A New Activation Function for Artificial Neural Net Based Habitability Classification

1st Snehashu Saha
Computer Science and Engineering
PES University
Bangalore, India
snehashusaha@pes.edu

2nd Archana Mathur
Systems Science and Informatics
Indian Statistical Institute
Bangalore, India
mathurarchana77@gmail.com

3rd Kakoli Bora
Information Science and Engineering
PESIT Bangalore South Campus
Bangalore, India
k_bora@pes.edu

4th Suryoday Basak
Computer Science and Engineering
University of Texas at Arlington
Arlington, USA
suryodaybasak@ieee.org

5th Surbhi Agrawal
Computer Science and Engineering
PESIT Bangalore South Campus
Bangalore, India
surbiagrawal@pes.edu

Abstract—We explore the efficacy of using a novel activation function in Artificial Neural Networks (ANN) in characterizing exoplanets into different classes. We call this Saha-Bora Activation Function (SBAF) as the motivation is derived from long standing understanding of using advanced calculus in modeling habitability score of Exoplanets. The function is demonstrated to possess nice analytical properties and doesn’t seem to suffer from local oscillation problems. The manuscript presents the analytical properties of the activation function and the architecture implemented on the function.

Index Terms—astroinformatics, machine learning, exoplanets, artificial neural networks, activation function

I. INTRODUCTION

For hundreds of years, astronomers and philosophers have considered the possibility that the Earth is a very rare case of a planet as it harbors life. This was partly due to the fact that after the initial missions exploring our neighbors Mars and Venus, no traces of life were found. However, over the past two decades, discoveries of exoplanets have poured in by the hundreds and the rate at which exoplanets are being discovered is increasing. The inference from this is that planets around stars are a rule rather than an exception with the actual number of planets exceeding the number of stars in our galaxy by orders of magnitude. In order to find interesting samples from the massive ongoing growth in the data, a sophisticated pipeline may be developed which can quickly and efficiently classify exoplanets based on habitability classes.

The process of discovery of exoplanets is rather complex, [1], as the size of exoplanets is small compared to other types of stellar objects such as stars, galaxies, quasars, etc. which can be discovered with greater ease. A very careful analysis of stellar signals is required to detect planetary samples. Some of the methods of detecting exoplanets include radial velocity based detections, gravitational lensing, etc. Imaging-based methods of discovery of exoplanets are not well developed yet and are at a rather controversial stage but could be more effective in exoplanet discovery with improvements. The data collected is imperfect and sometimes difficult to analyze with certainty. Given the rapid technological improvements and the accumulation of a large amount of data, it is pertinent to explore advanced methods of data analysis to rapidly classify planets into appropriate categories based on the physical characteristics.

There exist different approaches to solving the habitability problem. Explicit score computation, [2] giving rise to metrics is one way of addressing the issue. However, habitability is too complex a problem to be equated with Earth-similarity alone [3]. Therefore, model based evaluations [4], [5] need to be synthesized with feature based classification [6].

Existing work on characterizing exoplanets are based on assigning habitability scores to each planet which allows for a quantitative comparison to Earth. The Earth Similarity Index, Biological Complexity Index and Planetary Habitability Index are distance-based metrics which gauge the similarity of a planet to that of Earth; the Cobb-Douglas Habitability Score (CDHS), [2] makes use of econometric modeling to find the similarity of a planet to Earth. Recently, a collaborative effort between Google and NASA resulted in the discovery of two exoplanets. In Saha et.al. [7], an advanced tree-based classifier, Gradient Boosted Decision Tree was used to classify Proxima b and planets in the TRAPPIST-1 system. The accuracies were nearly perfect, giving us the basis of exploring other machine classifiers for the task.

Remainder of the paper is organized as follows. A novel activation function to train an artificial neural network (ANN) is introduced. We discuss the theoretical nuances of such a function. In the next section, the back propagation mechanism with the relevant architecture is described paving the foundation for ANN based classification of exoplanets. We conclude

978-1-5386-5314-2/18/$31.00 ©2018 IEEE 1781
by discussing the efficacy of the proposed method.

II. Saha-Bora Activation Function (SBAF) for a Neural Network

Neural networks [8], commonly known as Artificial Neural network(ANN), is a system of interconnected units organized in layers, which processes information signals by responding dynamically to inputs. Layers of the network are oriented in such a way that inputs are fed at input layer and output layer receives output after being processed at neurons of one or more hidden layers. Hidden layers consist of computing neurons that are connected to input and output layers through a system of weighted connections. The network has ability to learn from input patterns, whereby with every input fed to the network, weights are updated in such a way that the error between the desired and observed output is minimum. Hidden layers are equipped with a special function called activation function [9], to trigger neurons to process and propagate outputs across the network.

A special class of ANN called Back propagation [10] deals with computing the error between observed and desired output and later feeds this error back to the network with each cycle or ‘epoch’. The weights are updated correspondingly and learning or training of the network is performed till the error is minimized.

Activation function acts as a functional mapping between inputs and outputs. It allows the network to learn and model complex dataset like audio, video and text. Most popular activation functions are Sigmoid, hyperbolic tangent and Relu.

The activation function is as follows:

$$y = \frac{1}{1 + kx^\alpha (1 - x)^{1-\alpha}}.$$  

(1)

Computing the derivative of the function:

$$\frac{dy}{dx} = \frac{y^2}{y} \cdot \frac{\alpha - x}{x(1 - x)} \cdot \frac{1 - y}{y} \cdot \frac{1}{y}$$

$$= \frac{y(1 - y)}{x(1 - x)} \cdot (\alpha - x)$$

(2)

Remark: $x$ is the linear combination of surface temperature, called as input to the NN, and weights (normalized between 0 and 1) and $1 - x$ is the complement of that, together explaining the perfect discrimination between habitability classes as explained in TSS [6]. The new activation function to be used for training a neural network for habitability classification boasts of an optima. Evidently, from the graphical simulations below, we observe less flattening of the function and therefore the formulation should be able to tackle local oscillations more easily as compared to the more generally used sigmoid function. Moreover, since $0 \leq \alpha \leq 1, 0 \leq x \leq 1, 0 \leq 1 - x \leq 1$, the variable term in the denominator of SBAF, $kx^\alpha (1 - x)^{1-\alpha}$ may be approximated to a first order polynomial. This may help us in circumventing expensive floating point operations without compromising the precision.

A. Existence of Optima: Second order Differentiation of SBAF for Neural Network

From Equation 2 ,

$$\frac{dy}{dx} = \frac{y(1 - y)}{x(1 - x)} \cdot (\alpha - x)$$

$$\Rightarrow \frac{d^2y}{dx^2} = \frac{x(1 - x) \cdot y(y - 1)}{(x(1 - x))^2}$$

$$= \frac{y(y - 1)}{x(1 - x)}$$

(3)

Clearly, the first derivative vanishes when $\alpha = x$, the derivative is positive when $\alpha > x$ and is negative when $\alpha < x$ (implying range of values for $\alpha$ so that the function becomes increasing or decreasing, please see Eq. 3. We need to determine the sign of the second derivative when $\alpha = x$ to ascertain the condition of maxima (corresponding to maximum width of the separating hyperplane ensuring optimal discrimination between habitability classes). Assuming $0 < x < 1$, the condition of optimality, $0 \leq \alpha \leq 1$, $y$ by construction lies between $(0, 1)$. Hence, $\frac{d^2y}{dx^2} < 0$ or $> 0$ ensuring no saddle point of $y$. 

Fig. 1. Surface Plot of SBAF; $y$ vs. input, $x$ and $\alpha$; No saddle point

Fig. 2. Visualization of the activation: local oscillation seems to be absent
III. BACKPROPAGATION WITH SBAF

The basic structure of the neural network consists of input layer, hidden layer and output layer. Let us assume the nodes at input layer are \( i_1, i_2 \), at hidden layer \( h_1, h_2 \) and at output layer \( o_1, o_2 \).

A. Basic Structure

\[
\begin{array}{c}
\text{i}_1 \\
\text{w}_1 \\
\text{h}_1 \\
\text{w}_3 \\
\text{o}_1 \\
\text{i}_2 \\
\text{w}_4 \\
\text{h}_2 \\
\text{w}_5 \\
\text{o}_2 \\
\text{bias}
\end{array}
\]

Goal: to optimize the weights so that the network can learn how to map from inputs to outputs.

B. The Forward Pass

Calculate the total input for \( h_1 \).

\[
h_{1\text{net}} = w_1 \cdot i_1 + w_2 \cdot i_2 + b_1
\]

\[
h_{2\text{net}} = w_3 \cdot i_1 + w_4 \cdot i_2 + b_1
\]

Use SBAF to calculate the output for \( h_1 \), \( y = \frac{1}{1 + ke^{r(1-x)}(1-y)^{1-\alpha}} \).

\[
h_{1\text{out}} = \frac{1}{1 + k(h_{1\text{net}})^\alpha(1 - h_{1\text{net}})^{1-\alpha}}
\]

\[
h_{2\text{out}} = \frac{1}{1 + k(h_{2\text{net}})^\alpha(1 - h_{2\text{net}})^{1-\alpha}}
\]

Repeat the process for output layer neurons and compute the values of \( o_{1\text{net}}, o_{2\text{net}}, o_{1\text{out}} \) and \( o_{2\text{out}} \).

Calculating the errors,

\[
\text{Error} = \text{Error}_{o1} + \text{Error}_{o2}
\]

\[
\text{Error}_{o1} = \frac{1}{2} (o_{1\text{target}} - o_{1\text{out}})^2
\]

\[
\text{Error}_{o2} = \frac{1}{2} (o_{2\text{target}} - o_{2\text{out}})^2
\]

C. The Backward Pass

Update the weights so that the actual output is closer to target output, thereby minimizing the error.

1) Output Layer: Consider \( w_5 \); let’s find the gradient wrt \( w_5 \), i.e., \( \frac{\partial E_{\text{total}}}{\partial w_5} \).

\[
\begin{align*}
\frac{\partial E_T}{\partial w_5} &= \frac{\partial E_T}{\partial o_{out}} \cdot \frac{\partial o_{out}}{\partial o_{net}} \cdot \frac{\partial o_{net}}{\partial w_5} \\
\frac{\partial E_T}{\partial o_{out}} &= \frac{1}{2} \left( o_{1\text{target}} - o_{1\text{out}} \right)^2 + \frac{1}{2} \left( o_{2\text{target}} - o_{2\text{out}} \right)^2 \\
\frac{\partial E}{\partial o_{out}} &= 2 \cdot \frac{1}{2} \left( o_{1\text{target}} - o_{1\text{out}} \right) \cdot (-1) + 0 \\
\frac{\partial E}{\partial o_{net}} &= - \left( o_{1\text{target}} - o_{1\text{out}} \right)
\end{align*}
\]

Using the SBAF

\[
\begin{align}
o_{1\text{out}} &= \frac{1}{1 + k(1 - o_{1\text{out}})^{\alpha(1 - 1) - \alpha}} \\
\frac{\partial o_{1\text{out}}}{\partial o_{net}} &= \frac{o_{1\text{out}} - o_{1\text{net}}}{o_{1\text{net}}(1 - o_{1\text{net}})} \cdot (\alpha - o_{1\text{net}})
\end{align}
\]

Finally,

\[
\begin{align}
o_{1\text{net}} &= w_5 \cdot h_{1\text{out}} + w_6 \cdot h_{2\text{out}} + b_2 \\
\frac{\partial o_{1\text{net}}}{\partial w_5} &= h_{1\text{out}}
\end{align}
\]

Put derived values of (3) and (4) and (5) in \( \frac{\partial E_T}{\partial w_5} \).

IV. DATA

The data used in the current work is from the PHL-EC (University of Puerto Rico’s Planetary Habitability Laboratory’s Exoplanet Catalog). This dataset contains over 3600 samples, predominantly those of planets that are non-habitable. The different classes in the data are those of mesoplanet, psychro-planet, and non-habitable planets [11]. The number of samples in the non-habitable class is over a thousand times of the remaining classes put together. Further, the planets considered potentially habitable can have their planetary attributes in a narrow band of values. Putting together the class-dominance and the nature of the data, developing an automated method...
for the categorization of new samples would not only be an interesting academic exercise but also a useful tool which can quickly and efficiently classify newly discovered exoplanets into the habitability classes.

The classes in the data are briefly described below:

1) **Non-Habitable**: Planets that exhibit conditions unsuitable for habitability are classified as non-habitable planets.

2) **Mesoplanet**: Planets whose sizes lie between that of Mercury and Ceres falls under this category. These planets have mean global surface temperature between 0°C to 50°C, a necessary condition for complex terrestrial life. These are generally referred to as Earth-like planets.

3) **Psychroplanet**: These planets have mean global surface temperature between -50°C to 0°C. Temperatures of psychroplanets are colder than optimal for sustenance of terrestrial life, but nonetheless, some psychroplanets are considered as potentially habitable candidates.

Apart from these classes, the dataset also has the classes of thermoplanets, hypopsychroplanets and hyperthermoplanets. However, the number of samples in each of these classes is too less for us to include them in our exploration. Certain features, too, were dropped from the dataset prior to running the model and these mostly include features like name of the host star of a planet, the number of moons, year of discovery, etc. as these features would not reasonably affect the outcome of the classifiers. Additionally, only about 1% of all the data is missing and the missing attributes are filled in by the class-wise mean of the corresponding attribute.

After the preprocessing is done as above, the model is implemented and the results are collated.

V. **NUANCES OF THE ACTIVATION FUNCTION**

- $x$ is surface temperature (normalized between 0 and 1) and $1 - x$ is the complement of that, together explaining the perfect discrimination between habitability classes as explained in our TSS above. The motivation of SBAF is derived from this fact of TSS. Using $kx^\alpha(1 - x)^{1 - \alpha}$ shall maximize the width of the two separating hyperplanes in the SVM used in TSS as the kernel has a global maxima when $0 \leq \alpha \leq 1$. This is equivalent to the CDHS formulation when CD-HPF is written as $y = kx^\alpha(1 - x)^\beta$ where $\alpha + \beta = 1$, $0 \leq \alpha \leq 1$, $0 \leq \beta \leq 1$, $k$ is suitably assumed to be 1 (CRS condition), and the representation ensures global maxima (maximum width of the separating hyperplanes) under such constraints [2], [7].

- The new activation function to be used for training a neural network for habitability classification boasts of an optima. Evidently, from the graphical simulations below, we observe less flattening of the function and therefore the formulation should be able to tackle local oscillations more easily as compared to the more generally used sigmoid function. Moreover, since $0 \leq \alpha \leq 1$, $0 \leq x \leq 1$, $0 \leq 1 - x \leq 1$, the variable term in the denominator of SBAF, $kx^\alpha(1 - x)^{1 - \alpha}$ may be approximated to a first order polynomial. This may help us in circumventing expensive floating point operations without compromising the precision.

Habitability classification is a complex task. Even though the literature is replete with rich and sophisticated methods using both supervised [12] and unsupervised learning methods, the soft margin between classes, namely psychroplanet and mesoplanet makes the task of discrimination incredibly difficult. A sequence of recent explorations by Saha et. al. expanding previous work by Bora et. al. on using Machine Learning algorithm to construct and test planetary habitability functions with exoplanet data raises important questions. The 2018 paper ([7]) analyzed the elasticity of the Cobb-Douglas Habitability Score (CDHS) and compared its performance with other machine learning algorithms. They demonstrated the robustness of their methods to identify potentially habitable planets [13] from exoplanet dataset. Given our little knowledge on exoplanets and habitability, these results and methods provide one important step toward automatically identifying objects of interest from large datasets by future ground and space observatories. The variable term in SBAF, $kx^\alpha(1 - x)^{1 - \alpha}$ is inspired from a history of modeling such terms as production functions and exploiting optimization principles in production economics, [14], [15], [16]. Complexities/bias in data may often necessitate devising classificaiton methods to mitigate class imbalance, [17] to improve upon the original method, [18], [19] or manipulate confidence intervals [20]. However, these improvisations led the authors to believe that, a general framework to train in forward and backward pass may turn out to be efficient. This is the primary reason to design a neural network with a novel activation function. We shall use the architecture to discriminate exoplanetary habitability [21], [22], [23], [24], [25], [11]. The results of the new classification method are discussed in the next section.

VI. **THE NEW CLASSIFICATION METHOD AND RESULTS**

The PHL-EC dataset has 3771 samples of planetary data, consisting of 3 classes of planets along with the values of their 45 features (post-pruning unnecessary features). The dataset is run on a 3 layered-Multi Layered Perceptron (MLP) architecture implemented in python that utilizes gradient descent method to learn the weights and biases. The architecture consists of layers of fully connected neurons with 45 neurons in input layer, 11 neurons in hidden and 2 neurons in output layer respectively. The connection weights and biases are randomly initialized. The network is tuned to achieve best classification results at the learning rate of 0.1 and momentum of .001. The training set consists of 80% of samples and remaining 20% are used for testing. At 100 epochs, the classification results for PHL-EC dataset are as follows:
Before analyzing performance metrics of classification using SBAF, we note that class 1 samples are for non-habitable planets, class 2 samples are for Mesoplanets and class 3 samples are for Psychroplanet respectively. Also, the values of α and k used in SBAF function are tuned during the execution of MLP code on PHL-EC data. The best classification results are obtained at $\alpha = 0.5$ and $k = 0.91$. Results of classification are pretty interesting to inspect. The confusion matrix indicates that, in spite of considerably large number of class 1 samples, the MLP classifies all the class 1 and class 3 samples unmistakably, with the accuracy of 1 and 0.994 for the respective classes. Though, Class 2 samples (for Mesoplanets) are not flawlessly classified, (out of 9 samples, 5 were correctly labeled and rest of the 4 were mistakenly labeled to be of class 3), the reason can be attributed to the class distribution of the training set by generating synthetic data for classes of lesser samples.

VII. CONCLUSION

Machine classification on habitability is a very recent area. Therefore, the motivation for contemplating such a task is beyond doubt. However, instead of using “black-box” methods for classification, we embarked upon understanding activation functions and their role in Artificial Neural Net based classification. Theoretically, there is evidence of optima and therefore absence of local oscillations. This is significant and helps classification efficacy, for certain. In comparison to gradient boosted classification of exoplanets, [6], [7], our method achieved about 2 % more accuracy, a near perfect classification. This is encouraging for future explorations in to this activation function, including studying applicability of Q-deformation and maximum entropy principles. Even without habitability classification or absence of any motivation, further study of the activation function seems promising.

### REFERENCES

[1] W. Bains and D. Schulze-Makuch, “The cosmic zoo: The (near) inevitability of the evolution of complex, macroscopic life,” *Life*, vol. 6, no. 3, p. 25, Jun 2016. [Online]. Available: https://doi.org/10.3390/life6030025

[2] K. Bora, S. Saha, S. Agrawal, M. Safonova, S. Routh, and A. Narasimhamurthy, “Cd-hpf: New habitability score via data analytic modeling.” *Astronomy and Computing*, vol. 17, pp. 129 – 143, 2016. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S2213133716300865

[3] S. Agrawal, S. Basak, S. Saha, K. Bora, and J. Murthy, “A comparative analysis of the cobb-douglass habitability score (cdhs) with the earth similarity index (esi).” 2018. [Online]. Available: https://arxiv.org/abs/1804.11176

[4] S. Saha, P. Sarkar, A. Mathur, and S. Basak, “Model visualization in understanding rapid growth of a journal in an emerging area.” 2018. [Online]. Available: https://arxiv.org/abs/1803.04644

[5] A. Theophilus, S. Saha, S. Basak, and J. Murthy, “A novel exoplanetary habitability score via particle swarm optimization of ces production functions,” 2018. [Online]. Available: https://arxiv.org/abs/1805.08858

[6] S. Basak, S. Agrawal, S. Saha, A. J. Theophilus, K. Bora, G. Deshpande, and J. Murthy, “Habitability classification of exoplanets: A machine learning insight,” 2018. [Online]. Available: https://arxiv.org/abs/1805.08810

[7] S. Saha, S. Basak, K. Bora, M. Safonova, S. Agrawal, P. Sarkar, and J. Murthy, “Theoretical Validation of Potential Habitability via Analytical and Boosted Tree Methods: An Optimistic Study on Recently Discovered Exoplanets,” *ArXiv e-prints*, Dec. 2017. [Online]. Available: https://arxiv.org/abs/1712.01040

[8] R. Lippmann, “Book review: “neural networks, a comprehensive foundation”, by simon haykin.” *International Journal of Neural Systems*, vol. 05, no. 04, pp. 363–364, Dec 1994. [Online]. Available: https://doi.org/10.1142/s0129065794000372

[9] S. Elfwing, E. Uchibe, and K. Doya, “Sigmoid-weighted linear units for neural network function approximation in reinforcement learning.” *Neural Networks*, 2018. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0893608017302976

[10] A. S. Younger, S. Hochreiter, and P. R. Corwell, “Meta-learning with backpropagation.” in *ICNN 01, International Joint Conference on Neural Networks, Proceedings (Cat. No.01CH37222).* IEEE, [Online]. Available: https://doi.org/10.1109/ICNN.2001.938471

[11] A. Mendoza, “The habitable exoplanets catalog.” 2018. [Online]. Available: http://phil.upr.edu/hec

[12] D. A. Zighed, G. Ritschard, and S. Marcellin, *Asymmetric and Sample Size Sensitive Entropy Measures for Supervised Learning*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2010, pp. 27–42. [Online]. Available: https://doi.org/10.1007/978-3-642-05183-8_2

[13] S. Saha, K. Bora, S. Basak, G. Srinivasa, M. Safonova, A. Mathur, J. Murthy, and S. Agrawal, “Ebook-astroinformatics series machine learning in astronomy: A workman’s manual,” 2018. [Online]. Available: "https://www.researchgate.net/publication/322926268_EBOOK_ASTROINFORMATICS.Series.MACHINE.LEARNING_IN_"
[14] S. Saha, J. Sarkar, A. Dwivedi, N. Dwivedi, A. M. Narasimhamurthy, and R. Roy, “A novel revenue optimization model to address the operation and maintenance cost of a data center,” Journal of Cloud Computing, vol. 5, no. 1, pp. 1–23, Jan 2016. [Online]. Available: https://doi.org/10.1186/s13677-015-0050-8

[15] G. Ginde, S. Saha, A. Mathur, S. Venkatagiri, S. Vadakkepat, A. Narasimhamurthy, and B. S. Daya Sagar, “Scientobase: a framework and model for computing scholastic indicators of non-local influence of journals via native data acquisition algorithms,” Scientometrics, vol. 108, no. 3, pp. 1479–1529, Sep 2016. [Online]. Available: https://doi.org/10.1007/s11192-016-2006-2

[16] G. Ginde, S. Saha, C. Balasubramaniam, R. Harsha, A. Mathur, B. Dayasagar, and M. Anand, “Mining massive databases for computation of scholastic indices: Model and quantify internationality and influence diffusion of peer-reviewed journals,” in Proceedings of the fourth national conference of Institute of Scientometrics, SIoT, 2015.

[17] K. Mohanchandra, S. Saha, K. S. Murthy, and G. Lingaraju, “Distinct adoption of k-nearest neighbour and support vector machine in classifying EEG signals of mental tasks,” International Journal of Intelligent Engineering Informatics, vol. 3, no. 4, p. 313, 2015. [Online]. Available: https://doi.org/10.1504/ijiei.2015.073064

[18] V. N. Vapnik and A. Y. Chervonenkis, “On a class of perceptrons,” Automation and Remote Control, vol. 1, no. 25, pp. 103–109, 1964.

[19] C. Cortes and V. Vapnik, “Support-vector networks,” Machine Learning, vol. 20, no. 3, pp. 273–297, Sep 1995. [Online]. Available: https://doi.org/10.1023/A:1022627411411

[20] L. Khaidem, S. Saha, S. Basak, and S. R. Dey, “Predicting the direction of stock market prices using random forest,” 2016. [Online]. Available: "https://www.researchgate.net/publication/301818771_Predicting_the_direction_of_stock_market_prices_using_random_forest"

[21] D. Schulze-Makuch and W. Bains, “Time to consider search strategies for complex life on exoplanets,” Nature Astronomy, pp. 1–2, 5 2018. [Online]. Available: http://https://doi.org/10.1038/s41550-018-0476-2

[22] D. Schulze-Makuch, A. Méndez, A. G. Fairén, P. von Paris, C. Turse, G. Boyer, A. F. Davila, M. R. de Sousa António, D. Catling, and L. N. Irwin, “A two-tiered approach to assessing the habitability of exoplanets,” Astrobiology, vol. 11, no. 10, pp. 1041–1052, dec 2011. [Online]. Available: https://doi.org/10.1089/ast.2010.0592

[23] L. Irwin, A. Méndez, A. Fairén, and D. Schulze-Makuch, “Assessing the possibility of biological complexity on other worlds, with an estimate of the occurrence of complex life in the milky way galaxy,” Challenges, vol. 5, no. 1, pp. 159–174, may 2014. [Online]. Available: https://doi.org/10.3390/challe5010159

[24] C. J. Shallue and A. Vanderburg, “Identifying exoplanets with deep learning: A five-planet resonant chain around kepler-80 and an eighth planet around kepler-90,” The Astronomical Journal, vol. 155, no. 2, p. 94, 2018. [Online]. Available: http://stacks.iop.org/1538-3881/155/i=2/a=94

[25] A. Méndez, “The night sky of exoplanets,” 2011. [Online]. Available: http://phl.upr.edu/library/notes/syntheticstars