Debiasing the Dark Energy Survey's Search for Trans-Neptunian Objects

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I. INTRODUCTION

Over the course of the past decade, several large-scale astronomical surveys have attempted to characterize the outer Solar System. These efforts have resulted in the detection of over 1000 objects, whose semi-major axes are larger than that of Neptune. The objects in this classification are aptly named trans-Neptunian objects (TNOs). As we have continued to detect TNOs, we have gained some insight as to the structure of the Solar System beyond Neptune. A particularly interesting feature of this structure is the apparent clustering of several TNOs with relatively large semi-major axes. This clustering was the initial motivation behind the planet 9 hypothesis.[1] Recently, the Outer Solar System Origins Survey (OSSOS) team has challenged the significance of the clustering of these objects, arguing that the extreme TNOs they characterize in their survey are consistent with a uniform underlying population.[2] This argument has sparked an interesting debate about the effects of survey bias in the detection of such TNOs.

II. MOTIVATION

Astronomical surveys have intrinsic bias. That is, the likelihood that a survey will detect a given object varies based on many factors. These factors include the sensitivity of the instrument taking the measurements, the conditions under which the measurements were taken, and the cadence and location of telescope pointings. Understanding the intrinsic biases of a survey allows us to quantify the extent to which the TNO clustering that we see is physically significant. Thus, in order to properly interpret the results of any survey, it is important to characterize a survey's selection function. Doing so allows us to determine the true probability density function (PDF) of finding objects with particular orbital parameters. With this work, we add the voice of the Dark Energy Survey (DES) to the discussion of the significance of the clustering of TNOs.

The OSSOS team was the first TNO search team to properly characterize the selection function for their survey. While they claim that their results are indicative of a uniform underlying population of TNOs, it should be noted that their survey covered only 170 deg^2 on the sky. Thus, their conclusion is not as rigorous as would be a similar conclusion from DES, a 5000 deg^2 survey.

III. THE SURVEY SIMULATOR

To properly quantify the bias of our survey, we developed a survey simulator in Python. The simulator is self-contained, meaning that it is capable of performing all aspects of the debiasing process. We describe each step in detail in the remainder of this section.

A. Calculation of Limiting Magnitudes

The first function of our survey simulator is to calculate the limiting magnitude for each exposure taken over the course of the survey. To calculate these values, we use magnitude 20 (mag20) fake objects and supernova fakes embedded in DES imaging. All of the aforementioned fakes have gone through the DES difference imaging pipeline, `DiffImg`. We have data of the signal-to-noise ratio (SNR) for both the mag20 fakes and the supernova fakes. The SNR is simply the ratio of an object's flux to the error in the flux. Additionally, we have the limiting magnitudes of the supernova fakes. We use the relationship between flux and magnitude to empirically derive a relationship between SNR and limiting magnitude in each exposure. To do this, we fit a functional form of a second-order polynomial to the limiting magnitude of the supernova fakes, versus the log of their SNRs. We then plug the SNR of our mag20 fakes into our empirically derived equation, giving us the limiting magnitude for each fake in an exposure. We consider the limiting magnitude of the exposure to be the median of the limiting magnitudes of the fakes. Thus far we have only performed these computations on the narrow part of Stripe 82, as a proof of concept.

B. TNO Clone Generation

The next major function of our simulator is to generate clones of detected TNOs. We do this by passing the simulator the TNO's semimajor axis, eccentricity, inclination, and absolute magnitude. Each clone has the same value in these parameters as the original object. We generate clones uniformly distributed in the angular orbital elements Ω and ω, as well as mean anomaly. We impose the condition that the mean anomaly is constrained such that the object's apparent magnitude is ≤ 25. This ensures that we are not wasting computation resources by generating clones, whose absolute magnitude would not

[1] Batygin, K., Brown, M. E. 2016, ApJ, 151, 22.
[2] Shankman, C., Kavelaars, J., Bannister, M. T., et al. 2017, AJ, 154, 2.

allow them to be detected by DECam with any reasonable probability. Ω and ω can take on any integer value that divides 360. This corresponds to a resolution parameter of our simulations. In this paper, we make Ω and ω integer multiples of 6. We demonstrate the functionality of our simulator by using it on one of the OSSOS team's TNOs, 2013GP_136. We show the initial distribution of angular orbital elements in Figure 1.

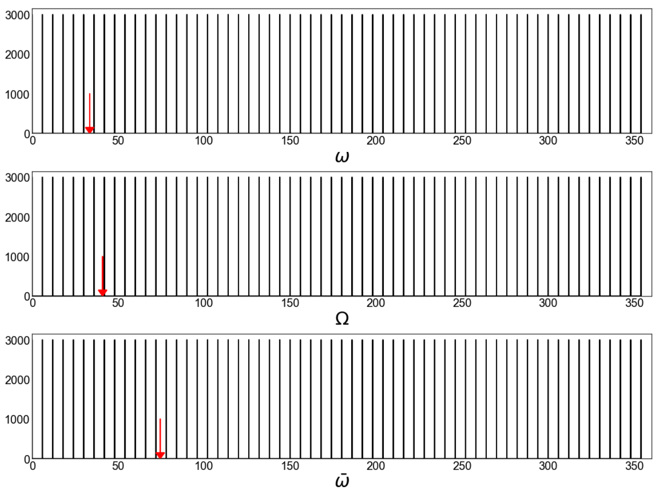

FIG. 1. The initial distribution of the angular orbital elements Ω, ω, and $\bar{\omega}$ ($\bar{\omega} = \Omega + \omega$) of our clones of the OSSOS team's TNO 2013GP_136. The red arrows indicate 2013GP_136's actual values.

C. Determining Which Clones are in Exposures

Once we have generated the clones, we need to determine which exposures each clone would have appeared in over the course of DES. This effectively makes a cut based on the geometry of our survey. That is, we determine the frequency with which a clone characterized by each value of our angular orbital elements falls within DECam's field of view. Since this quickly becomes computationally challenging, we first simplify the problem by imposing a limit that an object of interest will move no more than about 3 degrees on the sky over the 5-year span of DES. We accomplished this by building a k-d tree of all of the science exposures taken during DES and querying the tree for a list of exposures whose centers were separated from each candidate's right ascension and declination (calculated at some date in the middle of the survey) by at most 1.9 degrees. We chose a cut of 1.9 degrees because DECam has a 2.2 degree field of view. The 1.9 degree separation from the object, combined with the 1.1 degree radius of DECam, results in a 3 degree tolerance. Once we have narrowed down the possible exposures that each object could have appeared in, we recalculate the object's right ascension and declination at the date of the exposure. We then check to see if the object's position on the date of the exposure corresponds to it falling on one of DECam's CCDs. In Figure 2 we show the distribution of angular orbital elements that fell on at least one CCD.

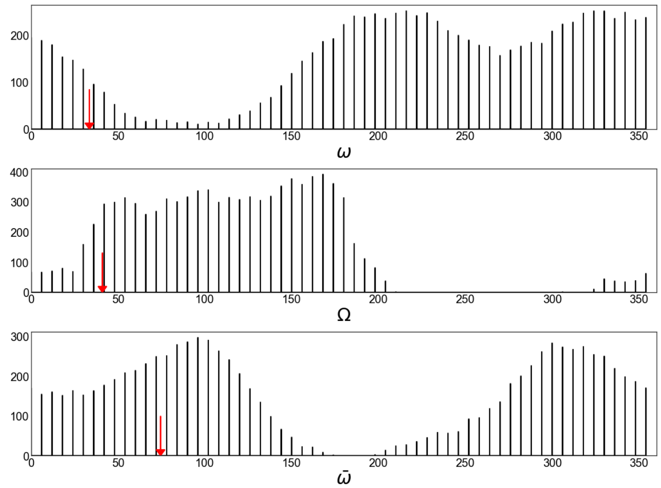

FIG. 2. Distribution of angular orbital elements corresponding to clones of 2013GP_136 that appeared in DES at least once.

D. Application of Magnitude Cuts

Since we only computed limiting magnitudes of exposures in the narrow part of Stripe 82, we cannot compute detection probabilities for any exposures outside of this region. As a result, the remainder of our computations will only consider the narrow part of Stripe 82. That being said, the simulator is fully generalized. This means that it is capable of computing as much of the survey as computational resources allow.

The natural way to apply cuts based on apparent magnitude is to take a probabilistic approach. To elaborate, we assume that our detection probability takes on some functional form, with the object's apparent magnitude as an independent parameter. We begin by binning our mag20 fakes in terms of SNR. We then apply the same binning parameter to the set of all mag20 fakes, which includes those that we cut out of our initial sample. Next we convert SNR to magnitude using the relationship we defined previously. Finally, we fit a hyperbolic tangent function to our data. We show this result in Figure 3. This hyperbolic tangent function gives us our probability of detecting an object of a given magnitude. We employ this by calculating the detection probability of each object that fell on at least one CCD over the course of DES. We then generate a random number between 0 and 1 and compare it to the detection probability. If and only if the random number is less than the detection probability of the object, we consider that object to be a detection. It is apparent that given many clones, we will begin to fill in the area beneath the curve with data points. This model is an accurate reflection of reality, as we have a high probability of detecting bright objects, and the probability lessens as we tend to fainter objects. In Figure 4, we show the distribution of the angular orbital elements of the clones that survived our magnitude cut.

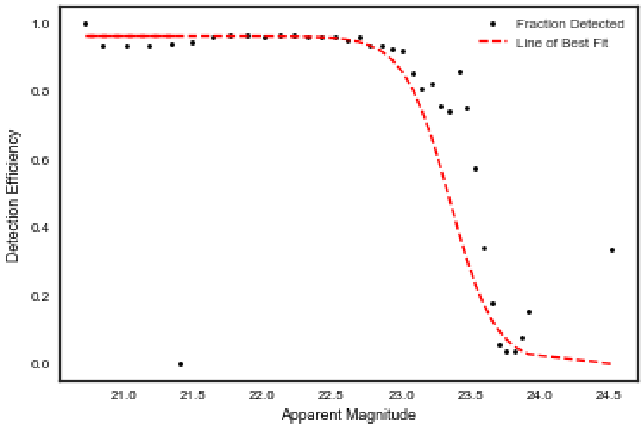

FIG. 3. Detection fractions in each of our apparent magnitude bins, overplotted with our best-fitting hyperbolic tangent function.

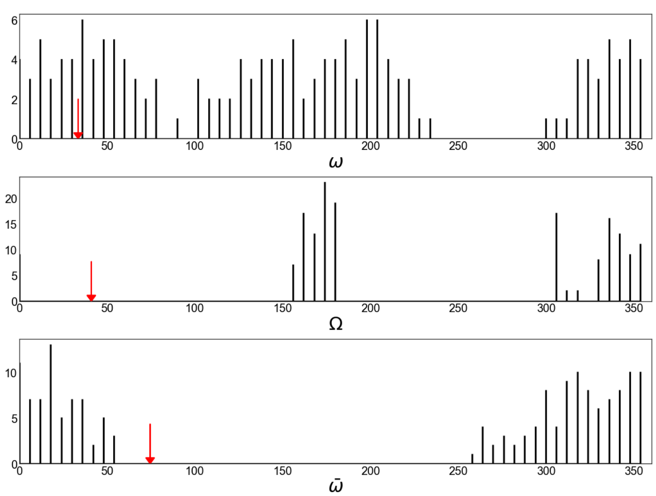

FIG. 4. Distribution of angular orbital elements corresponding to clones of 2013GP_136 that appear in DES at least once and survive our magnitude cut.

IV. CONCLUSIONS AND FUTURE WORK

Our results in Figure 4 are consistent with our expectations for running the simulator on a small portion of the sky. We expect our histogram to become more diversely populated as we simulate a larger fraction of DES. Additionally, a relatively small number of clones made it through our magnitude cut. In order to compensate for this, we have generated more clones by taking our angular resolution to 2 degrees (not shown in this paper).

While our survey simulator is currently in working condition, we still need to make some improvements. The most apparent task is to implement different color models when generating clones. To elaborate, we are currently generating our clones with no particular color model, assuming a g-band color when calculating detection limits. By testing on clones in each of the g, r, i, and z color bands, we can build a more accurate and sophisticated picture of our survey's bias. Pertinent to the implementation of a color model, we need to fit the hyperbolic tangent function to the detection efficiencies for r, i, and z-band exposures. Stephanie Hamilton, a graduate student in the TNO group, is in the process of making these improvements and running the simulator over the entirety of DES. While it is computationally intensive to run the simulator over the entirety of the survey, the result will reliably quantify our detection bias, allowing for more certainty regarding the statistical significance of the clustering of TNOs.

ACKNOWLEDGMENTS

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