnitude range to $r > 17.5$ and $grz > 17.0$, where grz is a weighted average of the three band fluxes (flux$(grz) = ($flux$(g) + 0.8\times$flux$(r) + 0.5\times$flux$(z)) / 2.3)$—at brighter magnitudes, QSOs are rare and stars abundant. To further reduce stellar contamination, we apply a stricter $W1 - W2$ cut to sources near the stellar locus in $g - r$ vs. $r - z$. We also impose a minimum signal-to-noise ratio in both $WISE$ bands.
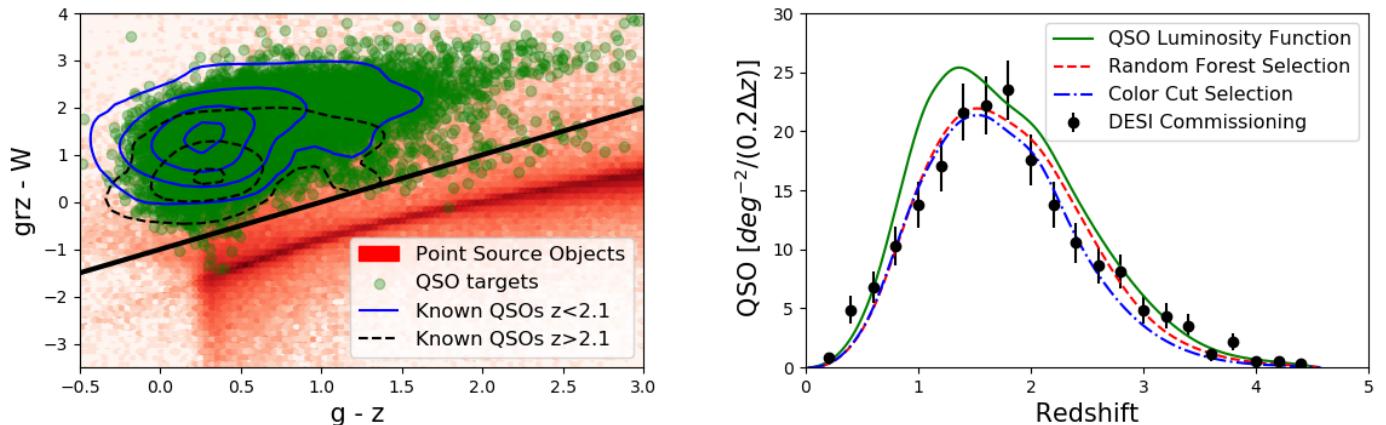
Figure 1. Left: Colors in the optical (grz is a linear combination of g,r and z) or near-infrared (W is a linear combination of W1 and W2) of objects photometrically classified as stars (red) or spectroscopically classified as QSOs (blue and black contours). The green circles show targets selected by the RF. The black line illustrates the "infrared excess" color cut (sources below this line are rejected in the color-cut selection). **Right:** Expected distribution of QSO redshifts from the color-cut (blue) or RF (red) selections, compared to the QSO luminosity function to $r < 22.7\,(AB)$ (green). The filled circles show observations obtained during DESI commissioning.

Neural-network-based algorithms implemented in BOSS (Yèche et al. 2010) were found to increase QSO selection efficiency by $\approx 20\%$ compared to color cuts. Similarly, to improve the success rate for DESI, we use a machine-learning algorithm based on Random Forests (RF). We train the RF on 230,000 known QSOs in the DESI footprint, and 210,000 "stars" defined as unresolved sources that are not known QSOs and do not exhibit QSO-like variations in their SDSS light curve. We normalized the r-band number counts of the stars to match the QSOs and trained the RF selection using $grzW1W2$ colors and r-band magnitude, varying the probability threshold with r. In addition to this RF covering the whole redshift range, we trained a specific RF to target much rarer high-redshift QSOs ($z > 3.5$). To implement the RF approach, we therefore split our 260 deg^{-2} fiber budget; dedicating 245 deg^{-2} fibers to the

all-redshift RF, and 15 deg^{-2} to the high-redshift RF. This approach improves targeting for high-redshift QSOs by $\sim 50\%$, with only a small loss of low-redshift QSOs.

The RF selection performs better than color cuts, particularly at $z > 2.1$ or at faint magnitudes. The expected QSO redshift distribution is shown in Figure 1. Accounting for the completeness of both algorithms as a function of redshift and magnitude, the luminosity function of Palanque-Delabrouille et al. (2016) implies 195 (180) QSOs deg^{-2}, of which 60 (48) deg^{-2} are at $z > 2.1$ for our RF (color-cut) selection. We were able to confirm these results in a 3.7 deg^2 field observed during DESI commissioning. The spectra were visually inspected to confirm the source classification and redshift. In this field, the RF (color-cut) approaches selected 197 ± 7 (176 ± 7) deg^{-2} QSOs, including 58 ± 4 (47 ± 4) at $z > 2.1$. About 98% of the QSOs selected by the color-cut approach are also contained in the RF selection.

CONCLUSION

We propose two QSO selections that meet DESI targeting requirements, and make the target catalog from the preliminary RF selection public[2]. We will test these two approaches during DESI Survey Validation (SV), and choose an algorithm for the subsequent DESI main survey. During SV, we will also test complementary quasar selections such as a dropout technique to select very high-redshift quasars ($z > 4.5$) and a highly homogeneous selection based on quasar variability in *WISE*.

ACKNOWLEDGMENTS

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[2] Available at https://data.desi.lbl.gov/public/ets/target/catalogs/ and detailed at https://desidatamodel.readthedocs.io