Assessing the detectability of exoplanets in the Magellanic Clouds

1. Introduction

One of the key questions in astrophysics today is whether different stellar populations host different planet populations. With the K2, and TESS and WFIRST surveys it may be possible to detect exoplanets outside the thin disk of the galaxy and explore the population of planets in the galactic bulge, thick disk and possibly even the Halo of the Milky Way. We propose to search for extra-Solar planets outside the Milky Way *entirely*: in the Large and Small Magellanic clouds. Although some exoplanet surveys have targeted planet populations outside the Solar neighborhood (for example the galactic bulge and the globular cluster 47 Tuc), no survey has successfully detected extrasolar planets in a stellar population as dramatically different from the thin disk of the Milky Way as those Magellanic clouds. Given its ability to perform exquisite photometry, the Dark Energy Camera (DECam) may provide an opportunity to search for extragalactic exoplanets. We propose to target the Magellanic clouds, both Large and Small, in a high cadence photometric survey, aiming to detect the first extragalactic exoplanet and to provide constraints on the population of giant planets, brown dwarfs and small stars in dwarf galaxy environments. In order to assess the feasibility of this study, we simulated light curves with realistic white noise properties and cadence. These simulations indicate that we may be able to detect inflated hot Jupiters orbiting Sun like stars. The first detection of even a single extragalactic planet would be a significant milestone for the field of exoplanets and a huge step forward in exoplanet research. With the detection of one or more giant planets and a planet detection pipeline with well understood completeness properties, it may be possible to place constraints on the *occurrence rates* of hot Jupiters in the Large and Small Magellanic clouds and thus, characterize the efficacy of planet formation in these radically different stellar populations.

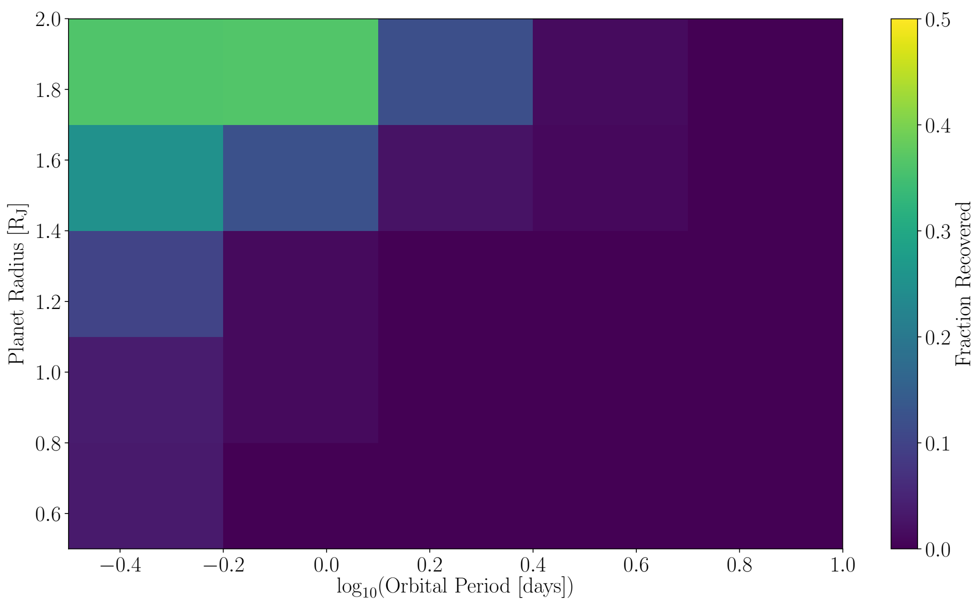
2. Method

We tested the potential for finding extra-galactic planets and small stars in this survey by simulating light curves with a cadence of five minutes and a white noise amplitude of 5.3%, estimated using the DECam exposure time calculator. We assumed that observations would take place continuously over 6 hours per night, for 9 nights. We generated transit signals for planets with a range of randomly generated radii and orbital periods, all orbiting Sun-like stars. The orbital periods of these planets ranged from around 8 hours to 10 days and the planet sizes ranged from 0.5 to 2 times the radius of Jupiter. 2000 Exoplanet transit signals were generated using the `batman` code (Kreidberg 2015), and injected into a set of 2000 simulated light curves.

In order to detect the planets in our simulated data set we used the box-least-squares, *BLS*, algorithm built into `astropy` (Astropy Collaboration et al. 2013). This algorithm fits an upside-down tophat, or 'box' function, approximating the shape of an exoplanet transit, to a light curve over a grid of orbital periods, transit epochs and transit durations. It reports the log-likelihood ($-1/2\chi^2$) of the light curve data, at each value of orbital period, transit epoch and duration. In high signal-to-noise cases the log-likelihood is greatest at the period of the injected transit. However, when the transit depth is small compared to the white noise in the light curve, and/or when its orbital period is long, the log-likelihood may not necessarily have a significant peak at the true period. When attempting to detect planet transits in our simulated light curves, we required that the maximum BLS log-likelihood was greater than 15 (this threshold was established from simulated light curves with *no* injected exoplanet transit). If a light curve met this criterion, we measured the difference between the maximum-likelihood period and the true orbital period of the planet and, if the difference was less than 10% of the period we injected, we classed that as a 'successful' planet detection. Figure 1 shows a completeness map of planet detectability as a function of injected radius and orbital period. The color of each grid rectangle represents the fraction of planets that were successfully recovered within that radius and period range. The fraction of detected planets increases with increasing planet size and decreasing orbital period due. In this experiment we successfully detected 113 out of the 2000 injected planets, preferentially recovering the larger planets on shorter orbital periods. This gives an overall completeness of around 6%, integrated over the entire orbital period and planet radius range tested here. Of the 113 detected planets, 5 were smaller than Jupiter. Our pipeline completeness for planets smaller than Jupiter is therefore around 0.25%.

There are some caveats and limitations to the simulations conducted here. Firstly, we only included white noise in our simulated light curves, however time series photometry obtained from the DECam is likely to have correlated noise due to changes in the point

Fig. 1.— The completeness of our exoplanet transit detection pipeline as a function of planet radius and orbital period. This figure summarizes the results of our injection and recovery tests and indicates that our planet detection pipeline is sensitive to inflated hot Jupiters (planets with radii between 1 and 1.5 $R_{\rm Jup}$) with orbital periods from around 8 hours up to 4 days. This figure shows the results of a simulated DECam survey with a cadence of 5 minutes over 6 hours of observations per night. Observations are simulated over 9 consecutive nights.



spread function as the instruments flex with shifting attitude, temperature and pressure. In addition, planet transits and eclipses may be superposed on time-variable signals from the host star due to its rotation. Another caveat to this study is that we only simulated transit signals with zero impact parameter, *i.e.* planets transit across the center of the star and have the longest duration (and deepest) possible transit. Finally, we did not convolve transit light curves with the integration window. Transit features are therefore sharper (and easier to detect) than they would be in a realistic survey.

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