Exoplanetary Detection with the Radial Velocity Method: A Literature Review

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Literature Review

Introduction

Exoplanets are any planets found outside of the solar system (NASA Exoplanet Archive). The search to uncover exoplanets is one of the fastest expanding fields in astrophysics, leading to the discovery of thousands of exoplanets in only a couple of decades, and revolutionizing the generic outlook on planetary physics and habitability. Moreover, the search for habitable exoplanets has long been the holy grail of many scientific experiments, allowing the field to progress closer to central question, "are we alone?" with every exoplanet detected and characterized (Faria et al, 2016). A planet is said to be habitable if it is located in the habitable zone for exoplanets (the area around the star at which a planet can orbit and possibly support life), and small and rocky enough to support an atmosphere with water and hydrocarbons necessary for life (Seager, 2013) (Faria et al, 2016).

Since the first discovery of the planet 51 Pegasi b in 1995, the exoplanetary detection field has skyrocketed. Researchers have since discovered 4,093 total exoplanets; however, over 3,000 exoplanets are discovered but are yet to be confirmed (NASA Exoplanet Archive). Because of renewed interest and funding in the field, exoplanet research has increased exponentially (D. Hall, 2018). Missions like the Hubble Space Telescope, Kepler, and TESS surveys have helped to increase the exoplanet population from one to 400. There are a variety of methods to detect exoplanets (NASA Exoplanet Archive) that are discussed in this paper. The most common of these are the radial velocity method and transit methods, which both rely on measuring either the star's light intensity (stellar luminosity) over time or the star's spectra blue-shifting or red-shifting over time (Lovis & Fischer, 2010). This paper aims to provide a general insight into the rationale, history, and process behind exoplanetary detection. First, an overview of milestones in exoplanetary detection are provided, and then a deeper look into detection methods used. Then, the radial velocity method is brought into focus, and Keplerian physics in relation to exoplanetary detection is explored. Exoplanetary recovery methods in radial velocity data and their problems are explored, and finally a more detailed insight the presence of stellar activity in radial velocity measurements is provided.

Section 1: Exoplanetary Detection Methods

This section explores the most common methods of exoplanetary detection, the transit method and the radial velocity method. The most common methods for detecting exoplanets are the transit method and the radial velocity method. The transit method for the detection of exoplanets is the most widely known and used method and relies on detecting the dimming of a star as a planet passes in front of it (Faria et al, 2016) (FIGURE 3). When an exoplanet passes in front of its parent star, it blocks some of the light emitted from the star. This causes a "dip" in the star's luminosity as the planet passes in front of it (Planetary Society). Such a dip is known as a light curve (Planetary Society).

Over the years, the transit method has allowed the detection of over 4,000 planets (NASA Exoplanet Archive), but consensus has been achieved that the radial velocity method is the most reliable method; it is commonly used to double-check results found through the transit method (Apai et al, 2018). The radial velocity method is the oldest and one of the most common exoplanetary methods innovated in the field (Lovis & Fischer, 2010). It relies on measuring the star's spectra and detecting any doppler shifts caused by the star rotating around the planet and the star's common center of mass, which may indicate the presence of an exoplanet (Lovis & Fischer, 2010). Moreover, the radial velocity method commonly requires fewer observations and has a higher probability in uncovering an exoplanet in a smaller time frame (Apai et al, 2018). Figure 1 provides more insight into the properties of planets most commonly discovered by each method. Figure 3 provides an in-depth flowchart of current and future exoplanetary detection methods **(Jeffers, 2008).**

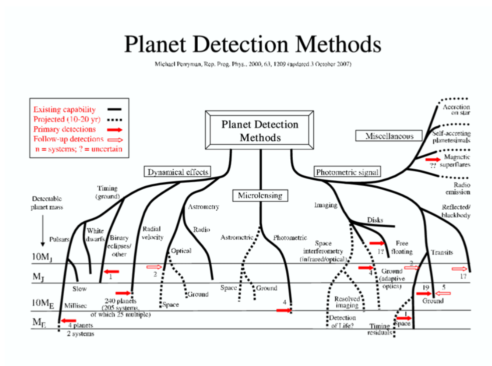

Figure 1: A flowchart with current and future exoplanetary detection methods (Jeffers, 2008).

Section 3: The Radial Velocity Method for Detecting Exoplanets

The radial velocity method for the detection of exoplanets is known as an indirect method, because it infers the presence of an exoplanet in a stellar system without directly measuring it. When a planet moves around its star, it exerts a gravitational pull on the star, and the star exerts a gravitational pull (in most cases, considerably stronger pull) on it (Lovis & Fischer, 2010). Therefore, a planet and star system rotate around their common center of mass. Because the center of mass is not often located at the center point of the star, the star also revolves around the center of mass, causing the star to wobble back and forth (Lovis & Fischer, 2010). This creates a doppler shift in the star's spectrum (Lovis & Fischer, 2010). When the star is moving towards the Earth in its revolution around the center of mass, the light that it emits is blue shifted. However, when the star is moving away from the Earth, its light is red shifted (Lovis & Fischer, 2010).

Researchers can use this doppler shift to indicate the existence of an exoplanet. This method is called the radial velocity method. The velocity at which the star rotates around its common center of mass is called the radial velocity, or magnitude. This is measured in meters per second (Lovis & Fischer, 2010). In summary, the radial velocity method offers a relation between the velocity at which a star rotates around its common center of mass with its planet and the resulting doppler shifting of the light that the star emits (Lovis & Fischer, 2010). This relationship can be most effectively described through the central radial velocity equation (Eq. 1) (Lovis & Fischer, 2010). K is the radial velocity of the star (measured in the SI units m/s), G is the universal gravitational constant, e is the eccentricity, m_2 is the mass of the planet, m_1 is the mass of the star (measured in the SI units kg), i is the inclination of the planet-star system with respect to the earth (see Figure 4), and a is the semi-major axis of the orbit (measured in the SI units meters).

$$K_1 = \sqrt{\frac{G}{(1-e^2)}}\, m_2 \sin i \,(m_1+m_2)^{-1/2}\, a^{-1/2} \;.$$

(Equation 1)

The radial velocity method, although extremely efficient and otherwise accurate, suffers from a few problems. For one, researchers are only able to measure the portion of the radial velocity that is in the direction of the Earth— hence the actual measured radial velocity is actually *VsinI*, where *V* is the actual radial velocity, and I is the inclination of the star in compared to the observer. This makes it possible only to uncover a component of the radial velocity unless the star's inclination is 90 degrees, or it is directly "edge on" with the observer. This is illustrated in Figure 2.

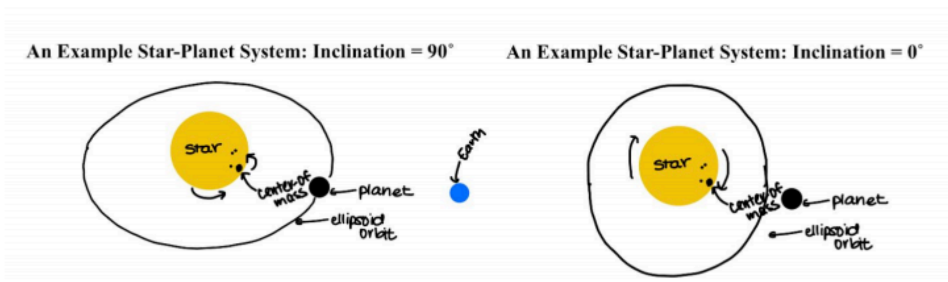

Figure 2: (Left) This schematic shows how the inclination of the star can affect its measurements. If a star has 90˚ inclination,, all of its velocity is directed towards the observer, and therefore the observer can measure the full radial velocity measurement. (Right) However, when the inclination is 0˚, (where the reader is assumed to be the observer), the star does not move towards the observer at all, therefore not inducing any measureable wavelength shift in the measurements, and making the planet undetectable.

Section 4: Keplerian Physics in Relation to Exoplanetary Detection

Exoplanets obey orbital mechanics governed by Kepler's laws, and hence it is helpful to derive their parameters for statistical knowledge of exoplanet property distributions and for a deeper understanding of different types of parameters (Lovis & Fischer, 2010). Stable keplerian orbits are ellipses and described by five main characteristics: period, eccentricity, true anomaly, argument of periastron, and inclination (Haywood et al, 2014).

Period is the time it takes for a planet to complete one orbit around its star. Eccentricity is known as the ratio of the ellipse's two foci and its length. The true anomaly is the angular position of the exoplanet at a certain time. The argument of periastron is the angle between a reference direction and the orbit's farthest position from the star. The inclination is the angle between the plane of frame of reference and the plane of the orbit. (Beaugé et al, 2012).

When talking about the detection of exoplanets using the radial velocity method, it is useful to use two more terms to describe an exoplanet system: multiplicity and amplitude. The amplitude of an exoplanet is its mean perturbation of the star, and the multiplicity of an exoplanet system is the number of planets in the system. Of these, the period, eccentricity, and amplitude often describe the most about the orbital dynamics of an exoplanet, as they can be directly inferred from the data and offer much insight into the shape of the exoplanet's orbit. Most of these orbital parameters can be directly inferred from the radial velocity data. Figure 3 provides a visual to the key orbital parameters when describing exoplanets as Keplerian objects, and their effect on radial velocity data.

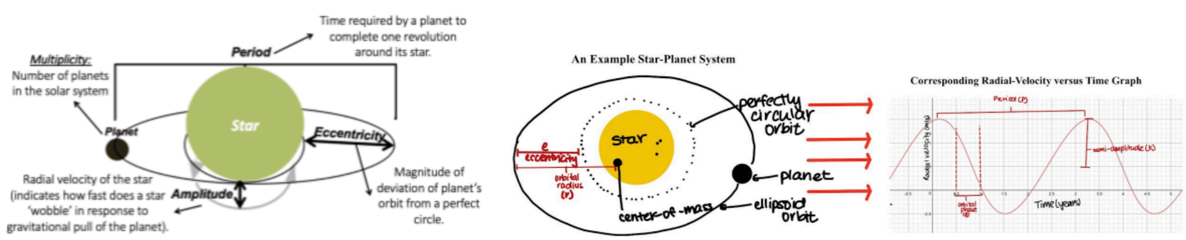

Figure 3: (Left) A diagram illustrating the keplerian orbital parameters of an exoplanet. (Right) A schematic illustrating the orbital parameters' relation in radial velocity data.

Keplerian orbits in radial velocity data as described in Figure 3 (Right) describe the various keplerian parameters. The semi-amplitude K is the actual radial velocity of the signal, or an average of the radial velocities found from that signal. This is measured according to SI units in m/s. The orbital period P is how long the object takes to orbit its star. This is usually measured in Earth-days. The eccentricity e is how much the orbit deviates from a circle, or how elongated the orbit is. The orbital phase $ø$ represents where the object is in its orbit during the observations. The orbital radius a of a signal is how far away the object is from its center of mass with its star.

Section 5: Exoplanet Recovery Methods

After obtaining radial velocity measurements from the telescope, the radial velocity time series can be formed from the spectra and then decomposed to give several contributing signals, due to factors such as noise, while other signals are because of an orbiting planet. These signals are decomposed using a periodogram, which assigns to a signal its power, or its "importance" or prevalence in the raw data. The most common method to do this is using a Lomb-Scargle periodogram (Khan, 2016), which decomposes signals based on a least-squares method.

After constraining the signals contained within the dataset, a Markov Chain Monte Carlo simulation algorithm (MCMC) is often utilized to identify the signal's orbital properties, as outlined in Section 4 (Foreman-Mackey, 2013; Price-Whelan, 2017; Fulton, 2018). MCMC is a probabilistic method that uses "walkers", or Monte Carlo simulations to approximate the distribution of a certain parameter. While not computationally effective (Foreman-Mackey, 2013), this method is often very precise and is the most widely used tool in exoplanet literature to approximate orbital properties of exoplanetary signals. This is also the basis of many radial velocity software packages, such as *RadVel* and *The Joker* (Price-Whelan, 2017; Fulton, 2018).

Section 6: Problems in Exoplanetary Recovery: Stellar Activity

Although the radial velocity method is the most reliable and accurate method for the detection of exoplanets (Apai et al, 2018; Fischer & Lovis, 2010), this method has a few drawbacks. The radial velocity method is known to be influenced by large amounts of noise, or false signals. Most notably, stars often present, through the inhomogeneities on their surface high amounts of noise that can almost exactly pose as exoplanets, and in many cases, even create false signals that cause the false detection of an exoplanet signal or mask it over the stronger, more prevalent noise as pointed out by (Dumusque et al, 2014; Desort et al, 2007; Apai et al, 2018; Haywood et al, 2014). Also, estimates of planetary mass often prove inaccurate in radial velocity methods because of the unfavorable inclination of the planetary system (Apai et al, 2018).

The most important source of noise in radial velocity measurements is likely stellar activity (Apai et al, 2018; Khan, 2016). Stellar activity is one of the biggest hindrances to small-planet characterizations, both in the radial velocity and the transit methods (Apai et al, 2018), because it can generate noise signals in the radial velocity data that appear to be exoplanet signals. Stellar activity produces inhomogeneities on the surface of a star, such as starspots and plages, which can produce doppler shifts that may appear similar to a possible planet orbiting the star. Stellar spots are notorious for at times resembling exoplanets when analyzed, exhibiting a sine-like light curve similar to those seen in exoplanets as they rotate across their stellar surface (Hébard et. al, 2015; Dumusque et al, 2014; Desort et al, 2007). A flowchart of contamination effects from different sources from stellar activity is provided in Figure 4 (Plavchan et al, 2015).

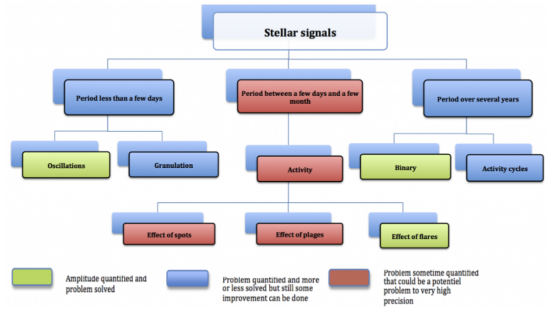

Figure 4: A flowchart illustrating the various contributors to radial velocity contaminations from stellar activity. The red boxes indicate sources uncharacterized as of yet (Plavchan 2015).

Section 6.1: Stellar Activity Characterizations using Activity Indicators

Measuring the star's influences on stellar spectra can be very difficult (Desort et al, 2007; Dumusque et al, 2014; Haywood et al, 2014). These influences can be from various aspects of stellar activity, such as stellar spots (Dumusque et al, 2014; Desort et al, 2007). These influences of spectroscopic data due to the star itself are known as stellar jitter. Oscillations and solar flares can be removed efficiently from the data but eliminating granulation and stellar spots remains an elusive challenge (Dumusque et al, 2014; Desort et al, 2007).

One of the unique benefits of utilizing the radial velocity method for exoplanetary detection is that many times information about the star can be characterized from the spectra obtained from the star to analyze its doppler shifts. Important descriptors of the star including its temperature, luminosity, and topology structure can be inferred from various aspects of its spectra (Desort et al, 2007; Lovis & Fischer, 2010). This is extremely helpful in determining whether a certain signal detected in the radial velocity measurements are from a valid exoplanet or in reality from side effects of the star itself, such as the star's starspots or other topological deformation. There are many characterizing descriptors found in the spectra to quantify the likelihood that a certain signal is from the star, not a planet, called activity indicators (Desort et al, 2007; Dumusque et al, 2014). These activity indicators are helpful because they allow researchers to distinguish whether a doppler shift on the spectra measured by reseaerchers is caused by an exoplanet or noise. These spectra are made up of various spectral lines, or peaks in the star's light emission at a certain wavelength. An example of a frequently used and extremely effective stellar activity indicator is a star's bisector-velocity (Desort et al, 2007). This is calculated by observing the average shape of a spectral line, which is a certain point in the spectra. Another way stellar activity is characterized is observing the spectral lines H-alpha, CaII H&K lines and the *Log' RK* obtained from the spectra, which are spectral lines that are known to change based on only stellar activity (Haywood et al, 2016; Dumusque et al, 2014). The previously mentioned methods rely on the spectrum of the star, which is usually available during spectroscopic surveys, but in general harder to find on public datasets. Still another approach uses follow-up photometric observations to look for light-curve variations that may indicate the presence of stellar activity due to starspots (as starspots are known to be considerably dimmer than their surrounding surface) (Desort et al, 2007; Dumusque et al, 2014).

Haywood et al (2016) looked at the effect of such stellar activity on the sun. Their research identified a number of correlations (and absence of correlations) between various stellar activity indicators and properties of the radial velocity time series. These correlations may prove crucial to further quantifying the relationship between stellar activity indicators and the actual radial velocity measurements. Their summary plot of the activity indicators versus radial velocity time series properties is illustrated in Figure 5.

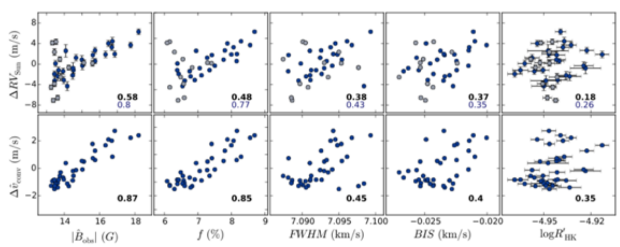

Figure 5: A summary plot of correlations between common activity indicators used to characterize stellar activity and (a) the overall radial velocity of the dataset, as well as versus (b) the rotational velocity of the star, as obtained from Haywood et al (2016).

Section 6.2: Common Exoplanet Detection Methods with Stellar Activity Contamination

Many times, an exoplanet's signal is characterized by preliminary analysis with a Lomb-Scargle Periodogram (VanderPlas, 2018; **Zechmeister, 2009**). This allows a series of hundreds of possible planetary signals to be characterized, some of which may be exoplanets (VanderPlas, 2018). The task then remains to characterize the planet. Often, the statistical significance of a signal, or "power" of the signal is employed to determine which signals are more likely to be exoplanets versus noise (**VanderPlas, 2018**). However, the power and periodogram alone of a certain signal is not enough to characterize the presence of an exoplanet. The constrained signal is usually checked for with follow-up photometric studies or stellar activity indicators. Moreover, just as the radial velocity method is used to double-check planets detected by transit, the transit method may also be used as follow-up measurements to a planet detected with the radial velocity method.

If a star's rotational period (the time it takes for star to rotate around its axis at its equator) is known, the stellar activity of the star can be characterized (Zechmeister, 2009). Because a starspot rotates on a star, it will have the same period as the rotational period of the star. Therefore, its radial velocity signal will have the same period, or a certain harmonic of the star's rotational period when using the Lomb-Scargle Periodogram (Zechmeister, 2009; VanderPlas, 2018). These signals can then be deleted from the data. However, many times the characterization of this rotational period is difficult because there is not much information available of the star itself. Many studies then aim to model the star's rotational period using inferential processes, such as Gaussian Processes or a modified Lomb-Scargle Periodogram (Zechmeister, 2009; Haywood et al, 2014). Many of these methods rely on modelling the follow-up photometry measurements of light curves, which is at many times expensive and time-consuming.

Another widely used method for the characterization of exoplanets is estimating the stellar activity in a system by analyzing its transit light curves, often in parallel with stellar activity analysis (López-Morales et al, 2016; Dumusque et al, 2014; Haywood et al, 2014). Usually this is done as a follow-up analysis to initial radial velocity measurements. However, there is recent interest in using machine learning to model the stellar activity of a star's light curve. For example, Lopéz-Morales et al (2016) modelled the stellar activity of the Kepler-78 system using a non-parametric Gaussian Process. This allowed the team to characterize the small, possibly habitable exoplanet Kepler-78b and even constrain its mass. This paved the way to use Gaussian Processes as a tool to model stellar activity and allow for small and habitable exoplanet detections using the transit method in parallel with the radial velocity method. Other teams such as Dumusque et al (2014), Haywood et al (2014), and Faria et al (2016) have accomplished this as well using nonparametric Gaussian Processes.

Section 6.3: Machine Learning Approaches to Combat Stellar Activity Contamination in Radial Velocity Measurements

Gaussian Processes are of increasing interest to researchers looking to model correlated noise, especially noise caused by stellar activity (Faria et al, 2016; Haywood et al, 2014; Dumusque et al, 2014). Because a starspot moves across its star's surface before disappearing from view, it can be modelled as quasi-periodic, and thus a Gaussian Process with a quasi-periodic kernel can be used to model the correlated noise (Faria et al, 2016). There has been interest in utilizing this method for characterizing stellar activity in the exoplanet detection field. For example, López-Morales et al (2016) used a Gaussian Process to deduce the presence of a fifth planet in the Kepler 21 system. The stellar activity was constrained using the Gaussian Process with a light curve, and an MCMC analysis was conducted to infer the orbital parameters of each of the planets in the system. Grunblatt et al (2015) did a similar analysis of Kepler 78, and used the analysis to infer the mass of Kepler 78b.

Section 7: An Overview of Artificial Neural Networks

Machine learning is gaining traction in the exoplanetary detection field, because of its efficiency, accuracy, and invaluable ability to generalize. Moreover, Convolutional Neural Networks, a class of neural networks are used often in the transit field to detect exoplanet transits in light curves (Jain et al, 1996; Zhao & Bilal).

Section 7.1: An Overview on Artificial Neural Networks

Artificial neural networks (ANNs) are a machine learning process. Overall, a neural network is a matrix of nodes with linear functions, and the linear functions' slopes and y-intercepts are optimized so that the final output value yields an accurate result for the maximum amount of the training set (Jain et al, 1996). An example of such a node is shown in Figure 6 (Jain et al, 1996).

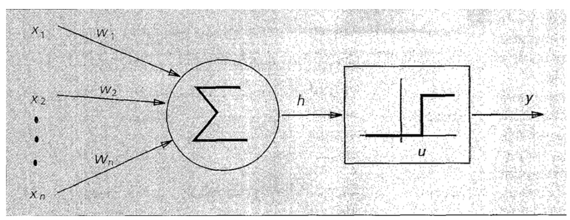

Figure 6: A visual representation of a neural network consisting of one node.

In the simple case, an artificial neural network may consist of only one node. This is called a perceptron (Jain et al, 1996). Each datapoint passes through the node. The datapoint is treated as an x value for a linear equation with randomized slope and y intercept. The output of the linear equation goes through another final function (often a ReLU or sigma function) with unchangeable constants. The final output of the node is used to calculate the cost, which is used to update the slope and y-intercept in the perceptron (Jain et al, 1996). Many algorithms are used to calculate this cost, the most common being the Gradient-Descent (backpropagation) algorithm (Jain et al, 1996). Moreover, this perceptron may be maximized to *n* number of nodes per layer for *n* number of layers, allowing for an indefinite level of complexity that the neural network can fit to. The arrangement of these nodes is called the neural network architecture. A diagram illustrating common neural network architectures is shown in Figure 7.

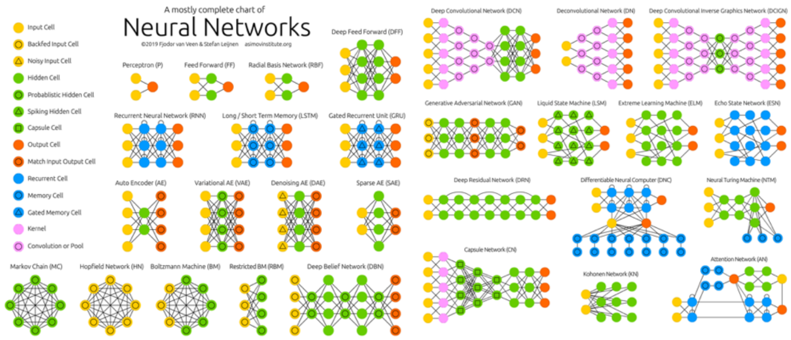

Figure 7: An infographic illustrating the most common types of neural network architectures (Educba). The transit method of detecting exoplanets most often utilizes a Multi-Layer Perceptron or Convolutional Network (Zhou & Bilal).

Many a times, a neural network is prone to either overfitting the data or misrepresenting it in the presence of imbalanced data (Schapire, 1990; Tekto, 1995). However, both overfitting and imbalanced classes can be avoided using various data preprocessing techniques (Tekto, 1995; Shcapire, 1990). Moreover, a popular method to overcome class imbalances is to employ an ensemble of neural networks with access to different data, thus allowing for a more reliable and accurate result.

Neural networks have not been used very widely in the radial velocity exoplanetary detection literature, mostly due to the fact that many times a holistic view is required for exoplanet characterization, and because many times the signal-to-noise ratio in exoplanetary detection measurements very low, making the training set incredibly imbalanced (Desort et al, 2007). However, these are used extensively in transit or photometry methods to analyze transit light curves more efficiently for exoplanets (Zhao & Bilal).

Section 9: Conclusion

The radial velocity method is one of the most reliable method for the detection of exoplanets. However, while there is over 4,000 exoplanets already detected, over 1,000 of these remain unconfirmed (NASA Exoplanet Archive, 2019). Moreover, the confirmation of these exoplanets involves weeks to years of follow-up studies with high-quality equipment and telescope time, thus making the characterization of exoplanets inefficient, uneconomical, and time consuming (Apai et al, 2018). This confirmation is also many times inaccurate, thus requiring more follow-up studies on the exoplanets. This is mainly due to the presence of noise, especially correlated noise due to stellar activity in the data (Desort et al, 2007; Dumusque et al, 2014). Therefore, there is a need for a more accurate, reliable, and efficient method of holistic exoplanet characterization in the presence of stellar activity without the need for follow-up measurements. This method should have a quantifiable scale of confidence that would make exoplanetary detection of low-mass and potentially habitable planets more accurate, efficient, and reliable.

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