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Galaxy Luminosity Function

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ABSTRACT

Context. This project is designed to show fittings for the galaxy luminosity function at z≃6, as well as to explain possible uncertainties and approximation.
Aims. The primary goal was to make sure that previous observations made by Bowler et al. (2014) and Bouwens et al. (2007) were correctly fitted, and to determine the function that would best fit the data collected by both papers.
Methods. In order to analyze and assess the validity of the data that was presented in the papers written by R. Bouwens and R. Bowler,we utilized various plots and Python functions.
Results. Through the use of MCMC and various best fit functions we were able to accurately replicate the data and figures found in the two papers we drew our research from.
Conclusions. The data presented in the papers written by Bowler and Bouwens can be reliably replicated through the use of plotting and best fit functions.

Key words. luminosity function, magnitude, parameters, double power law function, Schechter function

1. Introduction

The luminosity function which is a means of describing the density of a galaxy as a function of it's brightness is often used in order to show how populous a galaxy can be. The total number density of galaxies, n , and the luminosity density ρ were found to be,

$$n(M) = \int_{M'<M} \phi(M')dM' \tag{1}$$

$$\rho(M) \propto \int_{M'<M} 10^{-0.4M'}\phi(M')dM' \tag{2}$$

The papers written by R. Bowler and R. Bouwens present several figures which represent the luminosity function of several galaxies at red-shift z≃6. The luminosity function (LF) provides insight into star formation rates in galaxies, notably ones at UV wavelengths. The observational work and data produced by Bouwens et al. is widely supported for galaxies at the bright-end of the LF at high red-shift. It presents the conclusion that the Schechter function is a good fit for rest-frame UV LFs at -23 AB mag to -16 AB mag (Bouwens et al. 2007). The Bowler et al. paper expands on this by collecting data on a larger number of galaxies, and concluding that the Schechter function and Double Power Law (DPL) fit the resulting data equally well. Our project attempts to fit both functions to data observed by both papers, including bright-end and faint-end galaxy luminosity measurements. We start by detailing our approach to replicating the models and fittings determined by Bowler et al. using Python packages. In the results section, we present our findings and the corner plots produced by our program. Finally, we summarize our results and conclude that the conclusion drawn by Bowler et al. that both functions fit the data equally as well is well founded.

2. Methods

In order to verify that the figures presented are accurate and can be reproduced we need to utilize the initial data found in table 1 of the Bowler paper and i-dropouts from table 4 from the Bouwens paper. To plot the data we created a Python program to visualize the fits. Our first step was to import various python libraries as well as the emcee and corner functions. Next, we imported the data which can be done by either creating an array or importing the necessary data from a separate text file. We chose the latter option after being advised that it would provide us with more flexibility in maintaining the data format across multiple notebooks. Afterwords, we plotted the data in order to get an initial idea of what the data in the table is portraying. We were able to use the sample Schechter parameters provided by Table 5 in the Bowler paper in order to verify that the function we defined didn't have any errors. Once our functions were inputted properly, we used the following parameters to describe various elements of the galaxies described in the given data. One of the main challenges was to plot emcee and mcmc graphs in appropriate ways. Since our sample

Table 1. Bowler et al. data

$M_{U,V}/mag$	$\phi/mag/Mpc^3$
22.52	$1.16 \pm 0.67 \times 10^{-6}$
22.08	$5.98 \pm 1.64 \times 10^{-6}$
21.74	$1.90 \pm 0.41 \times 10^{-5}$
21.49	$3.92 \pm 0.70 \times 10^{-5}$
21.22	$9.14 \pm 1.39 \times 10^{-5}$

Table 2. Bouwens et al. data

$M_{U,V}/mag$	$\phi/mag/Mpc^3$
22.13	0.00054 ±0.00012
19.63	0.000832 ±0.00018
18.88	0.00197 ±0.00041
17.88	0.00535 ±0.00117

size is not as big as we want it to be. We chose to use chisqr diagram because we found it to be the most reasonable solution. During whole project we have been trying to build our own simulation to verify results that were taken from Bouwens and Bowler papers.

α Faint end slope
β Slope of bright end of luminosity function
ϕ number density
M magnitude

The Schechter function is defined as:

$$\Phi(M) = 0.4ln10\Phi^*[10^{-0.4(M-M^*)}]^{1+\alpha}e^{-10^{-0.4(M-M^*)}} \tag{3}$$

The Double Power-Law is defined as:

$$\Phi(M) = \frac{\Phi^*}{10^{0.4(\alpha+1)(M-M^*)}+10^{0.4(\beta+1)(M-M^*)}} \tag{4}$$

3. Results

Through our efforts in our Python notebook, we were able to accurately sample both the schechter function and double power law using mcmc and create corner plots for them through the corner library. This allowed us to identify which function is better at fitting the data as well as how much uncertainty was present for each of them. Figure 1 shows the results of putting both functions through mcmc with 30 walkers and 10000 steps each. A "burn-in run" of 4000 steps was first introduced which effectively erased the starting points of each of the parameters and forced them to start the actual run at a random spot. These two figures show the plots of each parameter as a function of the step size. Each of the many colors in the plots are a different walker with a different randomized path. The schechter function ran smoothly, but the double power law had some inconsistencies. Seen in the Φ^* and M^* one of the walkers took a highly exaggerated path unlike the others. This could have contributed to some of the uncertainty shown in the corner plots of Figure 2. Figure 2 was produced by using the corner functions of the corner library in Python. These diagonal plots on the corner plots are histograms of each of the parameters, while the other plots are 2D projections of each parameter against another. The corner plot for the schechter function is as expected, while there is some uncertainty as shown in the projection plots, it is not an unusual amount and is no cause for concern. The figures are centered meaning that most of the samples are within an acceptable range. As for the double power law, there is a much larger amount of inconsistency. There is a much larger amount of inconsistency, close to 10% on β. The projections also show a lot of uncertainty. The figures themselves are not centered and are typically hugging the sides which indicates a lot of uncertainty. This corner plot definitively shows that the schechter function is more accurate in fitting the data points that were collected in Bowler and Bouwens. Figure 3 shows three random samples from both the schechter function and the double power law from mcmc. While each of these fitted functions are close to fitting all the points accurately, none of them are perfect. The schechter function is able to fit both sets of data more accurately, especially towards the beginning and the end, while the double power law seems to be consistently missing the first and last points. While these are only three of thirty samples from each, they are still able to accurately show that the schechter function is better at fitting these data points.

4. Conclusions

At the beginning of the experiment the objective was to ensure the validity of the figures by using various Python techniques to replicate the results. Once these plots were successfully replicated with minor adjustments. It became apparent that the results provided in the papers could be replicated and were therefore valid. Through the use of the emcee and corner functions that were able to be utilized in a Python notebook, we were able to import the data, apply the necessary steps, plot the functions and then finally replicate Figure 9 of the Bowler paper. We knew that some of our methods have some assumptions and may cause greater errors. Still, we chose these methods because we think that it was the most efficient ways of doing it. From our previous experience with the practicals and some light research regarding various aspects that required modifying in order to properly display the figures at each step of the process to get the final result. While difficult, our figure depicting the two best fit models (Schechter and Double Power Law) looked fairly similar to what the earlier predictions, which were solidified as we plotted them individually before plotting them together. It is important to say that some of our graphs were scaled as a function of log(x). As a result, all errors are greater than it seems to be. Furthermore, by replicating these figures we were able to verify that both functions are equally good fits for the data. Because we were able to plot the best possible fit models successfully the project was fairly successful. To minimize errors more data must be collected and analyzed.

5. Figures

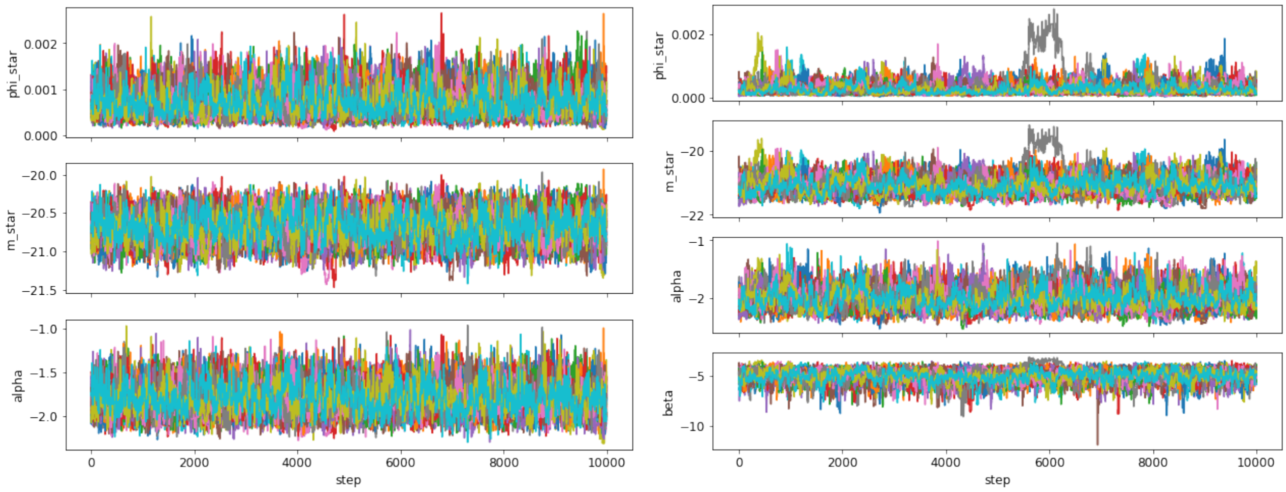

Fig. 1. 30 Random Walkers for the Schechter Function and the Double Power Law

Figure 3

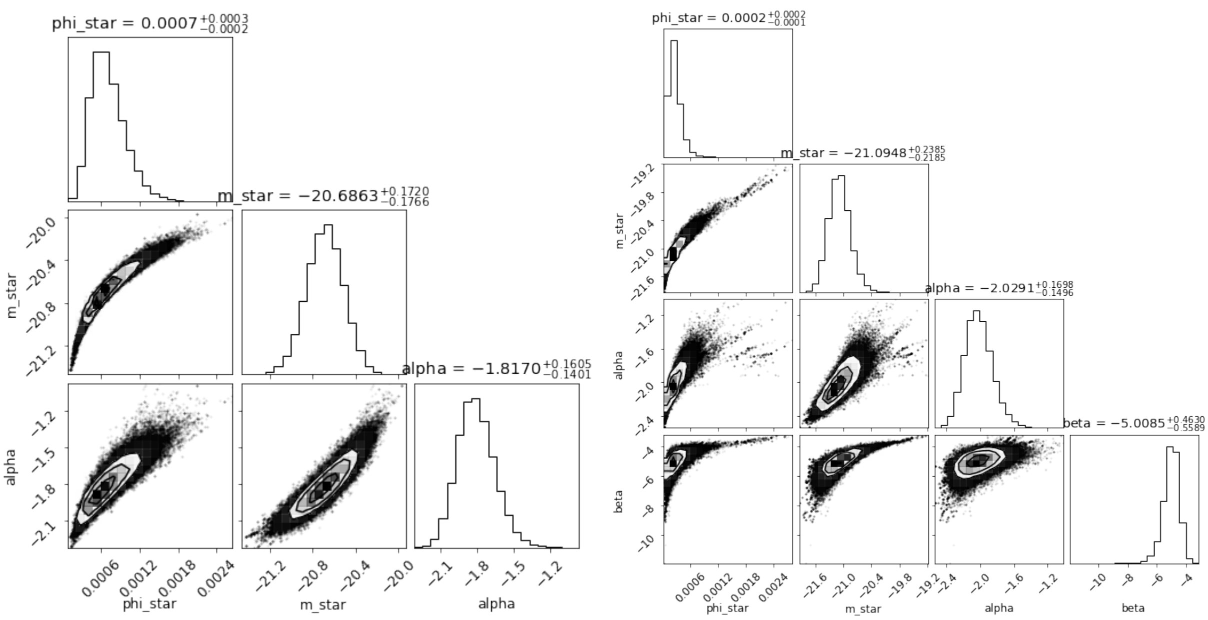

Fig. 2. Corner Plots for the Schechter Function and the Double Power Law

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2. Bouwens, R. J. et al. "UV Luminosity Functions at z0.5ex~4, 5, and 6 from the Hubble Ultra Deep Field and Other Deep Hubble Space Telescope ACS Fields: Evolution and Star Formation History". ApJ670. 2(2007): 928-958.

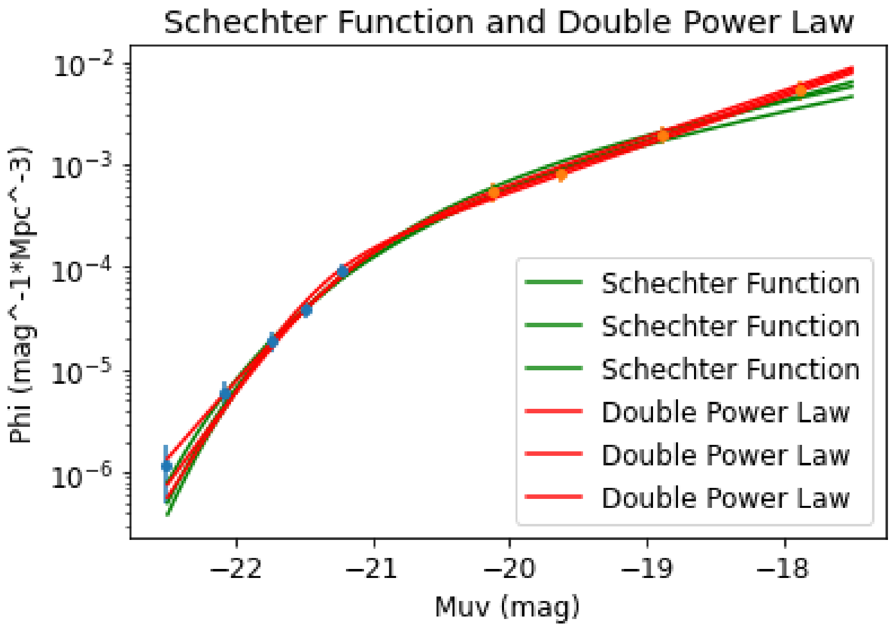

Fig. 3. Three Randomly Generated Samples Fitting Both Functions