Background Research Paper

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As of the 10th of May 2018, there have been 3,726 confirmed exoplanets discovered, and there are 4,496 exoplanet candidates from the data collected by NASA’s Kepler mission alone (NASA Exoplanet Archive, 2018). The Kepler mission is when NASA launched a spacecraft for the sole purpose of collecting data of other solar systems in the universe. An exoplanet is a planet that appears outside the solar system where Earth is located. Exoplanets are necessary to locate and study, because they answer the fundamental questions such as: are humans alone in the universe, or are there planets that are like Earth (Exoplanet Exploration, n.d.)?

Recently, a habitability index was created for the sole purpose of expressing the relative probability that an exoplanet could support liquid water, by taking into account many variables such as eccentricity of the planet, whether the planet is rocky or gaseous, and how much flux the planet has emitted (Barnes, Meadows, & Evans, 2015). There are more basic ways of detecting whether a planet is within the established habitability zone, including how far it is from the host star, the mass of the planet, or the temperature of the host star. The habitability zone boundaries are still being improved and more refined evidenced by the recent use of an updated 1D radiative-convective model, which allows for more accurate widths of the habitability zone for F, G, K, and M class stars. The new limits for the habitability zone are within 0.99 AU and 1.7 AU (Kopparapu et al., 2013).

NASA has direct criteria for what makes an exoplanet candidate included into the Exoplanet Archive. For one, the mass of the candidate planet has to be equal to or less than 30 Jupiter masses. Secondly, the candidate cannot be free-floating and must be orbiting a host star. Thirdly, further observations must be conducted to show the possibility of the object being a false-positive to be unlikely. Furthermore, all information to prove these things to be true and any other observations of the object must be available in peer-reviewed publications (NASA Exoplanet Archive, 2018).

One of the first methods of exoplanet detection was dubbed the Doppler Technique. The Doppler technique was first used on an object orbiting HD 114762, finding the objects residual velocities and comparing it to that of the orbiting of other planets, finding a relation. More massive planets are detected more easily by this method because how crucial gravity is to exoplanetary velocity (Fischer et al. 2015). If the planet’s spectral lines can be distinguished from the spectral lines of the star, the true radial velocity of the planet can be found; from the true radial velocity, the planet’s mass and inclination can be found (Rodler, Lopez-Morales, Ribas, 2012). The ability to distinguish between a planet’s spectral lines and a star’s spectral lines is not commonly available, meaning inclination and mass of planets found using the Doppler technique can’t always be found. Upon the realization of the limitation of using telescopes for this method, since they emit near infrared light, infrared spectroscopy was used as a technique for exoplanet detection. The spectrographs used for this are fiber-fed stabilized spectrographs, but were largely uncalibrated and varied much, until the use of uranium lamps as a way to calibrate them (Fischer et al., 2015). A spectrograph is a device for recording astronomical spectrum, the colors of the light as components shown as bands of color. Light enters a spectrograph through a slit, and bounces off an angled concave mirror towards a diffraction grating. At the diffraction grating, the light is split into its component colors and bounces off another concave mirror into a detector that transfers the data gathered by detecting the components into the computer itself (Obtaining Astronomical Spectra – Spectrographs, n.d.). Collecting a spectrum from stars and planets, from the gas in their atmosphere, is important because it tells what materials are from the celestial object.

Another technique of exoplanet detection is through an exoplanet’s transit of its host star. This transit reveals the exoplanet, because it blocks how much light is perceived by the host star upon observation from Earth, showing that there is an object in orbit, and upon further examination, with consistent transits providing further evidence of exoplanetary orbit. Through this technique of exoplanetary detection, the eccentricity, the mass, and the orbit of the planet can be found (Wright, Gaudi, 2013). Another technique of exoplanet detection is called microlensing, which occurs when two stars pass each other and the light from one of the stars bends the light from another allowing for the observation of objects undetectable before, such as exoplanets. Common degeneracies with this technique is the interference from parallax and orbital motion of the lens; exact orientation of the event should be recorded when microlensing occurs so that proper calculations can be done to remedy these degeneracies (Fischer et al., 2015).

Machine learning has recently become a large part of exoplanetary detection as new models and algorithms can be found when before, previously impossible. In a recent feasibility study, it was found that a convolutional neural network can be applied to test data on the transit of exoplanets to develop an algorithm to determine edge cases on exoplanet detection, caused by the presence of red noise in the light curves received by the telescopes (Zucker, Giryes, 2018). Red noise is just like white noise in that it is a kind of signal noise and messes with this collection of data.

The challenge with exoplanetary detection is not with larger planets of Jupiter size, but with smaller planets and smaller orders of magnitudes, because the traces of these planets are fainter and therefore requires more precise and accurate technology (Guyon, 2017). An alternative is to train a neural network to find these fainter traces and use this neural network to form an algorithm or model for this exoplanet detection. A group of MIT researchers used machine learning to create an algorithm to specifically find exoplanets amongst debris disks orbiting stars (Nguyen, Pankratius, Eckman, Seager, 2018). This is a significant breakthrough as debris disks reflect infrared radiation from the host star making it more difficult for exoplanets to be detected amongst them.

There hasn’t been much developed on the relationship to the number of exoplanets and properties of their solar system. This could be an important area of focus; for instance, if a star of larger size shows to have more planets, it would be a clear indicator that researchers need to look at larger stars for more exoplanets. Although a multi-variate approach would need to be taken as their most likely isn’t a simple relationship between two variables like this otherwise the relationship would have already been discovered. If taking a multi-variate approach, analysis of a graph for the relationship between these variable seems unlikely or hard to perform, so a machine learning approach will have to be taken instead. A supervised test group should be used to train the data for relationships between the number of exoplanets in the solar system, the size of the star, and the distance of the sun to the nearest planet. The only way to know the number of planets around the solar system is through exoplanet detection, so it will play a crucial role in the research.

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