Gravitational Microlensing

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Abstract

With the use of data collected by the Optical Gravitational Lensing Experiment (OGLE) team, our team's goal was to analyze their data with the Paczynski Light Curve model, and see what kind of model, blending or unblending, most accurately matched OGLE's model. From OGLE's Phase IV, we chose three microlensing events and found that the unblended model, although it matched the overall shape and had rough approximations for the parameters, did not perfectly match OGLE's model. However, by optimizing blending in our Paczynski Light Curve model, our results were within OGLE's margin of error.

1 Introduction

When an object passes in front of a star, an object that emits light, the gravity of the object that is passing by makes the light of the star behind it bend and focus. As an observer, we see a period of time in which the star appears to have brightened and dimmed again. This is called gravitational microlensing [Bre12].

Our team took data that was collected by the Optical Gravitational Lensing Experiment (OGLE) in 2019 and analyzed it with our own model based on the Paczynski Light Curve model [Pac86], to find and learn about the various parameters that come with gravitational microlensing. Of the thousands of data and stars that this project observed, our group chose three events from OGLE Phase IV to analyze - two observations that have concluded and one that is still ongoing by the OGLE team.

The main goal of this project was to find out whether or not the model we fit for OGLE's data matched the model OGLE published, and to determine whether optimizing the events for blending made a more accurate depiction of the microlensing events as opposed to not blending. Furthermore, by analyzing the changes in brightness, we were able to find the minimum distance between the lens and the star in the plane of the sky, and the blending fraction (how much of the microlensing brightness was from the source and how much was from other nearby sources).

2 Data

The data that was used in this analysis was collected from the OGLE-IV project. The OGLE (Optical Gravitational Lensing Experiment) project website has a database of microlensing events from 2019 [PSU+20]. OGLE-IV (the fourth phase of OGLE) is one of the largest sky variability surveys which targets the densest stellar regions of the sky (the main targets are the inner Galactic Bulge and the Magellanic System).

We picked the following three microlensing events (shown in Figure 1):

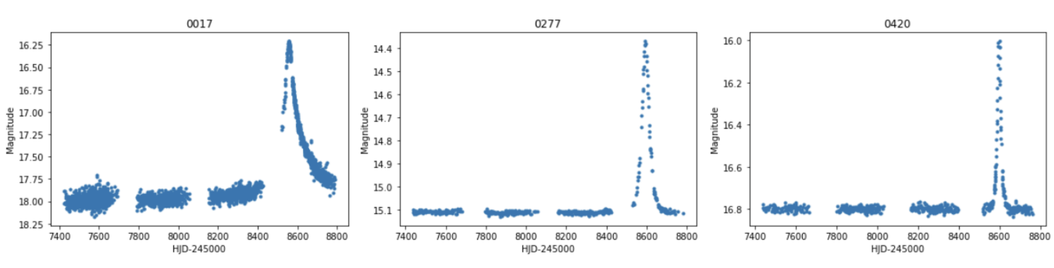

Figure 1: OGLE-2019-BLG-0017, OGLE-2019-BLG-0277, and OGLE-2019-BLG-0420

The 0017 event in Figure 1 was in Field BLG504.27, the measured star is Star Number 72160, and T_{max} is 2019-03-15.23 UT. The 0277 event in Figure 1 was in Field BLG648.24, the measured star is Star Number 19052, and T_{max} is 2019-01-28.62 UT. The 0420 event in Figure 1 was in Field BLG612.06, the measured star is Star Number 376, and T_{max} is 2019-04-23.53 UT.

In these figures, the x-axis measures time, the y-axis measures the magnitude, and the data points themselves represent a measure of brightness as a function of time.

We picked these specific microlensing events because they had a lot of data points while some other events had very few points, they all had a nice visible curve which would allow us to fit the model well, and the data from all three events did not look identical and had variations.

3 Methods

We used a point source Paczynski light curve model[Pac86] to describe our microlensing events. We used two variations of this model, one without taking blending into account, and one with taking blending into consideration. In both these models, we define the parameter u, which is the angular separation of the lens and the light source. We define this u in the following manner

$$u(t) = \sqrt{u_{min}^2 + \left(\frac{t - t_0}{t_E}\right)^2}$$

where u_{min} is the minimum angular seperation between the lens and the source, t_0 is the time of this minimum seperaton, and t_E is the Einstein time - the time needed for the lens to travel one Einstein radius relative to the source. We then define a scale factor, $A(t)$, which gives us the magnification of the light during the lensing event. This parameter is defined differently in our two models in the following way:

Non-blended model	Blended model
$A(t) = \frac{u^2+2}{u\sqrt{u^2+4}}$	$A(t) = f_{bl}\left(\frac{u^2+2}{u\sqrt{u^2+4}} - 1\right) + 1$

Note that the blended model is a generalization of the non-blended model. In other words, the non-blended model is just the blended model with $f_{bl} = 1$. f_{bl} is our blending ratio - the fraction of the lens light to total light. A ratio of 1 indicates that there is no background light being blended in with the light from our source. Lastly, we define our observed intensity, $m(t)_{mod}$ where mod is short for model. In both cases, we define m_{mod} as:

$$m_{mod}(t) = m_{bl} - 2.5\log_{10}(A(t))$$

m_{bl} here is the baseline intensity - the observed intensity under a magnification of 1.

To determine these various parameters, we defined a χ^2 function that returns the summed error-squared between our modeled intensity and the observed intensity. Then, we numerically found the optimized values to minimize the function. To note: we had to use different numerical methods between the two models as the blending model required strict boundaries on f_{bl}. Additionally, we required some guess starting parameters for both optimizations. For the non-blending model, we used simple guesses based on the scatter plots of the data. For the blending model, we used the values obtained from the non-blending model and set $f_{bl} = 1$ as our guess. Lastly, we used a Markov Chain Monte Carlo (MCMC) simulation on the parameter spaces for both models to analyse the errors on our estimates.

For the non-blended model, we optimized our χ^2 functions again using the parameters obtained from MCMC as starting guesses.

4 Results

As described in 3 we used a χ^2 minimization technique and MCMC analysis to fit the parameters each data set to two Paczynski models. Our first attempt assumed that there was no blending in the image and that all increases in brightness were a result solely of the microlensing event, i.e $f_{bl} = 1$. This was a fairly successful first attempt as were able to use this to match the shape and determine very rough approximations for our parameters that were close, but did not exactly match OGLE's results. The most egregious example of this comes in the case of event 0017 where two of the four parameters are orders of magnitude off of OGLE's results. The results of the non-blended model are summarized in Table 1.

After completing our non-blended model we wanted to try add a little more complexity to see if we would get results that matched OGLE's model. We did this by considering f_{bl} as another parameter to be fit to. We repeated the process outlined 3 but with this extra parameter. The results of blended Paczynski model are expressed in Table 2. Our blended model is plotted on top of the dataset of each event and compared to OGLE's version in Figure 2. As shown in Table 2 and evidenced by Figure 2, our blended model matches the OGLE's model very well and so we conclude that our results match those of OGLE.

Despite our best efforts, even with the blended model, we were unable to significantly determine the uncertainty in the fit of our model to OGLE's data. This is elaborated on a bit further in 5.

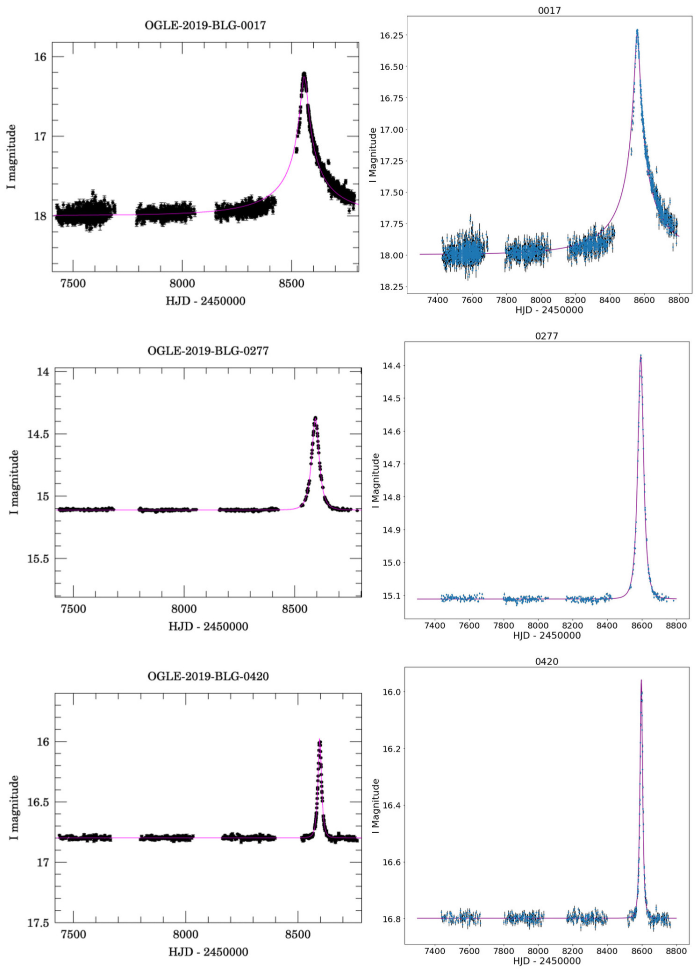

Figure 2: In this figure, the left column represents the OGLE's fitting for each of the three events we analyzed. The right column is our own attempt. Although numerically identical, the plots take on different aesthetic characteristics because it seems that OGLE ignored large earlier times before the event in question (such as in events 0277 and 0420). Despite these differences, because we used the full suite of data for each event provided by OGLE, our plotted points are identical. The purple line shown in each panel is an attempt at modelling the light curve from each data set. On the left, OGLE's model is represented and our attempt on the right. Our plots use a blended model as discussed in 3, the main body of 4, and Table 2.

Parameters↓ Event→	0017	0277	0420	OGLE 0017	OGLE 0277	OGLE 0420
u_{min}	0.221	0.565	0.504	0.36	0.565	0.503
t_E [days]	110.381	26.958	12.989	421.250	26.595	12.989
t_0 [HJD - 2450000]	8555.296	8593.624	8597.027	85557.734	8593.624	8597.030
m_{bl}	17.962	15.112	16.795	17.998	15.112	16.799

Table 1: Expressed in this table are our fitted parameters for each event. Importantly, we fitted each data set to the simplest Paczynski light curve model which does not account for blending. In other words, f_{bl} is assumed to be 1 for all cases. Interestingly, events 0277 and 0420 do fit to a f_{bl} = 1 however with nearly identical values to those in the blending model that can be viewed on Table 2. Our results that do not consider blending are decent for replicating the results OGLE produced. The general shape and trends of our fitted match OGLE's but our actual fitted parameters can differ substantially, such as in the 0017 event, or make relatively little differences such as some parameters in the 0420 event.

Parameters[Blended]↓ Event→	0017	0277	0420	OGLE 0017	OGLE 0277	OGLE 0420
u_{min}	0.036	0.565	0.503	0.036	0.565	0.503
t_E [days]	421.242	26.959	12.989	421.250	26.595	12.989
t_0 [HJD - 2450000]	8557.734	8593.624	8597.030	85557.734	8593.624	8597.030
m_{bl}	17.998	15.112	16.799	17.998	15.112	16.799
f_{bl}	0.152	1.0	1.0	0.152	1.0	1.0

Table 2: Expressed in this table are our fitted parameters for a simple Paczynski light curve model including blending. With this our results match OGLE's very nicely. All of our fitted parameters are within OGLE's margin of error, and all of OGLE's results are within our margin of error. It is interesting to note that events 0277 and 0420 ended up fitting to $f_{bl} = 1.0$ regardless, but the slightly more complex model yielded more accurate results for these events than the unblended model as shown in Table 1.

5 Error Analysis

As we were fitting our model to the data we also wanted to have some kind of estimation for how well our parameters fit for both models on each event. We had intended to do this using MCMC as mentioned several times throughout this paper. While we were successful in generating some kind of estimation, the values that we received from our MCMC analysis were not always reliable. A typical example of this is how several of the median values listed on the titles of the subpanels in 3 do not match the optimized values listed in Tables 1 or 2 from whence they came. Despite our best efforts we were unable to get MCMC to yield reasonable results, however we are still able to remark on some interesting aspects of our failed error analysis. The top row of Figure 3 contains panels that represent our unblended analysis and they all yield beautiful distributions despite the fact that the median values are often quite significantly different than the optimized guesses summarized in Table 1. Further, the reverse is true on the bottom row representing the blended model. Despite these corner plots showing a very unlikable distribution of parameters, the median values on the titles are a much better match to Table 2 than the top row is to Table 1.Future work on this subject would entail developing a more comprehensive error analysis for this kind of fitting.

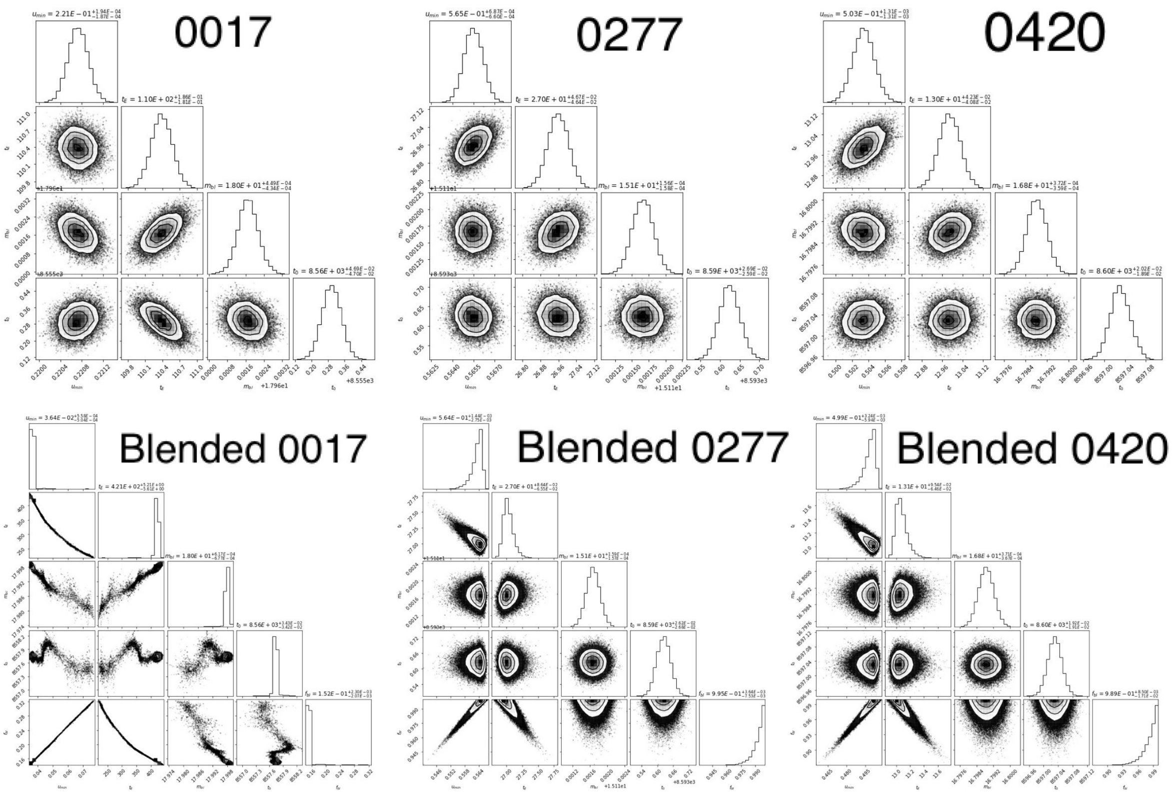

Figure 3: This figure contains information about our MCMC analysis for parameter uncertainty represented by corner [FM16] plots. The top row shows our MCMC results from our unblended model while the bottom row shows the results of the blended one. The titles of each subpanel show the median estimation calculated by MCMC and the 0.68 confidence on either end of that. Interestingly the parameter distributions in the top row are but more ordered despite the reported parameter being quite different than then our optimized value reported in Table 1. In the same way, the parameter distributions on the bottom row are much less ordered but the medians in the titles of the subpanels also tend be reasonable to compare to the optimized parameters reported in Table 2

6 Conclusions

With the use of the data from the OGLE Phase IV project, our team was able to make our own model based off of the Paczynski Light Curve Model. We made two different models for every event we looked at, an unblended model and a blended model, and compared them to OGLE's model to see which one more accurately represented the data. We found that optimizing the Paczynski's model for blending most directly matched the model that OGLE came up with, allowing us to conclude that the light observed during microlensing events are not only entirely from the source star, but also from other sources around the lens.

There are some limitations with this model. For instance, we are unable to find the mass of the lens in front of the star because we are missing information about the distances between us and the lens, between us and the star, and between the lens and the star - all information you need to calculate how massive the lens is.

Another limitation we came across was our inability to find the error in the blended model. This seems to be because the MCMC analysis was unsuccessful in our code even though our blended model reflected OGLE's.

Because the model we found did not hold much quantitative data such as the mass of the lens, a follow up to this experiment would be to find the missing information we would need, like the distances between the lens, the star, and us, to calculate the mass of the lens in these events.

References

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