The Quasar Luminosity Function at $z \sim 5$ via Deep Learning and Bayesian Information Criterion

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Abstract

Understanding the faint end of quasar luminosity function (LF) at a high redshift is important since the number density of faint quasars is a critical element in constraining ultraviolet (UV) photon budgets for ionizing the intergalactic medium (IGM) in the early universe. Here, we present quasar LF reaching $M_{1450} \sim -22.0$ AB mag at $z \sim 5$, about 1 mag deeper than previous UV LFs. We select quasars at $z \sim 5$ with a deep learning technique from deep data taken by the Hyper Suprime-Cam Subaru Strategic Program, covering a $15.5 \text{ deg}^2$ area. Beyond the traditional color selection method, we improved the quasar selection by training an artificial neural network to distinguish $z \sim 5$ quasars from nonquasar sources based on their colors and adopting the Bayesian information criterion that can further remove high-redshift galaxies from the quasar sample. When applied to a small sample of spectroscopically identified quasars and galaxies, our method is successful in selecting quasars at $\sim 83\%$ efficiency (5/6) while minimizing the contamination rate of high-redshift galaxies (1/8) by up to three times compared to the selection using color selection alone (3/8). The number of our final quasar candidates with $M_{1450} < -22.0$ mag is 35. Our quasar UV LF down to $M_{1450} = -22$ mag or even fainter ($M_{1450} = -21$ mag) suggests a rather low number density of faint quasars and the faint-end slope of $-1.6^{+0.21}_{-0.19}$, favoring a scenario where quasars play a minor role in ionizing the IGM at high redshift.

Unified Astronomy Thesaurus concepts: Quasars (1319); Bayesian information criterion (1920); Astrostatistics (1882); Reionization (1383); Neural networks (1933); Surveys (1671); Luminosity function (942)

1. Introduction

Quasars are the most luminous subpopulation of active galactic nuclei (AGNs) powered by the accretion of surrounding mediums to the supermassive black hole located at the center of its host galaxy. Although quasars contribute to maintaining the ionized state of intergalactic medium (IGM) along with star-forming galaxies in the post-reionization era ($z < 6$), the role of the quasar in explaining the ionizing background of the universe is not fully understood (Fan et al. 2006; Glikman et al. 2011; Ikeda et al. 2011; Giallongo et al. 2015; Boutsia et al. 2018; Parsa et al. 2018).

To evaluate the contribution of quasars to the IGM ionizing photon budget, many studies searched for high-redshift quasars (Glikman et al. 2011; Kim et al. 2015, 2019, 2020; Matsuoka et al. 2016; Akiyama et al. 2018; McGreer et al. 2018; Parsa et al. 2018; Giallongo et al. 2019; Wang et al. 2019; Grazian et al. 2020; Shin et al. 2020), especially at the absolute magnitude at $1450 \text{ Å}$ in the rest frame ($M_{1450} \sim -23.5$ mag where the ionizing emissivity of the quasar is considerable, as shown in Kim et al. (2020); hereafter K20). While the quasar UV luminosity functions (LFs) from different studies are now converging toward a common shape at $M \lesssim -23.5$ mag that can be approximated with a pure number density evolution at $z > 2$ (Kim & Im 2021), there remains great uncertainty in the LF at a fainter magnitude. If the number density of quasars is as high as some studies suggest at the faintest end (Boutsia et al. 2018; Giallongo et al. 2019; Grazian et al. 2020), quasars are still a viable candidate to be responsible for cosmic reionization at high redshift.

To extend the faint limit of the quasar LF, we can adopt two approaches: one to use deeper data, and another to select quasars using a new technique. As for the deeper data, the second public data release (PDR2; Aihara et al. 2019) of the Hyper Suprime-Cam Subaru Strategic Program (HSC-SSP; Aihara et al. 2018) provides an interesting opportunity. The deeper layers of the survey go down to $i \sim 27.0$ mag (Aihara et al. 2019) and yet an area wide enough (tens of square degrees) to negate the cosmic variance in number density. Therefore, such a data set is suitable for finding quasars with $M_{1450} \sim -22.0$ mag and probing the quasar LF $\sim 1.0$ mag deeper than previously constructed quasar LFs at $z \sim 5$ (McGreer et al. 2018; Niida et al. 2020, hereafter N20; Shin et al. 2020).

Another difficulty in extending the quasar LF to a fainter limit is that galaxies occupy a significant fraction of the high-redshift UV sources at $M_{1450} > -23$ mag (Ono et al. 2018; Adams et al. 2020; N20; Bowler et al. 2021; Kim & Im 2021) and can contaminate quasar samples made from a conventional color-selection technique. Also, as we explore the fainter limit, the number of sources becomes formidably large. This makes it challenging to apply time-consuming selection methods such as spectral energy distribution (SED) fitting for the quasar selection (Reed et al. 2017), although such methods may be efficient in discerning quasars from galaxies.

Therefore, we adopt a new and powerful approach that combines deep learning (DL) and Bayesian information criterion (BIC). Machine-learning algorithms are popular to classify quasars...
from the other objects these days (Richards et al. 2004; Jin et al. 2019; Nakoneczny et al. 2019; Schindler et al. 2019), with multiple strong points. (1) Machine learning can quickly judge each astronomical object (Gupta et al. 2014). (2) Unlike linear color-cuts defined arbitrarily by the human inspection of the color space, it can optimize a nonlinear boundary mathematically by minimizing the difference between the true label and the predicted label from the trained model (Kojima et al. 2020). (3) It can consider the estimates from all the bands as its input to decide the boundary between quasars and other astronomical objects, while the traditional color selection can utilize a few broad bands only. Thus, DL can perform a fast selection of quasar candidates with maximal completeness. The BIC selection is additionally optimized in the space, it can optimize a nonlinear boundary mathematically by minimizing the difference between the true label and the predicted label from the trained model (Kojima et al. 2020).

This paper is structured as follows. We described the HSC-SSP data in Section 2, and training data for DL and quasar and star models for BIC in Section 3. Section 4 describes the DL and BIC selection of quasars and the selected candidates. In Section 5, we show how the quasar binned LFs and parametric LF are derived based on the final candidates. In Section 6, we discuss how our quasar selection and the quasar LF compare with previous studies and how the improvement over previous works was possible. Section 7 summarizes the findings and the results of this study. Throughout this paper, the AB magnitude system is adopted for all filters (Oke & Gunn 1983), after the Galactic extinction correction by adopting the dust map of the Schlegel et al. (1998). We assume Ω_M = 0.3, Ω_Λ = 0.7, and H_0 = 70 km s^{-1} Mpc^{-1} of the ΛCDM cosmology, which has been supported by observations in the past decades (e.g., Im et al. 1997).

2. HSC-SSP Deep-layer Catalog

We used the catalog constructed from the Deep layer of the HSC-SSP in PDR2 with a survey area of 27 deg^2 and a 5σ image depth of ~27 mag for a point source in r band (Aihara et al. 2019). The Deep layer consists of four fields (Aihara et al. 2018): the XMM Large-Scale Structure Survey (Pierre et al. 2004), Extended-COSMOS (Scoville et al. 2007), the European Large-Area ISO Survey-North 1 (Rowan-Robinson et al. 2004), and the DEEP2-3 (Cooper et al. 2011; Newman et al. 2013). We used the data taken in five broad bands (g, r, i, z, y) and two narrow bands (NB816, NB921). The 5σ image depths of the seven bands (g, r, i, z, y, NB816, NB921) are (27.3, 26.9, 26.7, 26.3, 25.3, 26.1, 25.9) mag for a point-source detection, respectively (Aihara et al. 2019). An effective survey area of this layer in PDR2 is about 15.5 deg^2, calculated from a random source catalog provided in the HSC data archive system (Coupon et al. 2018).

We used the source catalog from the HSC-SSP PDR2 excluding objects whose photometry measurements are flagged to be affected by the cosmic ray, saturation, abnormal local background estimation, bad pixels, shallow depth, and the proximity to the survey edges. Also, we considered the objects that are primary and unique sources having no child in the survey. Table 1 lists the flags that we adopted to retrieve the catalog sources. The number of retrieved sources is about 3.5 million. For our analysis, we used the point-spread function (PSF) magnitudes (see Section 4.1).

3. Data and Models

3.1. Training and Test Data

To select reliable high-redshift quasar candidates using the DL technique, we should prepare a data set including training data representing quasars at z ~ 5 (qso) and the other objects (nqso), and data for testing the trained model. The nqso class includes HSC-SSP sources satisfying our point-source selection criterion. Although nqso class might contain few real quasar samples, the probability of including real quasars is too low (~<0.2%, please refer to Section 4.1). This kind of empirical approach to constructing the nqso sample has been used in previous works (e.g., Timlin et al. 2018) when the properties of the nqso population are poorly known. The qso data set is made up of quasar SED models (described in Section 3.2.1) because of a small number of spectroscopically confirmed quasars at z ~ 5 compared to the other classes. The training data set for each class is a randomly sampled subset, as described in Section 4.2.4.

We find six spectroscopically identified quasars and three promising quasar candidates at 4.5 < z < 5.5 in the Deep layer (McGreer et al. 2013; Pâris et al. 2018; Shin et al. 2020) with a matching radius of 1″.0. The matched quasars are used for testing the performance of the trained model independently.

3.2. Quasar and Star SED Models

3.2.1. Quasar

We created model spectra of quasars at z ~ 5 by creating a composite SED of Lusso et al. (2015) and Selsing et al. (2016) bluewards and redwards of 1450 Å, respectively. Compared to the composite quasar spectrum of Vanden Berk et al. (2001), their SEDs are more likely to be intrinsic ones, free from UV absorption and host galaxy contamination.

Then, we manipulated the equivalent width (EW) of Lyα and N V λ1240 and the continuum slope (α_λ) of the model following their empirical distributions of high-redshift quasars; a log-normal distribution with log EW = 1.524 ± 0.391 (Bañados et al. 2016) and α_λ = −1.6 ± 1.0 (Mazzucchelli et al. 2017). Concerning the IGM absorption at high redshifts, we used an updated version of the IGM attenuation model (Inoue et al. 2014). Finally, we rescaled the EW of the C IV emission line by multiplying the rate of the EW change of Lyα and N V λ1240. The Baldwin effect was not considered in this study (Baldwin 1977), not to bias our sample to be those that follow the Baldwin effect.

The quasar SED model has four parameters: the redshift (z), EW, α_λ, and M_{1450}. The redshift range of the model is 4.0–6.0 in steps of Δz = 0.01, and the α_λ range is −3.6–1.6 in steps of Δα_λ = 0.2. The log EW (angstrom units) grid consists of

| Flag                           | Value  |
|--------------------------------|--------|
| inputcount_value               | ≥2     |
| detect_primary                 | True   |
| Localbackground_flag_nogoodpixels | False  |
| pixelflags_edge               | False  |
| pixelflags_saturatedcenter    | False  |
| pixelflags_ccenter            | False  |
| pixelflags_bad                | False  |

Table 1: The Conditions Used for Retrieving Sources

Shin, Im, & Kim (2019)
evenly distributed. The black dashed line indicates the extendedness value we applied to our quasar selection. The median values of \((i - i_{\text{CModel}})\) distributions are marked with squares or circles. The error bars indicate the 68\% percentile of the distributions. The black dashed line indicates the extendedness value we applied to our quasar selection. The fractions of the HST point and extended sources with \((i - i_{\text{CModel}}) < 0.2\). The green squares indicate the point-source contamination rate caused by galaxies, and the pink circles represent the point source completeness.

Although the point source contamination reaches about 40\% at \(i < 25\) mag, the completeness is always \(\geq 90\%\).

First, we limited the \(i\)-band magnitude range from 19 to 25 mag, avoiding saturation and allowing to search quasars fainter as much as \(M_{i,450} \sim -21.0\) mag. Since quasars at \(z \sim 5\) are red objects with large \(r - i \gtrsim 1.2\), the magnitude limit also enabled us to obtain \(r\)-band photometry above its detection limit of \(r \sim 27\) mag. In addition, we set the error cut of \(\sigma_{r} < 0.2\) to select sources with reliable \(i\)-band detection, eliminating a few more objects (<0.01\%) that happen to be in shallow regions of the HSC-SSP images.

Next, we distinguished point sources from extended sources. We included this process because a quasar whose light is dominated by an AGN at its center would appear as a point source. An obvious disadvantage of this selection is that we miss AGNs where host galaxies are more dominant, especially for AGNs with \(M_{UV} \lesssim -23\) mag (Trebitsch et al. 2020; Bowler et al. 2021; Kim & Im 2021). Therefore, our survey is limited to the AGNs that have strong emission lines and outshine their host galaxies in UV.

The point-source selection can be done by comparing PSF magnitudes and CModel magnitudes. We called the difference the extendedness parameter and adopted it to classify point sources. While the extendedness parameter value is close to 0 for extended sources due to a mismatch in the object design and the minimal conditions required to be a quasar, significantly curtailing the number of the candidates. DL plays the role of judging an object’s class using the colors of the preselected candidates. Similar to DL, BIC indicates a likelihood of an object being a star or a quasar based on the results from the SED fitting. For candidates passing this BIC selection, we check the quality of images used for measuring their fluxes.

### 4. Quasar Selection

#### 4.1. Preselection

We first selected candidates in the following order. (1) Magnitude and error cuts were set to \(19 < i < 25\) mag and \(\sigma_{r} < 0.2\) mag, respectively; (2) we carried out a point-source selection using the \(i\)-band parameter; and (3) we set a \(g - r\) color cut to select red objects that are consistent with being at \(z > 4.5\). The role of judging an object’s class using the colors of the preselected candidates. Similar to DL, BIC indicates a likelihood of an object being a star or a quasar based on the results from the SED fitting. For candidates passing this BIC selection, we check the quality of images used for measuring their fluxes.

#### 4.2. Star

We adopted the stellar model spectra generated by the B2T-Settl models that use the “BT2” water vapor line list computed in Barber et al. (2006) and the “Settl” model accounting for dust formation and its gravitational settling (Allard et al. 2003) based on solar abundances of Asplund et al. (2009). We used a total of 14,342 spectra covering the parameter space of \(T_{\text{eff}}\) of 400–70,000 K with 50–100 K step sizes, \(\log(g)\) of \(-0.5–6.0\) with a 0.5 step size, \([M/H]\) of \(-4–0.5\) with step sizes of 0.2–0.5, and \([\alpha/M]\) of 0.0–0.6 with a 0.2 step size. Note that \([\alpha/M]\) varies only for the model with \(T_{\text{eff}} > 2600\) K, and we added a normalization factor \((f_{\text{N}})\) as a free parameter.

#### 4.3. Quasar Preselection

We used multiple methods sequentially to select quasar candidates at \(z \sim 5\): preselection, DL, BIC, and visual inspection. The preselection picks out the candidates satisfying our survey design and the minimal conditions required to be a quasar, accounting for 95.4\% of the entire quasar population, respectively, assuming that quasars follow the \(\alpha_{3}\) and EW distributions. As a result, there are 12 million model spectra in total.

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the dependency of the extendedness value of the HST point and extended sources on the $i$-band magnitude. The error bars correspond to the 16th and 84th percentiles of the distributions, respectively. As the $i$-band magnitude becomes fainter, they overlap more. Figure 1(c) shows the point-source completeness and contamination rates of the HST point and extended sources with $(i - i_{\text{Model}}) < 0.2$ as a function of $i$-band magnitude. The point-source completeness is $\sim 90\%$ at $i = 25$ mag, and 98.4% at $i < 25$ mag, while the contamination rate reaches about 40% at $i \sim 25$ mag.

Even though the point-source selection cut caused a high contamination rate of an extended source mimicking a point source, we focused on increasing the point-source completeness. The following selections using SED shape can further weed out high-redshift objects that are dominated by galaxy light.

In the third step, we eliminated the sources with the possible detections at the blueward wavelengths, which are clearly not high-redshift quasars with the IGM attenuation. We selected the sources that are not detected in $g$-band imposing signal-to-noise ratio $(S/N) < 3$, or had $g - r > 0.987$, which is determined from the minimum $g - r$ color of our quasar model at $z = 4.5$ (Section 3.2.1). After these steps, the number of preselected objects is 125,644 over 15.5 deg$^2$.

4.2. Deep Learning

4.2.1. A Brief Introduction

The first mathematical expression about a neural network was introduced by McCulloch & Pitts (1943). The successful performance of a convolutional neural network in the ImageNet project proved the potential of the neural network (Deng et al. 2009), and it spurred the application of DL to many other disciplines including astronomy.

A neural network consists of multiple layers: an input layer, an output layer, and hidden layers. The input layer receives an object’s information, and the output layer returns the object’s property that we want to know. The hidden layers connect the information in the input layer to the output object’s property. In this work, we implemented a supervised DL to predict a class for an object (output) based on its photometry (input).

Each layer has neurons, which are the smallest data-processing units. Each neuron in each layer except for the input layer has a weight, $w$, corresponding to each feature of an input, $x$, and a bias, $b$. The neuron calculates the weighted sum of the features, adds the bias to the sum, and passes the sum to an activation function, $A$. The activation functions rescale the sum and determine whether the output value, $y$, for each neuron should be activated or not ($y = 0$). The following equation shows how to calculate the output value for an $i$th neuron in an $l$th layer.

$$y_i^l = A \left( \sum_{j=1}^{n_i} [w_{ij}^l x_j^{l-1}] + b_i^l \right),$$

where $n_i$ is the number of neurons in the $(l - 1)$th layer. The output of the $i$th neuron in the $l$th layer ($y_i^l$) becomes the input to the neurons in the next layer. If the next layer is an output layer, then the output becomes the probabilities. Weights and a bias for each neuron contribute to predicting the final outputs. Thus, the main purpose of the model training is to find appropriate weights and a bias for each neuron. The optimal model parameters ($w$ and $b$) can be obtained by minimizing the loss function, which considers the difference between the true class and the predicted class by the model.

4.2.2. Hyperparameter Optimization

Before optimizing the weights and bias of each neuron, we examined the best combination of the hyperparameters. The hyperparameters are the parameters affecting the entire training process. It includes parameters related to the architecture of the neural network (the number of hidden layers and the number of neurons in each hidden layer), and rules for model training ($A$, loss function, weight decay, optimizer, batch size, epochs, initial values for $w$). The hyperparameter combination can influence the converge time for finding the optimal model parameters and the model performance. For efficient model training, we have to find the best configuration of the hyperparameters. The hyperparameters are explained in detail:

1. The number of hidden layers
2. The number of neurons in each hidden layer
3. Activation function. Each neuron has an activation function to decide whether the inputs contribute to minimizing the loss function or not. The activation function also enables us to calculate the gradient of the loss function with respect to the weights and the bias of each neuron according to the Backpropagation algorithm (Rumelhart et al. 1986). Among various activation functions, we adopted the Rectified Linear Unit (Nair & Hinton 2010), given as $f(x) = \max \{0, x\}$.
4. Loss function. This is the difference between the true and the predicted properties for a given model. We used the cross-entropy loss, which has been widely used due to the discrete property of the output, to calculate a mean loss of the training data in a batch.
5. Weight decay. This is the penalty for the large weights. The weight decay term was additionally applied to the loss function to avoid overfitting.
6. Optimizer. This is an optimization algorithm to minimize the loss function. We used stochastic gradient descent (SGD). The SGD calculates partial derivatives of the loss function of given weights or biases and updates the two parameters iteratively toward finding a global minimum. The SGD uses the randomly selected subsets of the training data (i.e., batch sample) at each iteration.
(a) Learning rate. This is the step size of model parameters to explore the partial derivatives of the loss function.
(b) Momentum. This is the fraction of taking into account the previous update to calculate the current update for a parameter. Adopting the momentum, we can accelerate convergence to the minimum by giving more weights to previous directions compared to the current direction, which may be biased toward a noise.
7. Batch size. This is the number of training subsets used to calculate a gradient descent
8. Epochs. This is the number of the passing of all training data to train the model.
9. Initial values for $w$. To implement the Backpropagation algorithm and update $w$ and $b$, we should assign initial values for $w$. In this paper, we randomly selected the initial values from a normal distribution in which the mean and standard deviation are 0 and 1.
We constructed a feed-forward four-layer neural network. To prevent the risk of overfitting, we set 20 epochs as an upper limit of the time for evaluating the derivatives and updating the model parameters. Except for the fixed hyperparameters (e.g., the number of hidden layers, activation function, loss function), we determined an optimal hyperparameter combination among the hyperparameter search spaces specified in Table 2. For this, we used the Bayesian model-based optimization algorithm of the RayTune Python package (Bergstra et al. 2013; Liaw et al. 2018), and tried 100 hyperparameter configurations. The hyperparameter set with the lowest loss was chosen as the final hyperparameter set for testing preselected sources in Section 4.1.

### 4.2.3. Preprocessing the Inputs

As the inputs of the training process, we used six colors from the catalog: $g - r$, $r - i$, $i - NB816$, $NB816 - z$, $z - NB921$, $NB921 - y$. When an $i$-band-selected source is not detected or fainter than the imaging depth of the other bands, we adopted $5\sigma$ imaging depths as their magnitudes in the corresponding bands. Considering the discriminative feature in $g$ band owing to the IGM absorption, we assigned $g = 30$ mag when the object is not detected or has a magnitude fainter than 30 mag in $g$ band.

After refining the magnitudes, we calculated the colors of the data set, standardized each color, and extracted six principal components using the scikit-learn Python package (Pedregosa et al. 2011). The standardization removes the mean of each color and scales its standard deviation, enabling the principal component analysis (PCA) to weigh each color equally. Note that we used all the six principal components derived from the PCA, although the PCA is frequently used for dimension reduction of input features.

### 4.2.4. Training

Our training set contains two classes of objects—the nqso class and the qso class. The nqso class denotes objects that are not quasars, and the qso class set consists of about $3.34 \times 10^5$ $i$-band-selected point sources in the Deep layer of HSC-SSP. The qso class denotes quasars, and the qso class set consists of millions of quasar model SEDs at $z = 4.5 - 5.5$ (Section 3.2.1). The class imbalance problem is handled by randomly sampling the nqso and the qso classes when making a total sample (Buda et al. 2017). In reality, the nqso contains real quasars in the survey area. However, given that the number of real quasars is expected to be small (a few tens), their contamination of the nqso sample is negligible. The number of sources in each class was fixed to 100,000, resulting in a total data set size of 200,000.

We set aside 20% of the data set as the test data set. The remainder was split into five subsets—four for the training data set and one for the validation set. To minimize possible dependence on a given training data set, we performed a five-fold cross-validation by changing the subset used for the validation set. If DL classified an object as qso more than or equal to 3 times, we considered the object as a quasar candidate of the trained model.

Also, to make our selection more robust, we trained additional 99 neural network models by following the above procedure (Ďurovčíková et al. 2020). From the 100 results of the 100 models, we classified an object as qso if the DL-selected candidates show qso label more than or equal to 80 times. Figure 2 shows the confusion matrix for our DL selection. The probability of an actual nqso to be predicted as qso class (false positive rate, FPR) is extremely low ($\sim0.5\%$). The probability is also as low as $\sim0.3\%$ for the trained model classifying an actual qso as nqso class (false negative rate, FNR). The low FNR can assure us high completeness of the quasar survey. In Section 6.4, we compare previous quasar selections and the DL selection. The number of quasar candidates from the ensemble learning is 1,599.

### 4.3. SED Fitting for BIC Selection

Although FPR is very low, misclassified nqso could occupy a large portion of the quasar candidates because the absolute number of nqso is larger than that of qso in a real world ($\sim10,000:1$). To remove misclassified nqso from quasar candidates, we performed the SED fitting and an additional BIC selection, as in Shin et al. (2020). We briefly summarize the procedure as follows.

First, we fitted the SED of the DL-selected quasar candidates with both quasar and star models. To allow margins for errors, we chose a redshift range spanning 4.0–6.0 for the quasar model fit, a bit broader than the redshift range of the model used for DL. Throughout the SED-fitting process, we adopted the chi-square calculation presented in Šawicki (2012), which deals with the upper limits of observation data. The fitting

| Hyperparameter | Search Space |
|----------------|--------------|
| The number of neurons in each hidden layer | [10,20,30] |
| Weight decay | uniform distribution from 1e-5 to 1e-4 |
| Learning rate | uniform distribution from 1e-4 to 1e-2 |
| Momentum | uniform distribution from 0.7 to 1 |
| Batch size | [32, 64, 128, 256] |
| Epochs | <20 |
| Initial values for $w$ | normal distribution |

Table 2

Hyperparameter Search Space
results provided the chi-square values and the best-fit parameters of the quasar and star models. We excluded the candidates with the best-fit quasar model of $\chi^2_{\text{qso}} > 30$.

Then, we calculated BIC, a criterion used for model selection considering a likelihood and the number of free parameters in a model, $k$. In general, a fitting result becomes better as $k$ increases. Giving a penalty to a model with many parameters, the difference between the BIC values of different models ($\Delta$BIC) can determine a preferred model. It is defined as

$$\Delta \text{BIC} = (\chi^2_{\text{star}} - \chi^2_{\text{qso}}) + (k_{\text{star}} - k_{\text{qso}}) \times \ln n,$$

where $n$ is the number of data points of an object, and $\chi^2$ is the chi-square value of a best-fit model. The "star" and "qso" subscripts mean the best-fit model for the star and quasar. If $\Delta$BIC of a DL-selected candidate is greater than 10, we regarded the candidate as the BIC-selected candidate (Liddle 2007).

After the BIC selection, the number of quasar candidates becomes 78. Note that one of three promising candidates reported in Shin et al. (2020) and a known quasar at $z = 4.564$ were excluded in this process. We discuss this issue in 6.2.

4.4. Visual Inspection

We visually inspected images of the 78 candidates and excluded 25 of them due to spurious photometry results caused by bright neighbors, background variations, optical ghosts, satellite tracks, or scattered lights. These features caused the local background overestimates, resulting in flux underestimates in $g$ band that mimicked the redshifted Lyman break.

Then, we examined if the remaining 53 candidates were previously reported by querying NASA/IPAC Extragalactic Database (NED) using the astroquery. We recovered 5/6 confirmed quasars (McGreer et al. 2013; Shin et al. 2020) and two promising candidates in Shin et al. (2020). We also recovered a candidate with a probability to be a quasar $P_{\text{qso}} = 1$ in McGreer et al. (2018), CFHTLS J021800.49-044718.5, and another possible AGN at $z = 4.549$ in Chaves-Montero et al. (2017), ALH3L490. In addition, our candidates include a spectroscopically confirmed galaxy at $z \sim 5$ (Ono et al. 2018; refer to Section 6.3.1).

4.5. Final Candidates

To assess whether a visually inspected candidate was realistic or not, we checked the probability of finding each candidate in our survey. First, we made a completeness function shown in Figure 3, $F(z, M_{1450})$, of our survey. This function is the fraction of the quasars satisfying the preselection, the DL, and $\Delta$BIC selections among our simulated quasars within given bin sizes of $M_{1450}$ and $\Delta z$. The side panel shows the normalized $M_{1450}$ distribution.

Figure 3 shows that the 53 quasar candidates selected with the DL+BIC+Visual inspection have a bimodal distribution, with a peak in their numbers at $M_{1450} \sim -21$ mag and another peak at $M_{1450} < -22.0$ mag. Considering that the quasar selection completeness is very low at $M_{1450} > -22$ mag, the large fraction of faint quasar candidates at $M_{1450} > -22$ mag are likely to be contaminated by $z \sim 5$ galaxies that are known to be the dominant population at those magnitudes. To remove galaxy interlopers, we considered the candidates with $M_{1450} < -22.0$ mag as our final quasar candidates. The number of the final candidates is 35 with $z_{\text{phot}} \sim 5.0$, excluding a spectroscopically confirmed galaxy at $z \sim 5$ (Ono et al. 2018) mentioned in Section 4.4. The HSC-SSP photometry of 35 final candidates is listed in Table 3, and their SED-fitting results are plotted in Figure 4.

5. Quasar Luminosity Function at $z \sim 5$

To construct the quasar LF at $z \sim 5.0$, we assumed one redshift bin ranging $= 4.4-5.8$ and split the 49 visually inspected candidates with $-26 < M_{1450} < -21$ into six magnitude bins with $\Delta M_{1450} = 1.0$ or 0.5 mag. It is worth noting that the binned LFs were calculated with 49 of the 53 visually inspected candidates; only the final candidates of 35 were used for deriving a parametric LF due to the possible contamination from the high-redshift galaxies in the binned LFs with $M_{1450} > -22.0$ mag.

To describe the bright end of the quasar LF, we used 96 bright quasars at $z \sim 5$ from Yang et al. (2016). We redistributed the bright quasar sample to four $M_{1450}$ bins covering $-28.5$ to $-27.0$ mag, considering the differences between the adopted cosmological parameters in our and their works. In the same manner, we additionally secured quasars with moderate luminosity ($M_{1450} = -27.0$ to $-23.0$) from K20 to better determine the quasar LF.

We calculated the effective survey volume using the updated $1/V_\text{a}$ method (Page & Carrera 2000). In the original version of $1/V_\text{a}$ method, the volume available to find the quasar at a given redshift range does not consider a dependency of the maximum detectable redshift on a given luminosity, while the updated $1/V_\text{a}$ method does. Thus, the updated $1/V_\text{a}$ method can estimate the survey volume accurately, especially for a faint magnitude bin near the detection limit of the survey. It is
The magnitude errors are mostly less than 0.03 mag. The magnitude bin were calculated using the following equations,

\[ V = \frac{1}{\Delta M_{1450}} \int_{\Delta m_{1450}} \int_{z_{\text{min}}}^{z_{\text{max}}(M_{1450})} F(z, M_{1450}) \frac{dV}{dz} dM_{1450}, \]  

where \( z_{\text{min}} \) is the lowest redshift of the redshift bin, and \( z_{\text{max}}(M_{1450}) \) is the maximum redshift to discover quasars within a given magnitude bin. \( \frac{dV}{dz} \) is the cosmological volume element. \( F(z, M_{1450}) \) is the survey completeness defined in Section 4.5.

The number density and its error corresponding to each magnitude bin were calculated using the following equations,

\[ \Phi = \frac{N}{V \Delta M_{1450}}, \quad \delta \Phi = \frac{\Phi}{\sqrt{N}}, \]  

where “\( N \)” is the number of quasars or quasar candidates in a magnitude bin, and “\( V \)” is the effective volume introduced in Equation (3). The uncertainty of \( \Phi \) was estimated by the Poisson noise of \( N \).

We calculated the binned LFs based on the samples and survey completeness maps of Yang et al. (2016), K20, and our survey. Except for ours, we rescaled the binned LFs at \( z \sim 5.05 \) to \( z \sim 5.0 \) using the relation about the redshift evolution of number density at the break magnitude, \( \Phi^*(z) = \Phi^*(z = 5.0) \times 10^{k(z-5.0)} \) with \( k = -0.47 \) (Fan et al. 2001). Table 4 provides the binned LFs for quasars in Yang et al. (2016) and K20, and the 49 quasar candidates in our survey. Our binned LFs at \( M_{1450} = -22.0 \) mag increase dramatically as shown in Figure 5, implying possible galaxy contamination.

To obtain the parametric quasar LF, we introduced a double power-law function of which the form is expressed as

\[ \Phi_{\text{model}}(M_{1450}) = \frac{\Phi^*(z = 5.0)}{10^{0.4(\alpha+1)(M_{1450}-M_{1450}^*)} + 10^{0.4(\beta+1)(M_{1450}^*-M_{1450}^*)}}. \]  

Using the log-likelihood function defined as

\[ S = \sum_{ID=1}^{n} \left( -2 \sum \ln[\Phi_{\text{model}}(M_{1450}) F_{\text{ID}}(z, M_{1450})] + 2 \int \Phi_{\text{model}}(M_{1450}) F_{\text{ID}}(z, M_{1450}) \frac{dV}{dz} dM_{1450} \right). \]
the ID is a survey id corresponding to ours, Yang et al. (2016), or K20, and $F_{ID}$ is a completeness function of a survey with the “ID.” Giving a uniform prior to each parameter, we sampled the posterior distributions of the parameters by using the emcee (Foreman-Mackey et al. 2013) python package to implement Markov Chain Monte Carlo (MCMC). The best-fit
parameters and their uncertainties were determined from the 50th percentiles and 68% credible intervals of MCMC samples, respectively. The parametric LF was calculated using our 35 final quasar candidates, the bright quasars from Yang et al. (2016), and with or without the moderate luminosity quasars from K20.

Table 5 summarizes the best-fit parameters of the parametric quasar LFs for whether the moderate luminosity quasars in K20 are included or not. Also, the fitted quasar LF model and binned LFs in this work are shown in Figure 5. Note that all the quasar LFs from the literature in the figure are scaled to \( z = 5.0 \).

### 6. Discussion

#### 6.1. Comparison with Previous LFs and Implications on IGM Ionization

As we explained earlier, we consider our quasar UV LF to be reliable down to \( M_{1450} = -22.0 \) mag, which goes about 1 mag deeper than the recent LFs (N20; K20). Here, we compare our LF with previous LFs in several aspects.

We note that our two best-fit faint ends (\( \alpha \sim -1.64^{+0.36}_{-0.30} \) and \( -1.60^{+0.21}_{-0.19} \)) are consistent with those of N20 (\( \alpha \sim -2.0^{+0.40}_{-0.63} \)) and K20 (\( \alpha \sim -1.2^{+1.36}_{-0.64} \)), which are based on a deep and wide-area surveys (>80 deg²), within 1σ level. McGreer et al. (2018) derived a steeper faint-end slope (\( \alpha \sim -1.97^{+0.09}_{-0.07} \)) than ours. However, their value should be taken with caution since the LF of McGreer et al. (2018) is based mostly on quasars with \( M_{1450} < -24 \) mag. Kulkarni et al. (2019) also showed a steep \( \alpha \) of \( \sim -2.31 \) using the same data set of McGreer et al. (2013)

plus Glikman et al. (2011), but their data points are limited to \( M_{1450} < -24 \) (McGreer et al. 2018) or a small number statistics due to a coverage of \( \sim 2 \) deg² (Glikman et al. 2011). Clearly, this comparison demonstrates how uncertain the LF faint-end slope could be without sufficiently deep data.

Giallongo et al. (2019) and Boutsia et al. (2018) presented a near-infrared (NIR) + X-ray-selected AGN UV LF, but their LF at the faint end is about 10× higher than ours. Shen et al. (2020) discuss a possible tension of AGN LF of Giallongo et al. (2019) with other LFs. The AGN LF of Giallongo et al. (2019) has been considered as possible evidence for quasars making nonnegligible contribution to IGM ionization at \( z \sim 5 \) (e.g., Grazian et al. 2020, 2022). Our LF, along with other previous LFs, shows a rather low number density of faint AGNs, supporting claims for quasars contributing little in IGM ionization at \( z \sim 5 \) (McGreer et al. 2018; K20; Shin et al. 2020).

N20 used color-selected quasar candidates as well as a few spectroscopically confirmed quasars to derive quasar LF. They excluded the binned LFs at \( M_{1450} \lesssim -23.3 \) mag due to possible
contamination by Lyman-break galaxies (LBGs). On the other hand, we extend our LF to \( M_{1450} \lesssim -22.0 \) mag, over 1 mag fainter than the N20 limit. At \( M_{1450} = -22.0 \) mag, the quasar number density from our work is several times smaller than N20 LF, suggesting an efficient rejection of LBGs through our selection method. We discuss this point in detail in the next subsections.

Finally, we note that our binned LF at \(-22 < M_{1450} < -21\) is comparable to the LFs of Giallongo et al. (2019) and Boutsia et al. (2018), although our faintest quasar sample is significantly contaminated by LBGs. The expected level of contamination is very high, with \( \gtrsim 12\% \) of LBGs contaminating the quasar sample at these magnitudes (Section 6.2). Correcting such a level of LBG contamination would bring the binned LF points down to the extrapolated portion of the parametric LF or below it. Therefore, the binned LFs at \(-22 < M_{1450} < -21\) mag can serve as additional evidence against \( z \sim 5 \) quasars making a significant contribution to the IGM ionization. One caveat is that AGNs at these magnitudes may not appear as quasars (point-like sources) and have their light dominated by host galaxies. Our selection method would miss such objects since we pick up point sources with quasar-type SEDs as quasars (e.g., Kim & Im 2021).

6.2. Recovery of Known Quasars with Our Selection

We examine how many known quasars are recovered by our selection method. There are six \( z \sim 5 \) quasars identified by spectroscopy in our survey area (McGreer et al. 2013; Pâris et al. 2018; Shin et al. 2020) and three medium-band-selected quasars reported in Shin et al. (2020).\(^4\) While five of the six spectroscopically identified quasars and two of the medium-band-selected quasars are recovered as the final sample, HSC J021844–044824 (spectroscopically confirmed) and IMS J160732+544750 (a medium-band-selected quasar in Shin et al. 2020) dissatisfy the \( \Delta \)BIC criterion with \( \Delta \)BIC \(\sim 5\) in this work. Missing two out of nine quasars (22% of the sample) can be explained by the completeness of the survey. The brighter one, HSC J021844–044824 is at \( z = 4.5 \), which corresponds to the parameter space where the completeness is low \((\sim 0.27\%\) IMS J160732+544750 at \( z \sim 5 \) has a low luminosity of \( M_{1450} = -22.9 \) mag where the completeness starts declining rapidly.

As demonstrated in the right panels of Figure 6, the selection can be improved with additional filters. For example, IMS J160732+544750 was selected as a quasar with an addition of a medium-band and NIR upper limits (Shin et al. 2020). HSC J021844–044824 could have been selected as a quasar if there was an additional NIR-band data. In conclusion, our selection method with HSC-SSP photometry data may miss \( \sim 22\% (2/9) \) of known quasars at \( z \sim 5 \). However, the quasar recovery can be improved by including additional multiband data.

6.3. Contamination Rate of Our Quasar Survey

6.3.1. High-redshift Galaxies

We checked if our quasar sample is contaminated by high-redshift galaxies using spectroscopically confirmed galaxies at \( z \sim 4–7 \) from HSC-SSP (Ono et al. 2018). This is because of two reasons: (1) Several quasar surveys have indicated a high contamination rate of high-redshift quasars samples by high-redshift galaxies in a faint regime (Matsuoka et al. 2018; N20). The number density of LBGs is significantly higher than that of quasars at \( M_{1450} > -23 \) mag (Ono et al. 2018; see Figure 9), and (2) our selection has no explicit criteria for separating high-redshift galaxies from quasars at \( z \sim 5 \). Specifically, the DL selection considers the \( i \)-band-selected point sources only, and the BIC statistics makes use of the star models only.

\(^4\) Medium-band-selected quasars indicate quasar candidates with \( \Delta \)BIC \( \gtrsim 30\) that are highly likely to be real quasars at \( z \sim 5 \) based on multiwavelength measurement from UV to NIR.
We searched for spectroscopically confirmed galaxies at \( z \sim 5 \) in our survey area and found 8 galaxies with \( i < 25 \) mag at \( 4.0 < \zspec < 6.0 \). Among them, we find only one galaxy at \( z \sim 5.0 \) satisfies the precriteria, the DL, and \( \Delta \text{BIC} \) criteria of our quasar selection, meaning that the contamination of the sample by LBGs is low at 12.5\% (1/8). The preselection reduced the galaxy number from 8 to 5. The DL selection removes another galaxy, and the \( \Delta \text{BIC} \) calculation removes 3 out of 4 galaxies passing the preselection and DL selection.

We compared the galaxy contamination rate of our selection method with a traditional high-redshift quasar selection made from a color–color diagram. High-redshift objects show a distinctive feature in color–color space due to redshifted Lyman break, and are often selected from a specific region in a color–color space (e.g., see Shim et al. 2007; Kang & Im 2009 for galaxies; Choi et al. 2012; Kim et al. 2015; Jeon et al. 2017 for quasars). N20 selected \( z \sim 5 \) quasars based on their broadband colors and point-source appearance, and noticed a possible, significant contamination of their sample by galaxies at \( M_{1450} \sim -23 \) mag. We applied the N20 color selection criteria to our point sources, finding that the galaxy contamination fraction is 3/8 (37.5\% contamination rate). This example demonstrates that our quasar selection adopting the DL and BIC statistics can lower the contamination rate of the quasar sample by compact galaxies by a few times.

The role of each selection process in selecting final quasar candidates and evaluating the suitability of its criterion is discussed further below. First, we checked the dependency of the contamination rate on the point-source selection cut in the preselection process. If a looser cut \( (i - i_{\text{Model}} < 0.3) \) was adopted instead of 0.2, we have three more galaxies (i.e., 8/8 of known galaxies in the area) as quasar candidates in the preselection process. However, after applying the DL and BIC selections, the remaining galaxy is one at \( z \sim 5.0 \), which is identical to the case of the tighter point-source cut. The contamination rate of the quasar selection process is insensitive to the choice of point-source selection if the cut is realistic enough to contain almost all of the point sources.

DL selects 4/5 galaxies satisfying the preselection criteria. This means that our DL process is not very effective in excluding \( z \sim 5 \) galaxies from the sample. On the other hand, the \( \Delta \text{BIC} \) calculation based on the best-fit result of SED-fitting could exclude 3/4 remaining galaxies in quasar candidates, suggesting its effectiveness in reducing the galaxy contamination.

To figure out the reason why the \( \Delta \text{BIC} \) calculation improves the faint quasar selection, we compared the SEDs of 9 quasars and quasar candidates (McGreer et al. 2018; Shin et al. 2020) with those of 8 LBGs (Ono et al. 2018) with \( i < 25 \) at \( 4.0 < \zspec < 6.0 \) by normalizing them to their \( i \)-band fluxes. Then, we calculated the mean SED for the quasar (QSO class) and LBG (LBG class), and the 68th percentile region of two classes for each band. In Figure 7, we show the difference between the mean SEDs of the two classes. The mean SED of the QSO sample has redder colors than that of the LBG sample due to the bluer continuum slope of LBGs than quasars at high redshift (e.g., Jiang et al. 2013). This distinctive feature could not be adequately sampled in color selections using 3–4 broadband filters, whereas our selection could extract the feature and filter out candidates whose SEDs are dissimilar to the quasar SED models.

Since the BIC is related to the \( \chi^2 \) value of the best-fit model, the absolute value of \( \Delta \text{BIC} \) decreases as the photometric uncertainties increase. Indeed, the fractions of the DL-selected candidates satisfying the \( \Delta \text{BIC} > 10 \) at \( i < 23 \) mag and \( i > 23 \) mag are \( \sim 0.19 \) and 0.05, respectively. Therefore, the exclusion of galaxies from the quasar sample through the \( \Delta \text{BIC} \) selection may be merely due to the \( \Delta \text{BIC} \) selection preferentially excluding the faint objects \( (i < 23 \text{ mag}) \) with large photometric errors. Hence, we estimated how the photometric uncertainties influence the \( \Delta \text{BIC} \) selection at fainter magnitudes.

To do so, we added the median magnitude errors of the HSC-SSP sources with \( i = 24 \) mag to DL-selected candidates with \( i < 23 \) mag, and repeated the \( \Delta \text{BIC} \) selection. Note that \( i = 24 \) mag is close to the \( i \)-band magnitude of the faintest quasar candidate. The fraction of DL-selected candidates passing the \( \Delta \text{BIC} \) selection decreases only moderately from the original 0.19 to \( \sim 0.14 \) for this noise-added sample, not as much as 0.05 in the real data. Therefore, the photometric error only partially explains the decreasing fraction of the excluded candidates through the \( \Delta \text{BIC} \) selection at fainter magnitudes. This result supports our suggestion that the \( \Delta \text{BIC} \) selection excludes high-redshift galaxies efficiently, which are expected to be more numerous among the fainter UV high-redshift galaxies.

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**Figure 7.** The \( i \)-band normalized SEDs of the galaxies at \( z \sim 5 \) (LBG) and quasars at \( z \sim 5 \) (QSO). The light red and green solid lines in the left and middle panels show the SED of each object in the QSO and LBG samples, respectively. The red and green solid lines correspond to the mean fluxes of the QSO and LBG objects. The pink thick line in the right panel represents the mean fluxes of model quasars at \( z \sim 5 \). The error bars with the solid lines indicate a 68\% range of normalized fluxes.
sources. Additional deep spectroscopy of the final candidates would validate this conclusion.

### 6.3.2. Stars and Quiescent Galaxies

Common contaminants in high-redshift quasar surveys are faint stars whose colors are similar to those of quasars (e.g., Matsuoka et al. 2019). To estimate the fraction of stars satisfying our selection criteria, we generated a mock catalog of 100,000 stars uniformly distributed in $i < 24$ based on stellar model spectra (Section 3.2.2) and scaled their SEDs to $i = 24$ mag. Their magnitude errors are assigned by randomly selecting a value from a Gaussian distribution of which standard deviations are median magnitude errors of HSC-SSP sources that have similar magnitudes to theirs. We adopted this approach because few spectroscopically confirmed faint stars ($i > 22.5$ mag) are in the Deep layer of the HSC-SSP. Among the 100,000 randomly sampled mock stars, 100,000 and 20,131 stars pass the preselection criteria (1) and (3), assuming the extendedness values of all stars are within 0.2. 3,213/20,131 stars are DL-selected candidates; however, the BIC selection finds no promising candidate in the 3,213 candidates due to their redder colors ($i - NB816, i - z, i - NB921, \text{and } i - y$) than those of quasars. As a result, the fraction of preselected faint stars passing our DL and $\Delta$BIC selection criteria is 0/20,131.

Other possible contaminants are quiescent galaxies at $0.5 < z < 1.0$ whose 4000 Å breaks can mimic the sharp Lyman breaks of quasars at $z \sim 5$ (Euclid Collaboration et al. 2019). To test how many quiescent galaxies can be selected with our selection process, we prepared a catalog of quiescent galaxies at $0.5 < z < 1.0$ from Weaver et al. (2022) in the COSMOS field, which are selected to be the objects that form red envelopes in the $r - i$ color and photometric redshift space (e.g., Im et al. 2002). In a 0.3 deg$^2$ area where the multiband HSC-SSP Deep and COSMOS fields overlap, we identified 1847 quiescent galaxies with $i \leq 24$ mag at $0.5 < z < 1.0$ within a matching radius of 1$''$.0.

These galaxies have a median $i$-band magnitude of $\sim 22$ mag. Hence, we rescaled their SEDs to $i = 24$ mag by adding the difference between $i = 24$ and their $i$-band magnitudes to their SEDs. We increased the quiescent galaxy sample size up to 100,000 by assigning photometric uncertainties to the rescaled magnitudes. The uncertainties were randomly given in the same way as the mock stars. Among the 100,000 simulated galaxies, 87,801 galaxies meet the preselection criteria (1) and (3) based on an assumption that they satisfy our point-source selection cut. Although DL classifies 538/87,801 galaxies as qso candidates, the $\Delta$BIC calculation filters out all the candidates, resulting in the fraction of preselected quiescent galaxies satisfying our DL and $\Delta$BIC selection of 0/87,801.

Given that there are 125,644 sources passing the preselection criteria, the very low contamination rates by preselected simulated stars (0/20,131) and quiescent galaxies at $0.5 < z < 1.0$ (0/87,801) imply that these two types of objects cannot significantly contaminate the quasar candidates sample. This is because photometric errors of HSC-SSP Deep data are small enough at our effective depth of $i < 24$ to accurately trace the red colors of late-type stars and detect $g$-band fluxes of quiescent galaxies at good $S/N$. When we calculated the FPR of the DL and BIC selection for qso, it was as low as 0.015%. This expected FPR is in line with the fractions calculated from the above results.

### 6.4. Comparison of DL and Color Selections

To compare the performance of the DL selection with that of the traditional color selection method, we devised three different types of color cuts (loose, best, tight) in $r - i$ versus $i - z$ (riz) and $r - i$ versus $i - y$ (riy) spaces. These cuts are guided by considering the distribution of quasar models at $z = 4.5 - 5.5$ on each color space. The loose cut represents a selection cut for maximizing the recovery rate of the quasar models (i.e., minimizing the miss rate of quasars, minimizing FNR), whereas the tight cut indicates a selection cut for minimizing contamination rate (i.e., minimizing FPR). The best cut stands for an optimal cut selecting as many quasars as possible while minimizing contaminants. Figure 8 shows these cuts, our DL-selected candidates, and 35 final candidates. As
shown in the figure, even if the loose cut is applied, two of the 35 candidates are excluded, implying that DL selection is effective in including more quasars in the candidate sample. The tight cut encloses 74% of the 35 candidates, whereas the color cuts used in N20 miss about a half of the candidates, since the cuts of N20 are tailored for quasars only at \( z = 4.7 - 5.1 \).

In Figure 9, we present the confusion matrices for the three cases of color criteria. The loose cut has the highest recovery rate of quasar models (e.g., true positive rate, TPR) among the three cases, but the contamination rate in the quasar selection is also very high (~30%). The tight cut shows a very low contamination rate in the quasar sample, but misses ~45% of quasar models. The best cut has relatively reasonable FPR and TPR; however, its FPR is ~3 times larger than that of DL selection (~0.5%), and its TPR is well below that of the DL selection (~100%). Compared to color selections, the DL selection gives a high recovery rate of quasars with a low FPR. For example, the DL method can select quasar candidates at \( z \sim 4.5 \), which is difficult to do so in the color cut method. One can loosen the color cuts to make it as inclusive as DL for quasar selection. But, this makes FPR too large (60× or more of DL), and hence selects too many contaminants that the \( \Delta \text{BIC} \) selection needs to weed out (1500 for DL versus 9000 for color cut). DL is a more complete, efficient selection method than the traditional color selections. A shortcoming of DL is that it cannot account for the difference between the absolute number of \( n_{qso} \) and \( qso \), but this can be augmented with an additional selection procedure such as the \( \Delta \text{BIC} \) calculation.

7. Summary

To construct a quasar LF at \( z \sim 5 \), we selected quasars using a new technique that combines the DL and \( \Delta \text{BIC} \) selections. Quasars were chosen from the Deep layer of the HSC-SSP imaging survey covering 15.5 deg\(^2\).

We found that our selection outperforms the traditional selection methods based on color cuts, sampling more quasars at a wider redshift range while minimizing contamination from LBGs. The former advantage was made possible by DL with its flexible color criteria. The latter merit was achieved through the \( \Delta \text{BIC} \) selection that enabled us to distinguish quasar SEDs from bluer SEDs of LBGs. Compared to the color selection of N20, we achieved three times less contamination rate by galaxies at \( z \sim 5 \). Our selection process recovered most of the confirmed quasars as well.

Thanks to our selection, we constructed a \( z \sim 5 \) quasar LF reaching \( M_{1450} \sim -22.0 \) mag, about 1 mag deeper than previous LFs. The overall shape of the LF is similar to LFs in recent works at \( z \sim 5 \) (N20; K20) down to \( M_{1450} \sim -24.0 \) mag, indicating a flatter faint-end slope of \( \alpha = -1.60^{+0.23}_{-0.19} \) than some previous studies (McGreer et al. 2018; Kulkarni et al. 2019). We even tried to estimate the LF at \( z = 22 \) to \( -21 \) mag. Knowing that the faintest quasar sample could be contaminated by LBGs significantly (about 10% or more of LBGs classified as quasars), the LF at the faintest bins agrees with the flatter faint-end slope. These results suggest that quasars—AGNs with point-like appearance—are not contributing significantly to the IGM ionization.

In this paper, we demonstrated the feasibility of our selection and the importance of attempting a novel and efficient approach to select promising quasar candidates from numerous faint objects. Future spectroscopic observations of our final quasar candidates will confirm the validity of our method, and adding multiwavelength data would help select high-redshift quasars more reliably.

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