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2020 12th International Conference on Computational Intelligence and Communication Networks

CICN 2020

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Discovering Exoplanets in Deep Space using Deep Learning Algorithms

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Abstract— **Exoplanets are those planets that are located outside of our solar system. These planets come in a huge variety of sizes and are placed in various orbits. Some planets are humongous and are close to their parent stars while many others are icy or rocky. NASA, as well as the whole world, is looking for exoplanets that are placed in the same habitable zone orbiting a star as the earth and are of a similar size. The goal of this project is to find similar planets using Deep Neural Networks and Support Vector Machines in conjunction with NASA's Kepler Space Telescope dataset of flux intensity of distant stars.**

Keywords—Kepler, Artificial Neural Network, Transit Theory, Backpropagation, PCA, Exoplanet, Gaussian Distribution, Gradient Descent, Confusion Matrix, Coverging Accuracy, Data Augmentation, Data Modeling

I. INTRODUCTION

For many decades, humanity has been foraging exoplanets in search of a new place to live and to contact potential living beings in other galaxies. In 2009, NASA launched its Kepler Space Telescope to hunt new planets in the outer space that are earth-sized and orbiting in the habitable zone around its star. The primary method of searching for a planet is known as the "**transit method**". The starlight intensity drops when the planet passes between the telescope and the star, thus obscuring the view. The starlight re-emerges as the planet crosses the star. We are utilizing the flux intensity of 3198 stars to see if there is a planet orbiting a star in the deep space. We will be utilizing Deep Neural Networks and Support Vector Machines to hunt down more exoplanets than ever discovered.

The Solar System was born around 4600 million years ago. This has been confirmed from meteoric and radioactivity studies. This all started with a cloud of gas and dust. This cloud was calm, but an adjacent supernova explosion caused an apparent perturbation of this cloud, which further shrank due to gravitational pull, and formed a flat, rotating disk like structure where all the material was centered in the core: **the protosun**. Subsequently, this gravitational pull forced the residual material into clumps and sphere shaped material, creating planets and other celestial bodies. The residue dust which was unshaped resulted into meteors, asteroids and comets.[1] This is also called the Big Bang Theory.

But what are Exoplanets?

Exoplanets are those planets which exist beyond our solar system in faraway galaxies. The exploration and discovery of these exoplanets should be credited to NASA's Kepler Space Telescope.[2]

Exoplanets can have plethora of sizes and varying orbits. Some are humongous transiting very close to their parent stars; while other are rocky and icy like Pluto. The main of NASA and other allied space agencies is to find a similar planet to the earth in size and shape, transiting a sun-like star in the habitable zone.

The **habitable zone** is the zone or area around a sun-like star where an optimum temperature prevails for liquid water to endure on planet's surface. If we even consider the Earth to be at the position of Pluto, the sun would only be barely visible to the naked eye and much of the Earth's water bodies and the atmosphere would refrigerate.[3]

II. THEORY

A. Detecting Exoplanets by Transit Method

Seemingly mainstream, but finding an exoplanets is a very daunting task. Sci-fi movies usually show the existence of life and abundance of other resources, but they don't say anything about the detection of those heavenly bodies. Planets on their own emit very little candelas of luminance. We are only able to observe Saturn or Mars in the night sky because they reflect the light emitted by the sun. Now, if we are looking of the possibility to detect an exoplanet (the nearest one is over 4 light-years away), it would be in the proximity of the brilliantly-illuminated star making the exoplanet impractical to observe. [4]

Researchers developed an effective way to detect exoplanets; exoplanets by themselves do not illuminate, but the stars around which they orbit do emit light. Deliberating

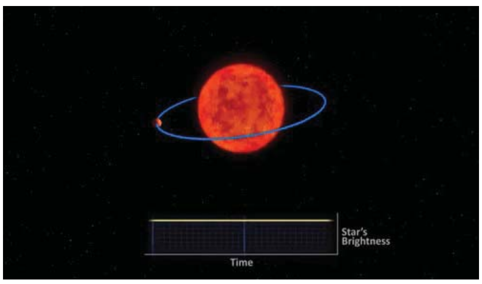

Figure 1. Transit method of observing brightness

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around these facts, scientists at NASA developed a **transit method** in which a digital camera like structure measures miniscule nadirs in a star's brightness as a planet encroaches in front of the star. With these calculations and observational tactics, scientists calculate the ratio of a planet's radius to that of its star — that is essentially the shadow it makes — and with that ratio, planet's size can be estimated. Kepler Space Telescope's primary method of searching for planets was the "**Transit**" method.[5]

B. Kepler Objects of Interest (KOI)

The Kepler collects and materializes the data and thus, raw light curves are plotted. Brightness values are then augmented to compensate for the variations in brightness caused due to rotations of spacecraft. The light curve is then processed in to an observable form and a Machine Learning algorithm selects the potential candidates. From now on, any signal that shows potential transit-like characteristics is called a threshold crossing event. These extracted curves are then individually checked in two inspection rounds First round examines only few moments per the target planet. This inspection eliminates erroneously selected signals caused by extraterrestrial noise and eclipsing binaries.

Threshold crossing events that go well through these inspections are called Objects of Interest (KOI), and are further archived. Further inspection of KOIs are done more thoroughly with the assistance of a process called dispositioning. The candidates which clear the dispositioning test are called potential Kepler planet candidates. The KOI archive is dynamic in nature, a candidate on the list could end in the false positive list after subsequent inspections. Also vice-versa could happen, KOIs that by mistake in calculations marked as false positives could upgrade up back to the archive.

Some circumbinary planets show eccentric crossings, and they ought to be detected using other mentioned methods. Different research groups use different signal processing algorithms to designate an exoplanet. Consequently, those planets are not included in the KOI archive. [6]

C. Formation of Exoplanet Candidates

Once, the exoplanet candidates are formed, there is an urgent need to eliminate the false positives to save our time from researching about them in the future. This is done by the follow-up tests mentioned below.

Further, potential exoplanet candidates are exhaustively imaged with sophisticated terrestrial telescopes in order to remove the background clutter that could adulterate the brightness signature of the transiting exoplanet signal.

There also other methods prevail to discriminate between a real exoplanet candidate to a false positive planet.. Doppler spectroscopy can be used to do the aforementioned stuff, but it requires complementary follow-up observations from the land-based telescopic observatories. This method is comprehendible if planet is Jupiter-sized or is encircling a relatively bright star. Currently dopper spectroscopy lacks the depth to observe

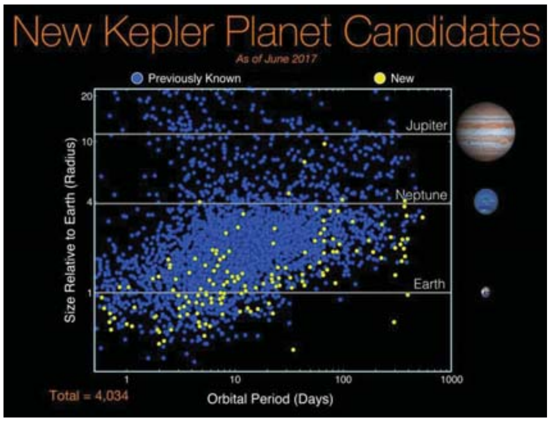

Figure 2. Kepler Candidates discovered till date

small-sized rocky planets or which those orbit relatively dim stars. To relief, such spectroscopy can be used for examining peripheral massive non-crossing exoplanet candidates around observed stars. [7]

In the systems containing multiple planets, celestial bodies are asserted by observing the transit times between the periodic transits of the planet, which can fluctuate due to gravitational forces provided by other planets. Thus, low mass planets can be easily asserted even when the star being observed is several light years away. The fluctuations in the orbital period show that the two planets are from the same multiplanetary system. Sometimes, due to luck, some non-transiting planets are also discovered through this way.

Circumbinary planets have a massive transit timing fluctuations between that those planets who are affected by disturbances due to external gravitational fields by other celestial bodies. But, their transit times only vary significantly. Transit duration variations/fluctuations of circumbinary planets are due to the orbital motion of their parent stars around which they are orbiting. Additionally, if the planet has a gigantic mass, it can also perturb the orbital period of host star. Circumbinary planets are hard to detect due to their varying transiting time, but it is easier to confirm them, as timing patterns of transits cannot be overshadowed by a background star system.

D. Dataset Analysis

This dataset has been taken from Kaggle and contains flux intensity variation of several thousand stars. Each data or star has a target label of either 1 or 2. 2 indicate that the targeted star has at least one exoplanet orbiting it; some observations are of the nature of multi-planetary systems.[8]

As already informed in the above sections, the planets do not illuminate on their own, but they obstruct the light from the parent star they are transiting. If the targeted star is observed over a long time, there exists a regular dimming of the light flux intensity. This is concrete evidence that a planetary body is orbiting the star and hence, it is classified as a candidate exoplanet. Further study of our candidate will indeed confirm its existence as an exoplanet.

In the dataset that is used here, a target star is orbited by a blue planet. At t = 1, the flux intensity of the star drops because it gets obscured by the transiting exoplanet candidate, given the telescopic position. The light from the star bounces back to its original value at t = 2. The graph in each box shows the measured flux intensity at each time instant.

- The Dataset is composed of a test and a training set, containing two different labels, 2 is an exoplanet star and 1 is a non-exoplanet-star.
- Trainset:
- 5087 rows or observations.
- 3198 columns or features.
- Column 1 is the label vector. Columns 2–3198 are the flux values over time.
- 37 confirmed exoplanet-stars and 5050 non-exoplanet-stars.
- Testset:
- 570 rows or observations.
- 3198 columns or features.
- Column 1 is the label vector. Columns 2–3198 are the flux values over time.
- 5 confirmed exoplanet-stars and 565 non-exoplanet-stars.

III. PREPARE YOUR PAPER BEFORE STYLING

A. Working of Artificial Neural Networks

Artificial Neural Network is a system that has been developed for machines that can mimic human nervous systems. These types of systems can thus, learn to perform tasks by taking a huge input of examples, without being explicitly programmed.

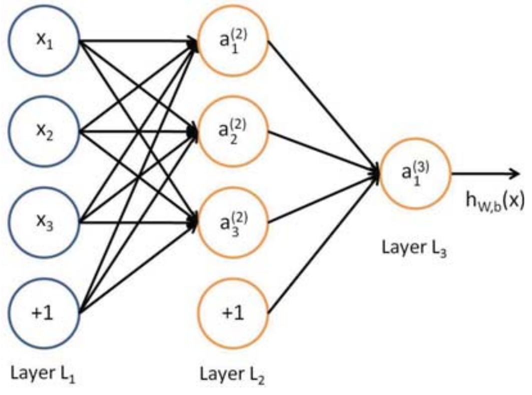

Figure 3. ANN Model

Artificial Neural Network consists of three layers: 1. Input layer — for collecting data to train the network. 2. Hidden layers — where computation is performed and data patterns are identified and learned. 3. Output layer — outputs the results for stored patterns.

The yellow circles above represent the input layer and denoted as X. The green and blue circles show the hidden layers respectively. These demonstrate activation nodes and are denoted by weights W or θ. The red circle shows the output answer or class to a test input.

Each node is connected to every other node in the succeeding layers by the arrows which demonstrate weight on the interconnections between the nodes. Weights can be thought of as an impact of one node to the other.

B. Model Representation by Mathematics

To understand the mathematical modeling, we will use a simpler neural network with only one hidden layer. The model has 3 input and hidden nodes, with 1 bias each and 1 output layer.

Marking the biases on both layers as x_0 and a_0 respectively. The input vector is represented by *X* and the hidden layer vector is *A*. [9]

The interconnection weights between layers are represented by *θ* or *W*. This project would represent as *θ*. The weights between the input and the only hidden layer will represent *3x4* matrix. Similarly, interconnection weights between hidden and output layers will be represented *1x4* matrix. [26]

If network has **x** nodes in layer j and **y** units in layer j+1, then θ_j will be of dimension **y×(x+1)**.

Now, the activations for the hidden layer nodes would be computed. So, now we would multiply input vector X and interconnection weights matrix θ^1 for the first layer ($X*\theta^1$)and then apply the activation function g. What we get is :

$$h_\theta(x) = a_1^{(3)} = g(\theta_{10}^{(2)} a_0^{(2)} + \theta_{11}^{(2)} a_1^{(2)} + \theta_{12}^{(2)} a_2^{(2)} + \theta_{13}^{(2)} a_3^{(2)})$$

Mutiply the vector for hidden layer with weight matrix and hence now (***A*θ***) we get output equation which is also termed as hypothesis:

Generalizing this for multiple hidden nodes, and multiple layers, we get the equation:

We have assumed here that we have *L* layers with *m* nodes and *L-1* layer with *n* nodes.

Forward Propagation is used to compute the output provided the given inputs. Thus, it is used to calculate the loss function or the cost function.

After getting the hypothesis h(x), we calculate the cost function using the initial inputs:

The main aim is to depreciate the loss function ***J(θ)*** utilizing the upgraded and reformed values for ***θ*** (interconnection weights). In order to calculate the ***partial derivates of the loss function J(θ)*** or the cost function, we use the Backpropagation Algorithm. [10]

These partial derivates are further computed and used in the reducing algorithms such as gradient descent or stochastic gradient descent for calculation of the ***θ*** values for our network to manage and lower the loss value of ***J(θ)***.

$$\theta_j := \theta_j - \frac{\partial}{\partial \theta_j} J(\theta)$$

Backpropagation algorithm consists of the following five steps:

- Set ***X = a(1)*** *;* for the training examples
- Execute forward propagation to compute ***a(l)*** for the other layers ***(S = 1…S)***
- Use ***y*** and calculate the error value or delta for the last layer ***δ(L) = h(x) — y***
- Compute the ***δ(l)*** values reversely for each layer (as said in the backpropagation section)
- Calculate derivative values ***Δ(l) = (a(l))^T ∘ δ(l+1)*** for each layer, which represent the derivative of cost ***J(θ)*** with respect to ***θ(l)*** for layer ***l***

Certainly, it propagates the error in a reverse nature. While tracing back, it calculates how much a given weight contributes to the loss function ***J(θ).*** The weight that has a large contribution would have a larger derivative value than the rest of the weights and must be reduced for reducing the error function.

IV. RESEARCH

A. Dataset Processing

These adjustments in brilliance are portrayed by extremely little plunges and for fixed timeframes, for the most part in the region of 1/10,000th of the star's general splendor and just for merely hours. These progressions are likewise occasional, causing similar plunges in brilliance each time and for a similar measure of time. In view of the degree to which stars diminish, space experts are likewise ready to acquire imperative data about exoplanets. [29]

For these reasons, Transit Photometry is viewed as a hearty and solid strategy for exoplanet discovery. Of the 3,526 extra-sun powered planets that have been affirmed to date, the travel strategy has represented 2,771 revelations – which is more than the various techniques consolidated.

The target label contains two label, one is 1(Demonstrates absence of exoplanet) and **2**(Demonstrates existence of explanet). For simpler processing of data, converting into the labels of **0** and **1.**

We can also reduce the memory used by our dataset, which is entirely optional.

Memory optimization step will increase the testing time efficiency by 55.1%, and can also be performed on training data patterns. [11]

Visualizing the training dataset to get more information about class distribution.

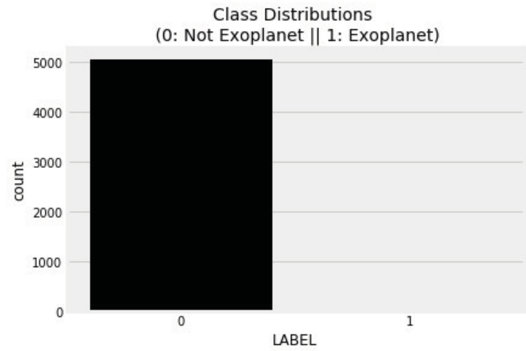

Figure 4. Skewed Class Distribution

It seems to be skewed, or heavily imbalanced, so certain data processing techniques would have to be done.

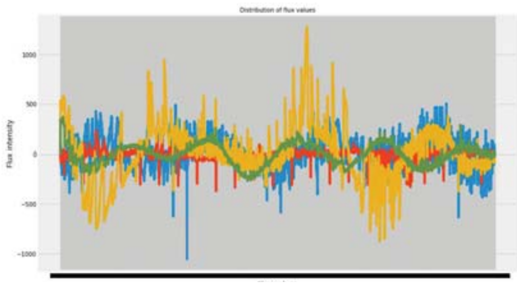

Figure 5. Flux intensity of first four stars

To observe the intensity of the variations of flux intensity, we plot the data of four stars

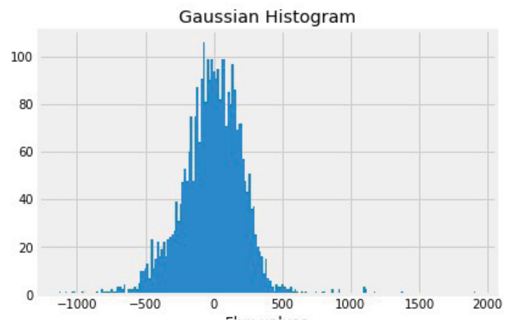

Figure 6. Gaussian Distribution of Non-Exoplanet class

The data is not clean and hence, need to be normalized. Plotting the Gaussian Distributions of non-exoplanet and exoplanet data

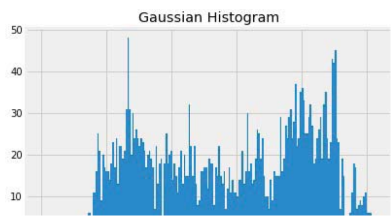

Figure 7. Gaussian Distribution of Exoplanet Class

Data Normalization is a tool used for preprocessing the data in machine learning if the data values pertain to different scales. The whole crux of normalization is to bring all the columns in a dataset to a common standardized scale, without changing their standard deviation and differences in range of the values. [12]

Further, we applied Gaussian Filters to both test and training data. According to the theory of probability mathematics, the normal distribution is an omnipresent continuous probability distribution. They are very imperative in statistics and are often used in natural sciences like biology or physics to represent real random variables whose distribution is ambiguous.

Feature Scaling is subsequently performed so that all the values remain in the stipulated range. There 5087 rows and 3198 columns in our training dataset and hence, we are working on an immense amount of data. It is therefore, crucial for us to decimate the number of fields (Dimensionality Reduction) to remove the possible occurrence of **Curse of Dimensionality**. [13]

For reducing the number of dimensions in our dataset as a precautionary measure, we would utilize the i.e. **PCA(Principal Component Analysis)** algorithm. [14] For implementing PCA, we have to choose number of features to be retained in the data so that the possibly redundant ones no longer matter and we may not be another epitome of the curse of dimensionality.

The scikit-learn decomposition code gives **k=37** which would be an optimum value for the number of features. Taking **k=37** and applying Principal Component Analysis on our scaled dataset.

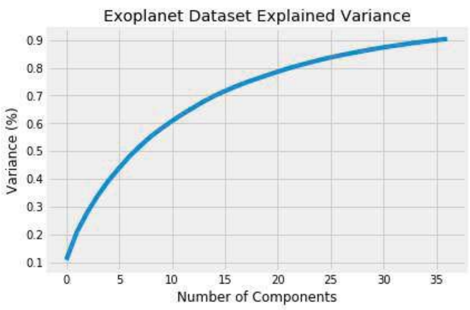

Figure 8. PCA Analysis of Optimum Classes

The calculation seemed correct, by selecting 37 most important features, we have preserved aroung 98.8% or 99% of the total data variance. It is symbolical and thus by eliminating many redundant features we have just lost 1% variance, which is a good result.

Keras library allows sequential placing of layers one by one in a conventional fashion. Four One-Dimensional layer are used as a conventional filter, and pooling stems out the data length by a quadraple factor. At the end, we have placed two dense layers just like an image classifier. Batch normalization layers have exponentiated the rate of convergence. [15]

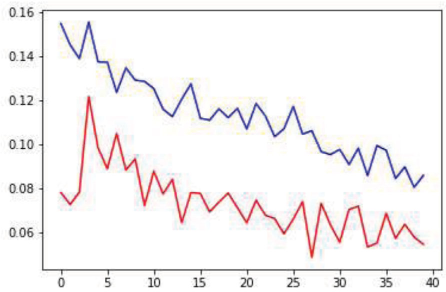

Figure 9. Converging Accuracy of Model

As already mentioned in the upper sections, the data is highly skewed. So, we would use the positive examples repeatedly, so that our model sees these positive examples at least 50% of the time. Data augmentation is also being considered here to generate new examples by rotating them arbitrarily. It is very similar to what we do on the images by rotating or mirroring them to generate more examples, this is called data augmentation. [16]

Initially, a miniscule learning rate was chosen to fasten the convergence to a minima and Adam Optimizer was used instead of Stochastic Gradient Descent approach and the results were terrific, anyway. [17]

Five positive examples in this graph approach a decent score in the 0.95-1.00 range. Almost every negative example is near the zero threshold, excluding some which are at 0.9-1.00 range. This is encouraging. The false positives have thus, to be removed.

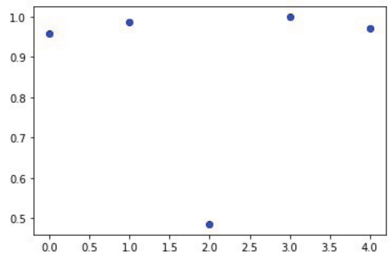

Figure 10. Exoplanet Candidates

We will now use Scikit-Learn library to assist us in selecting the perfect cutoff score for classifying exoplanets.

Now, we will be looking for false positives or misclassified exoplanets:

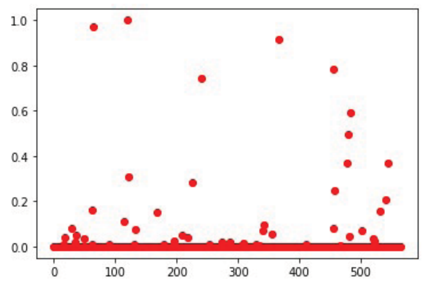

Figure 11. Negative Candidates

V. RESULTS

```
Accuracy mean: 1.0
Accuracy variance: 0.0

accuracy_score : 0.9912280701754386

classification report :
              precision    recall  f1-score   support

           0       0.99      1.00      1.00       565
           1       0.00      0.00      0.00         5

    accuracy                           0.99       570
   macro avg       0.50      0.50      0.50       570
weighted avg       0.98      0.99      0.99       570
```

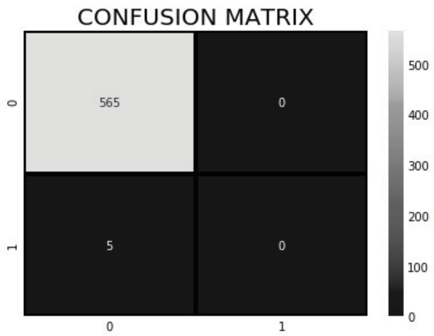

Figure 12. Confusion Matrix and Classification Report

As from the matrix we have found that in the NASA readings, one planet was misclassified as false positive. In the initial readings it was predicted only four exoplanets existed, but from our experimental deliberations, we have found one more exoplanet from the dataset. The readings from confusion matrix are above, and they too confirm that from the test dataset of 571 planets , the number of true positives are 5. Hence, our deliberations were right.

VI. ADVANTAGES AND DISADVANTAGES

A. Advantages

Probably the best bit of leeway of Transit Photometry is the manner in which it can give precise requirements on the size of recognized planets. Clearly, this depends on the degree to which a star's light bend changes because of a travel. Though a little planet will cause an unpretentious change in splendor, a bigger planet will cause an increasingly perceptible change.

At the point when joined with the Radial Velocity technique (which can decide the planet's mass) one can decide the thickness of the planet. From this, space experts can evaluate a planet's physical structure and piece – for example deciding whether it is a gas mammoth or rough planet. The planets that have been examined utilizing both of these strategies are by a long shot the best-described of all known exoplanets.

Notwithstanding uncovering the breadth of planets, Transit Photometry can take into account a planet's air to be explored through spectroscopy. As light from the star goes through the planet's climate, the subsequent spectra can be broke down to figure out what components are available, consequently giving hints with respect to the compound creation of the air. [18]

Last, however not least, the travel strategy can likewise uncover things about a planet's temperature and radiation dependent on optional shrouds (when the planet goes behind it's sun). On this event, space experts measure the star's photometric power and afterward deduct it from estimations of the star's force before the auxiliary obscuration. This takes into account estimations of the planet's temperature and can even decide the nearness of mists developments in the planet's climate.

B. Disadvantages

Travel Photometry additionally experiences a couple of significant downsides. For one, planetary travels are discernible just when the planet's circle happens to be entirely lined up with the cosmologists' view. The likelihood of a planet's circle harmonizing with an onlooker's vantage point is comparable to the proportion of the breadth of the star to the width of the circle.

Just about 10% of planets with short orbital periods experience such an arrangement, and this reductions for planets with longer orbital periods. Accordingly, this strategy can't ensure that a specific star being watched does for sure host any planets. Consequently, the travel strategy is best when looking over thousands or a huge number of stars one after another.

It likewise experiences a significant pace of bogus positives; now and again, as high as 40% in single-planet frameworks (in light of a 2012 investigation of the Kepler crucial). This requires follow-up perceptions be directed, frequently depending on another strategy. Be that as it may, the pace of bogus positives drops off for stars where various competitors have been recognized. [19]

While travels can uncover much about a planet's breadth, they can't put exact limitations on a planet's mass. For this, the Radial Velocity technique (as noted prior) is the most dependable, where cosmologists search for indications of "wobble" in a star's circle to measure the gravitational powers following up on them (which are brought about via planets).

To put it plainly, the travel strategy has a few constraints and is best when matched with different techniques. By the by, it remains the most broadly utilized methods for "essential recognition" – identifying up-and-comers which are later affirmed utilizing an alternate strategy – and is answerable for more exoplanet revelations than every single other technique consolidated.

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