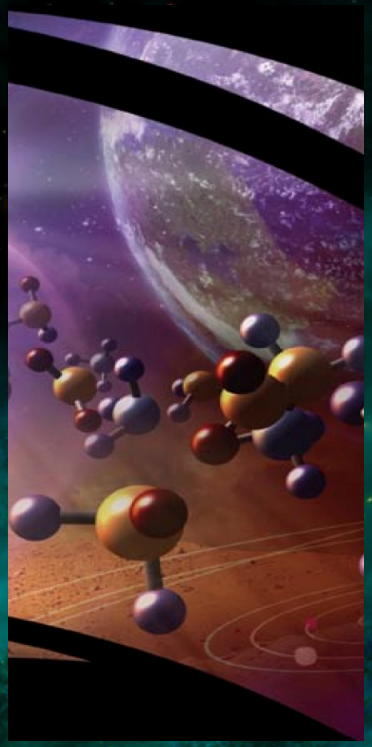
The SETI Institute: Using GPUs for Systems Science, Technology, and Exploration

Nathalie A. Cabrol
SETI Institute
Director, Carl Sagan Center for Research

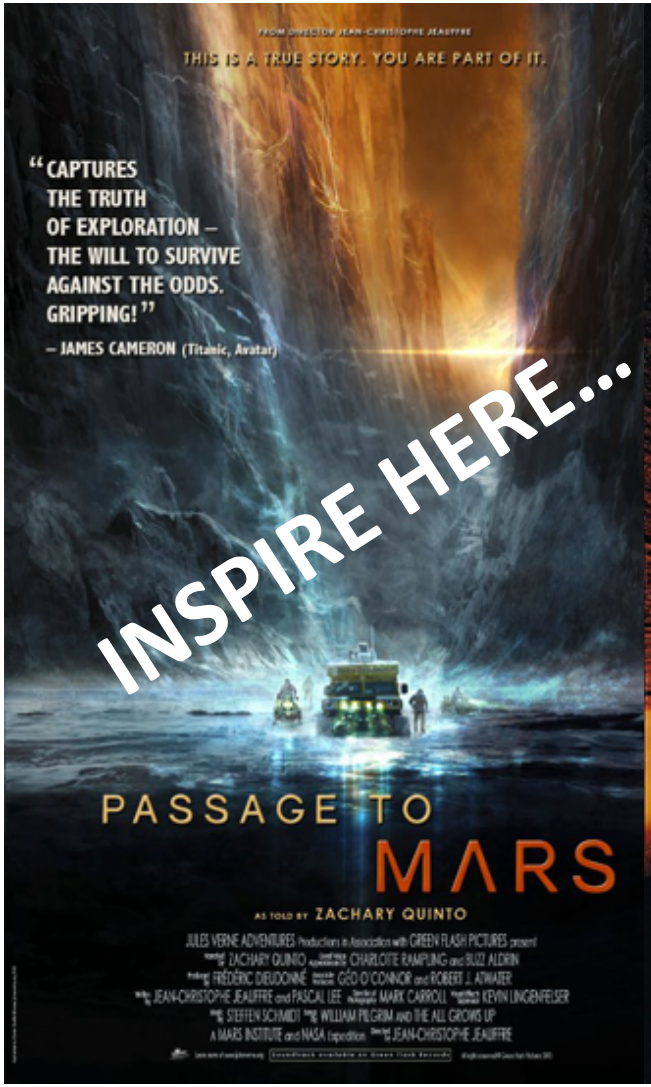
Graham Macintosh
SETI Institute AI Consultant

Mission Statement



Explore, Understand and Explain the Nature and Origins of Life in the Universe and the Evolution of Intelligence

We Share our Work with the Public to Inform, Educate and Inspire Current and Future Generations



INSPIRE HERE...

SOFIA Airborne Astronomy Ambassadors Program

SI – managed education program for teachers
NASA funded

Summer Research Experience for Undergraduates (REU)

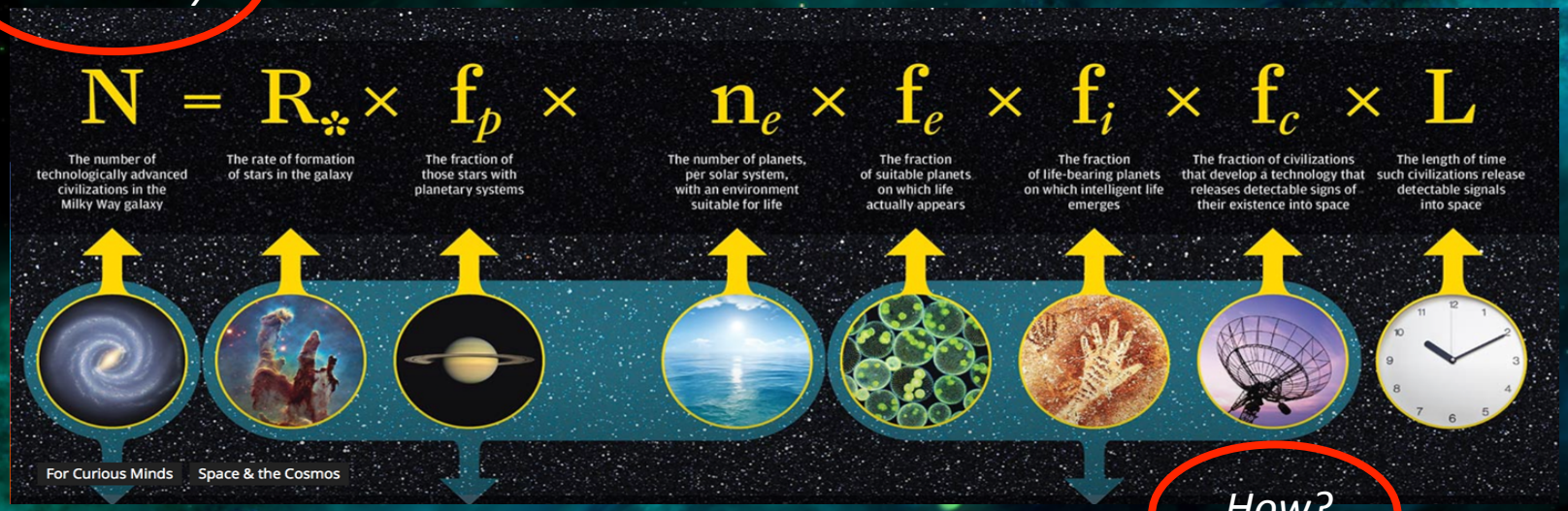
Undergraduate summer internship at SETI Institute
NSF funded

Reaching for the Stars NASA Space Science for Girl Scouts

Space STEM Badges for Girls Scouts USA
NASA funded

Are We Alone?

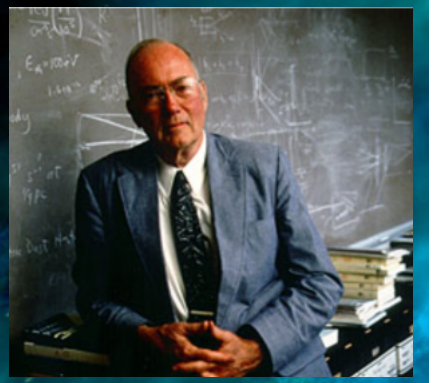
How Many?



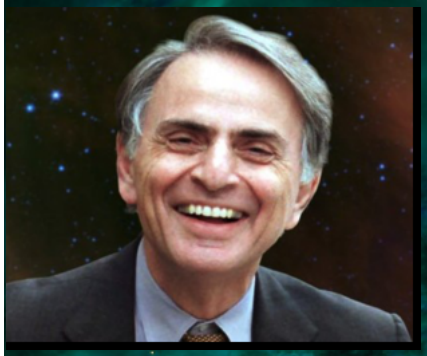
How?

Standing on the Shoulders of Giants

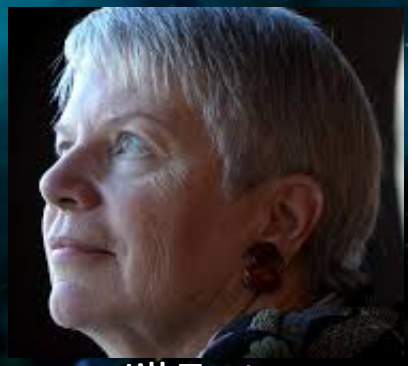
Frank Drake



Charles Townes



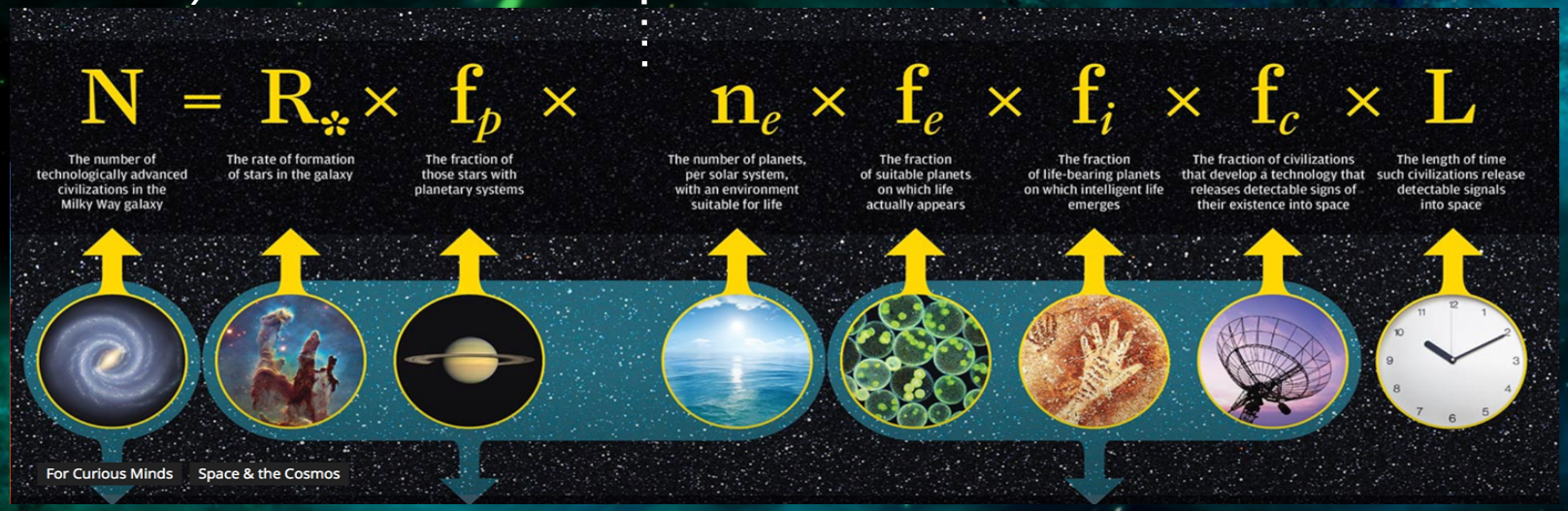
Carl Sagan



Jill Tarter

Habitability vs. Coevolution

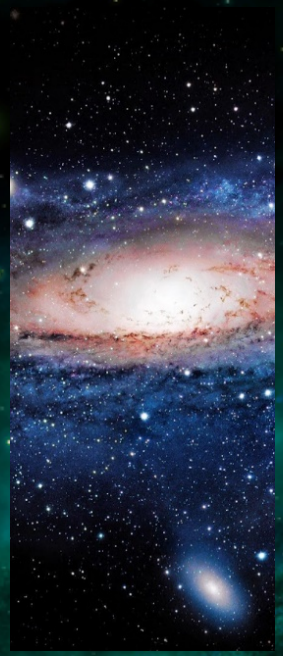
How Many?

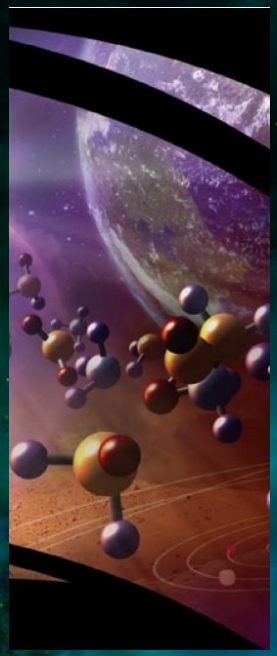


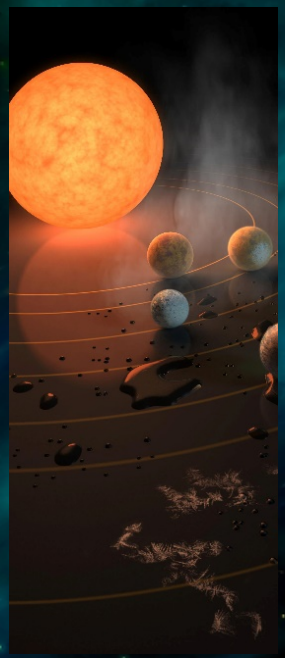
Where? *What?* *Who?* *How?*

CARL SAGAN CENTER

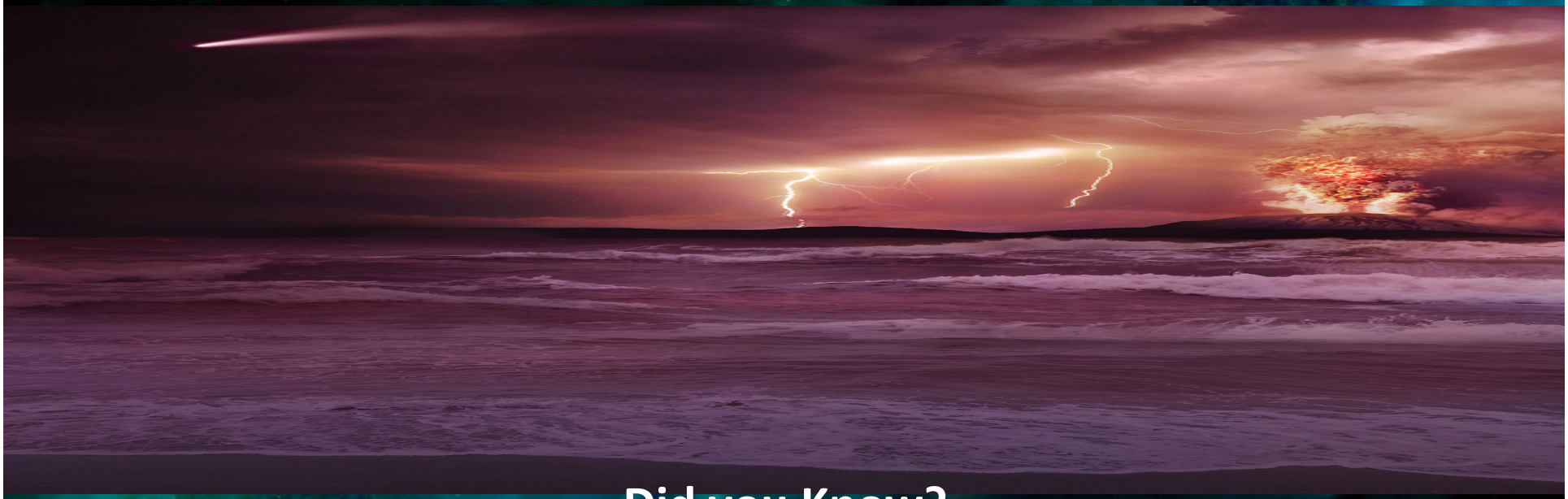
- Astronomy & Astrophysics
- Astrobiology
- Climate & Geoscience
- Exoplanets
- Planetary Exploration
- Radio & Optical SETI







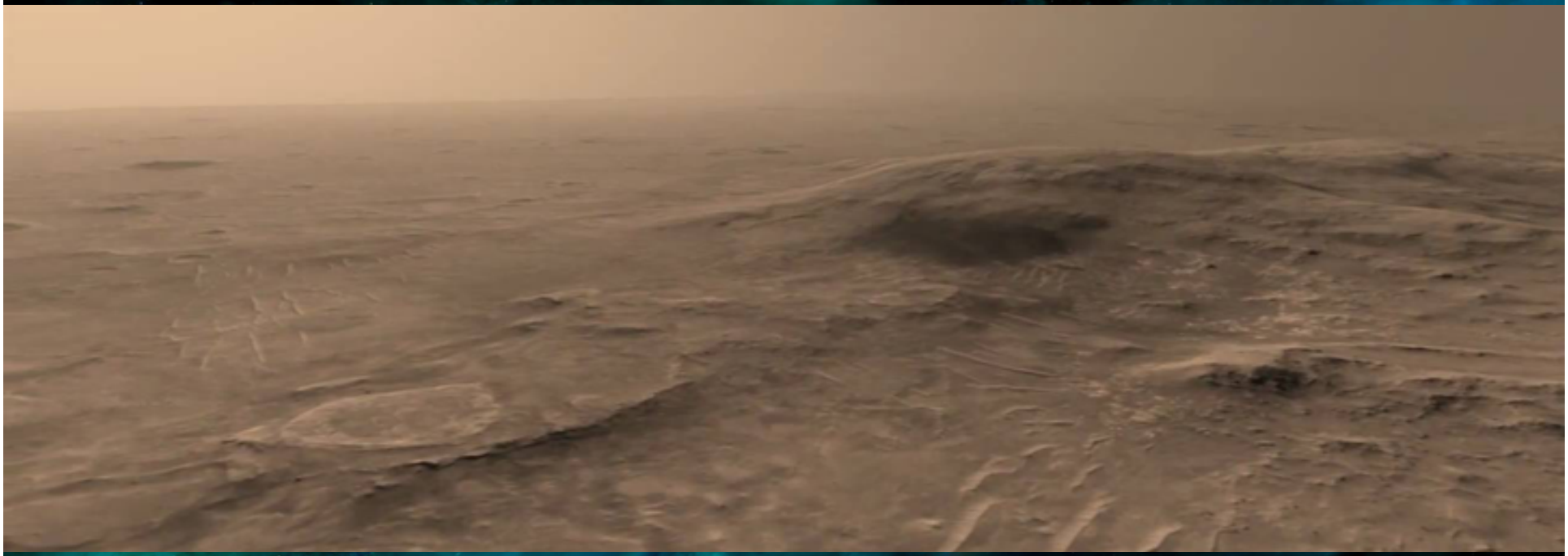
Searching for Life Beyond Earth



Did you Know?

Formation of Organic Molecules and Delivery to Planets

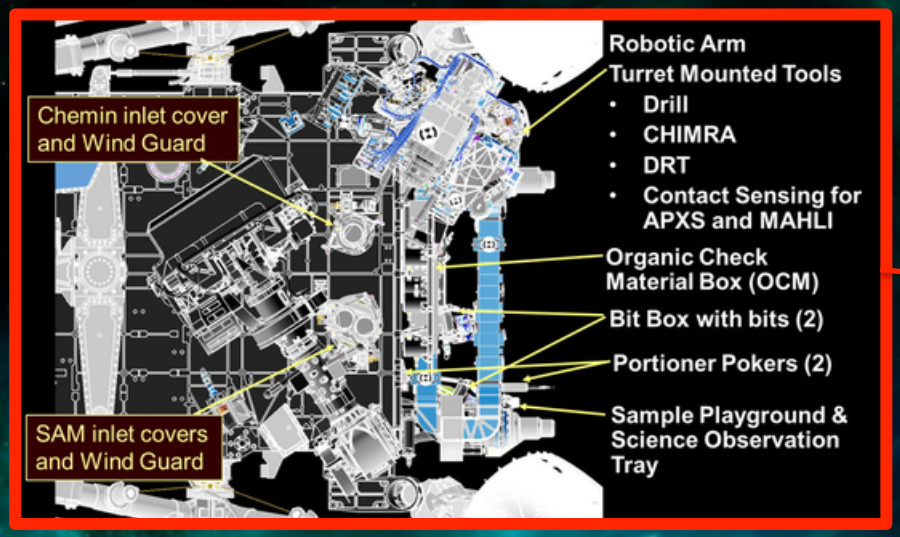
Understand Planetary Habitability

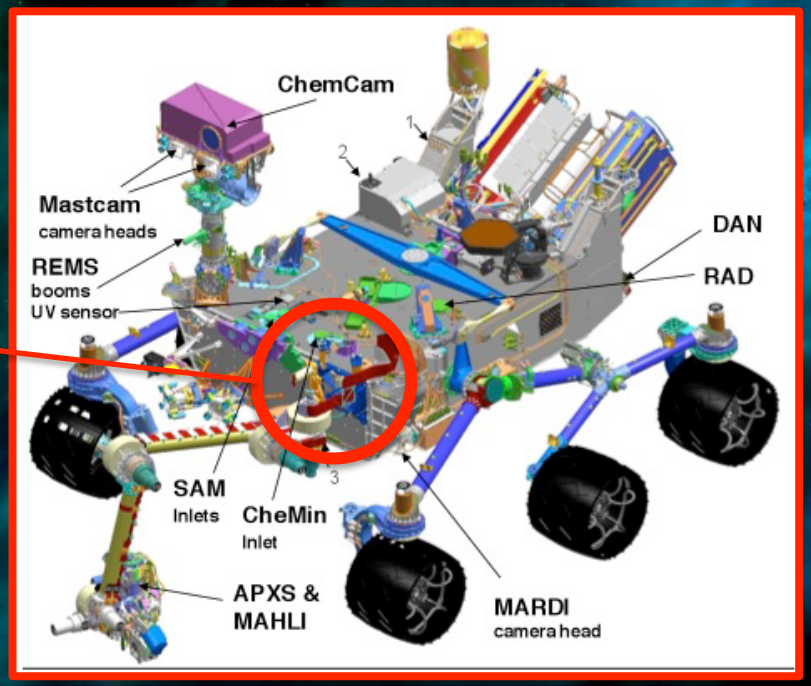


Did you Know?

Support Landing Site Selection and Planetary Missions

Understand Planetary Habitability





Did you Know?

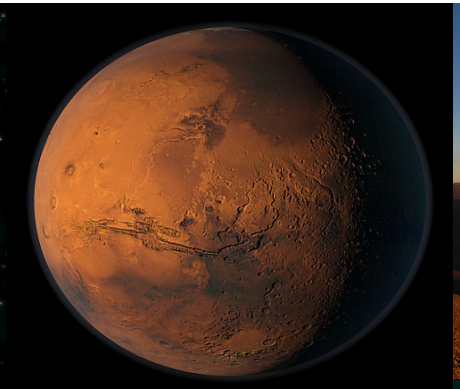
Develop Planetary Instrument & Surface Operations

Imagine the Future of Planetary Exploration

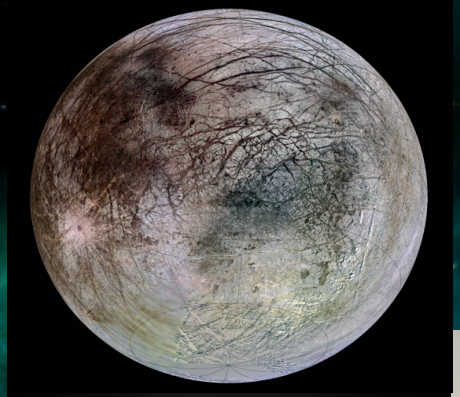
Did you Know?

Design and Test Technology for Future Robotic and Human Exploration

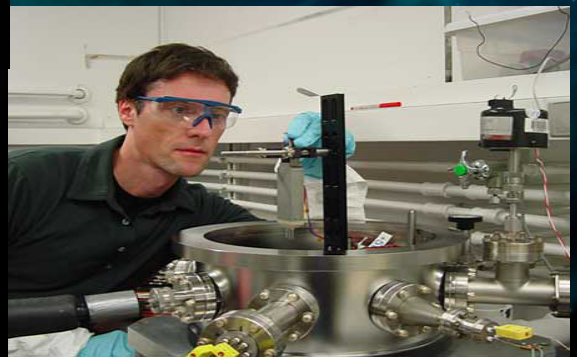
Did you Know?



Explore
Terrestrial Analogs



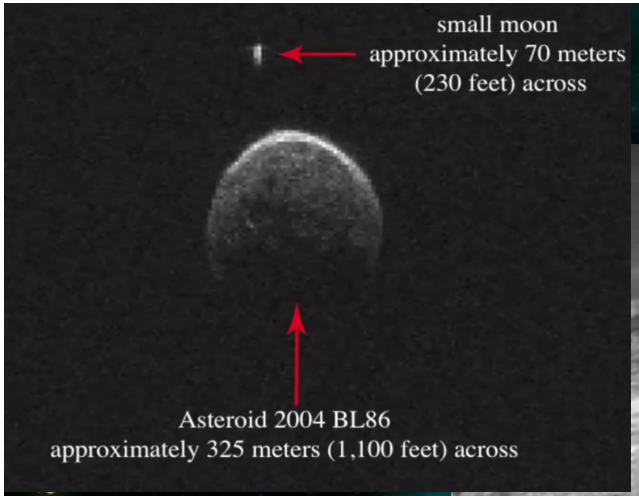
Characterize the
Fingerprints of Life

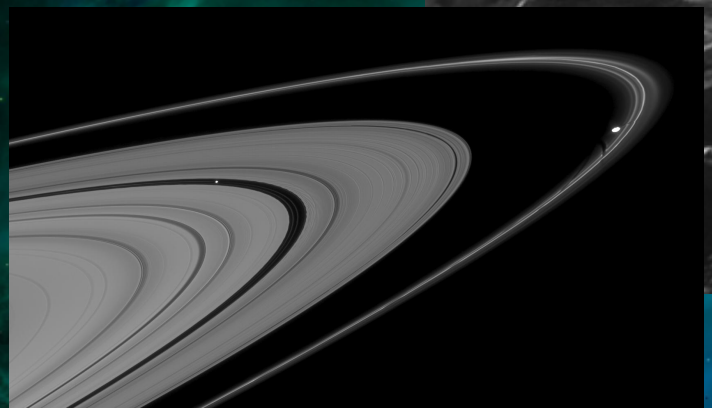


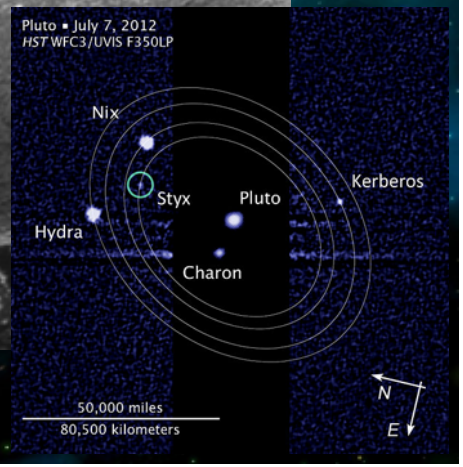
Develop New
Instruments and
Exploration Strategies

Did you Know?

Monitor Asteroids
& Learn How to Protect the Earth



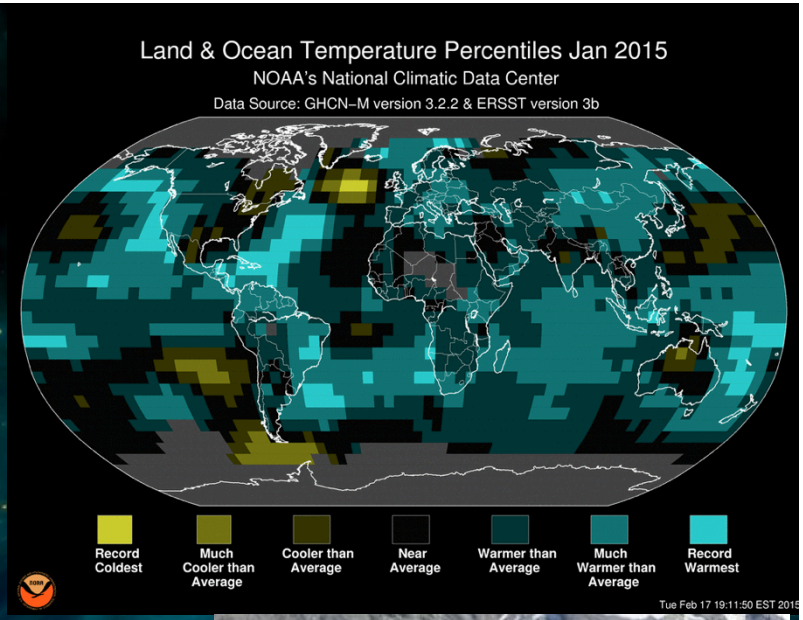




Discover Moons
And Guide Spacecrafts

Did you Know?

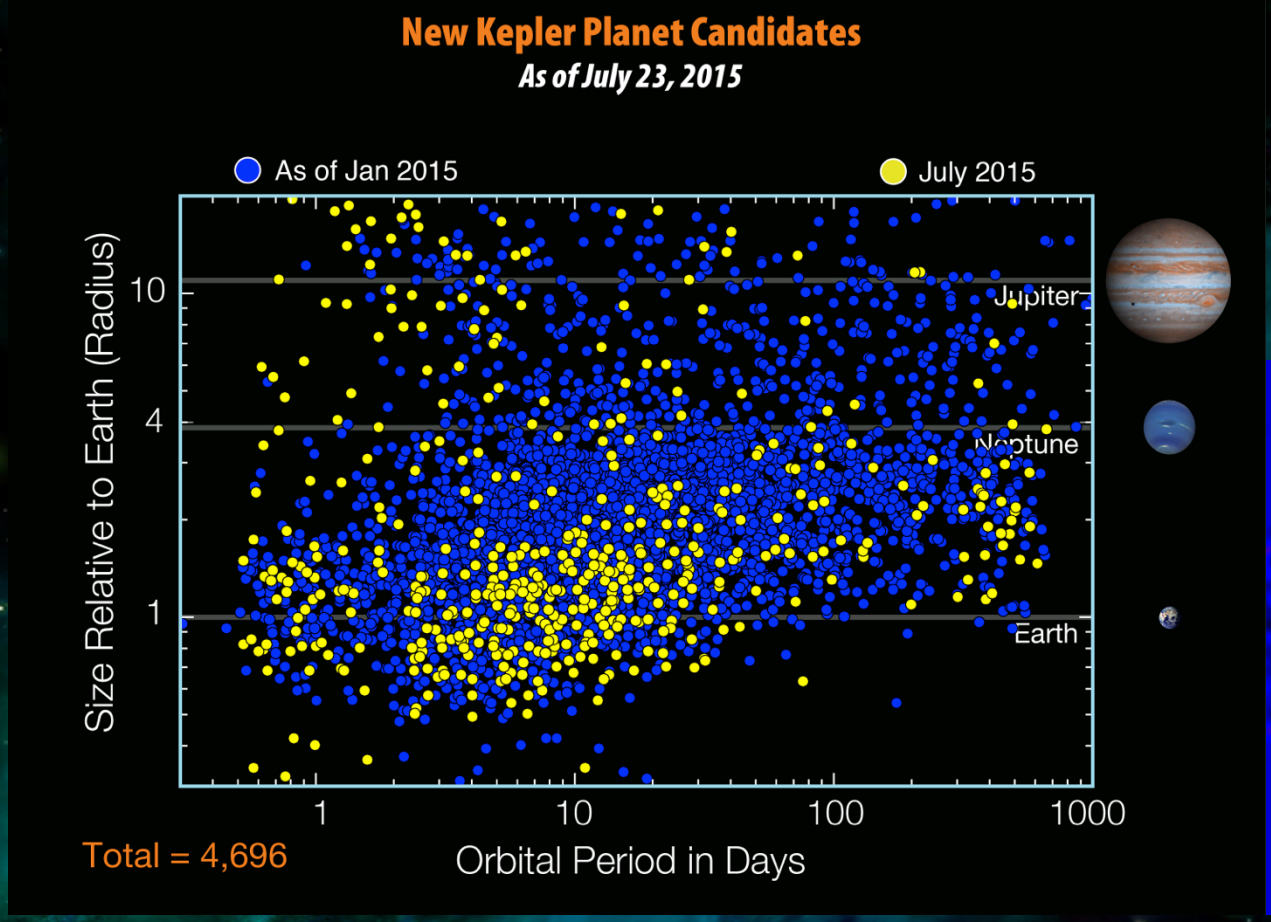
Use the Technology
Developed for Planetary Exploration

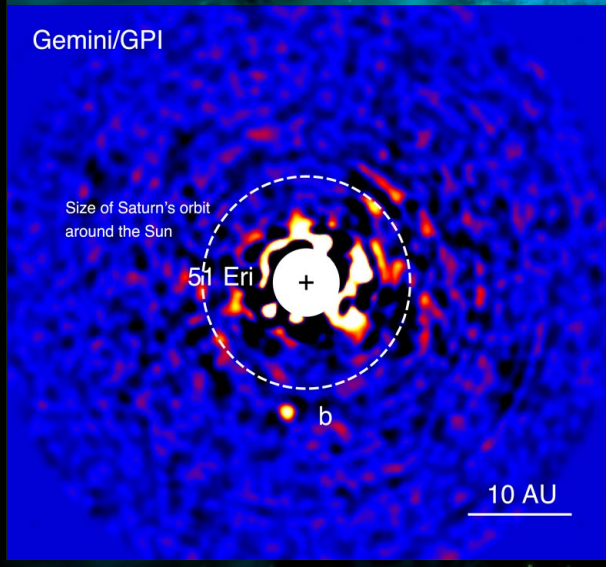


To Monitor the Changes on
our own Planet

Did you Know?

Discover New Worlds and New Earths

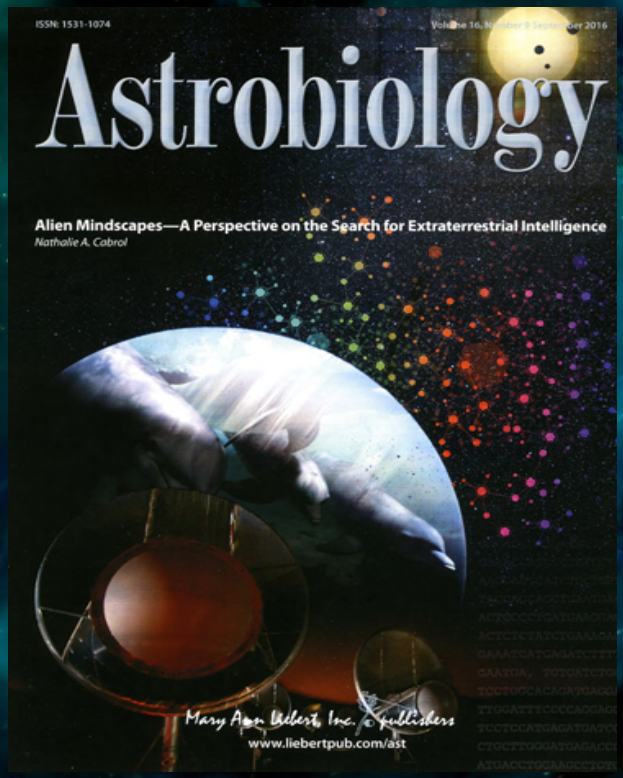




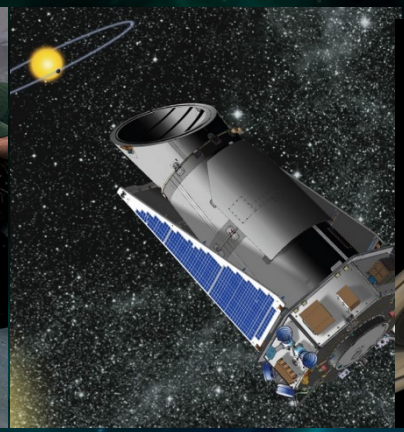
From Space and From the Ground…and


Understand the Rise of Intelligence and Civilization in the Universe (Who and Where?)
How to Communicate…
And Make Contact

Redefining The Exploration of Life in the Universe

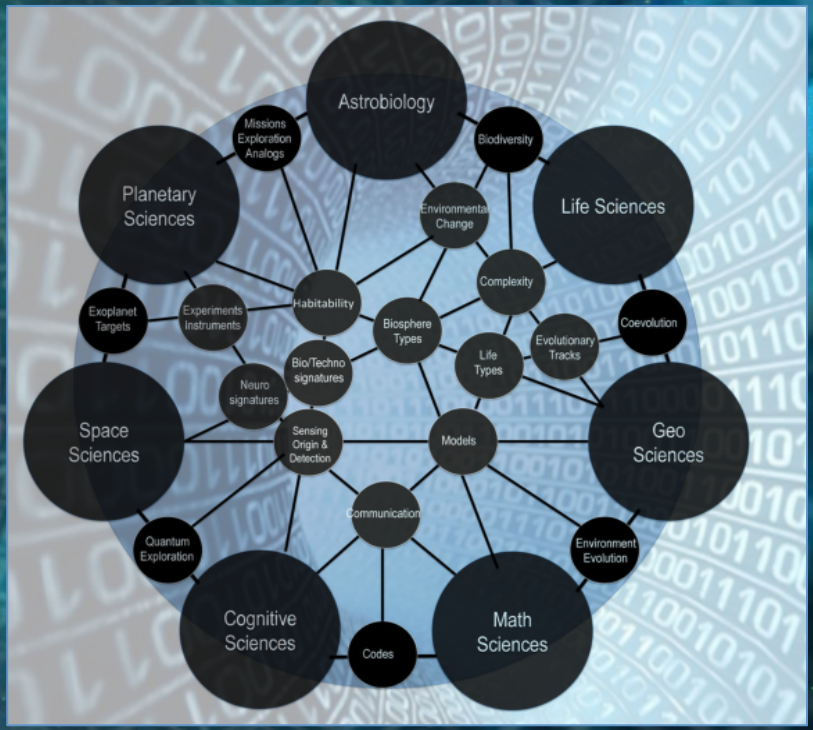


From Microbes to Intelligence and Technology

NASA Astrobiology Institute (NAI)	Arctic/Antarctic Extremophiles Research	KEPLER Space Telescope Data Pipeline	NASA Rings Node Database	Radio & Optical SETI Research
				
SETI Institute leads one of the NAI Teams NASA Funded	Dale Anderson at Lake Untersee Antarctic Privately Funded	SI Manages Data Pipeline for Kepler and K2 NASA Funded	SI Manages the Rings and Moons node for PDS NASA Funded	Allen Telescope Array and SETI Research Privately Funded

Life Beyond Earth

- Connect the dots.
- Go after the big knowledge Gaps and make quantum leaps.
- Revolutionize how science and exploration are done.
- …FDL is showing the way



SETI INSTITUTE

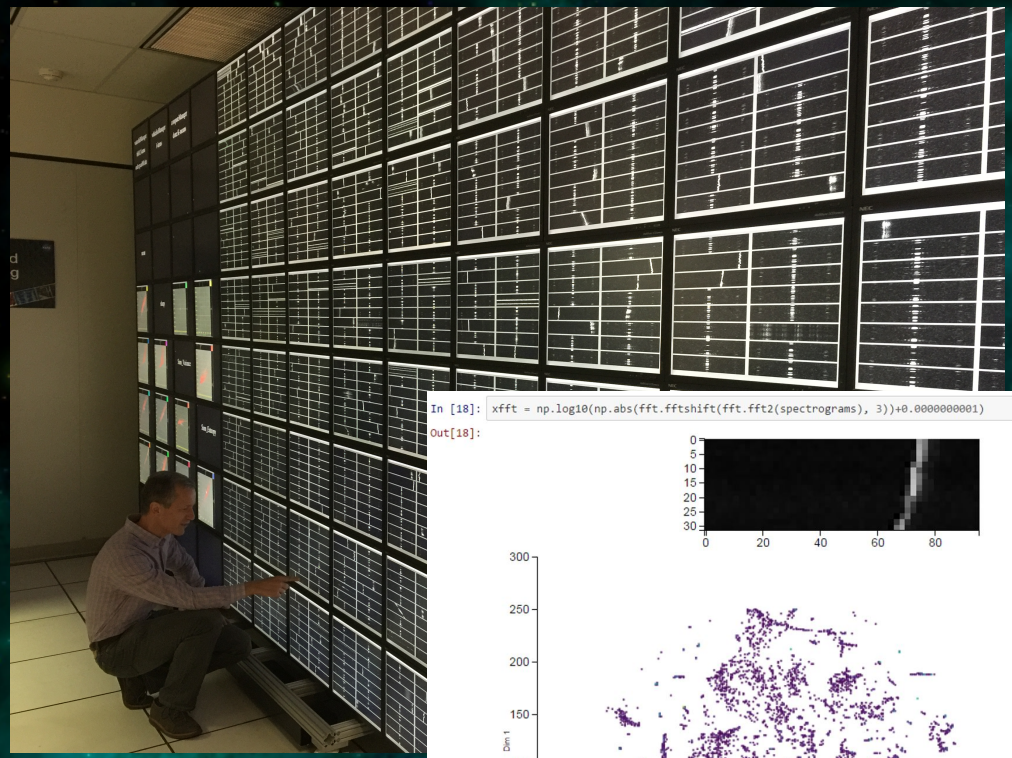
NASA FRONTIER DEVELOPMENT LAB

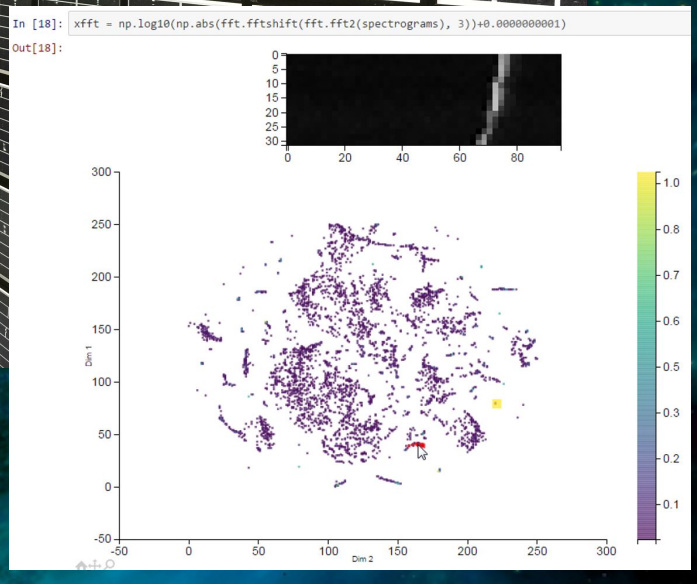
Applied artificial intelligence research accelerator that combines the AI capabilities of NASA, academia, and private sector companies in support of NASA's science priorities and mission goals.

SETI and AI – Initial Steps

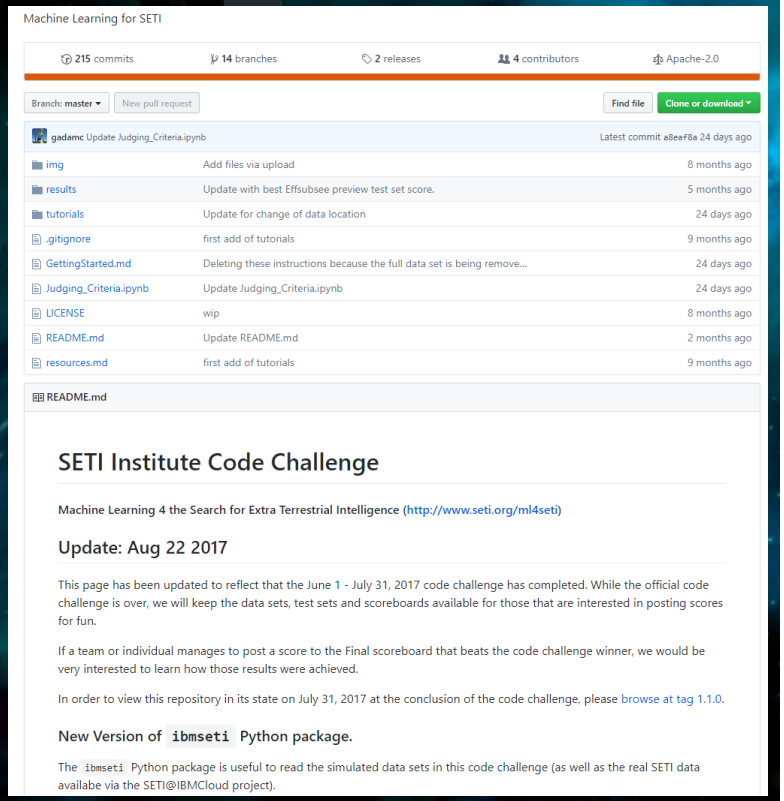
- 4.5TB data coming from the beamformers every hour
- Data searched for narrow-band signals using FFT in custom hardware
- "Blind" to other types of potential signals of interest
- Most data is dumped – only the data with detected signals is saved for later analysis

SETI and AI – Initial Steps





setiQuest/ML4SETI



Machine Learning for SETI

215 commits | 14 branches | 2 releases | 4 contributors | Apache-2.0

Branch: master | New pull request | Find file | Clone or download

gadamc Update Judging_Criteria.ipynb — Latest commit a8eaf8a 24 days ago

img	Add files via upload	8 months ago
results	Update with best Effsubsee preview test set score.	5 months ago
tutorials	Update for change of data location	24 days ago
.gitignore	first add of tutorials	9 months ago
GettingStarted.md	Deleting these instructions because the full data set is being remove...	24 days ago
Judging_Criteria.ipynb	Update Judging_Criteria.ipynb	24 days ago
LICENSE	wip	8 months ago
README.md	Update README.md	2 months ago
resources.md	first add of tutorials	9 months ago

README.md

SETI Institute Code Challenge

Machine Learning 4 the Search for Extra Terrestrial Intelligence (http://www.seti.org/ml4seti)

Update: Aug 22 2017

This page has been updated to reflect that the June 1 - July 31, 2017 code challenge has completed. While the official code challenge is over, we will keep the data sets, test sets and scoreboards available for those that are interested in posting scores for fun.

If a team or individual manages to post a score to the Final scoreboard that beats the code challenge winner, we would be very interested to learn how those results were achieved.

In order to view this repository in its state on July 31, 2017 at the conclusion of the code challenge, please browse at tag 1.1.0.

New Version of `ibmseti` Python package.

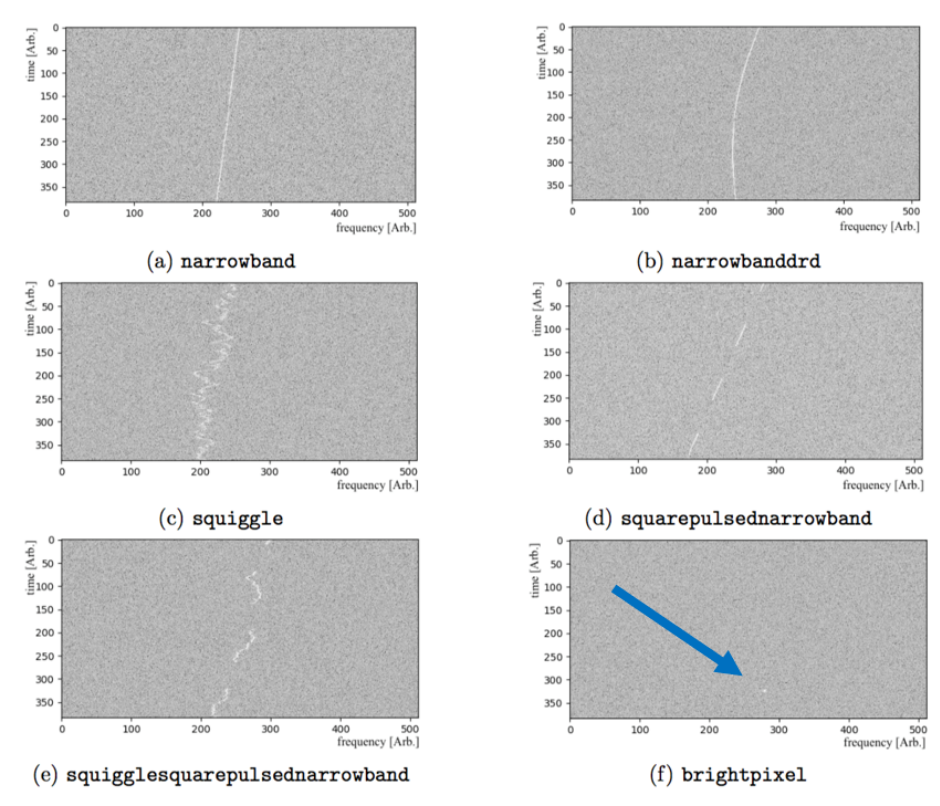
The `ibmseti` Python package is useful to read the simulated data sets in this code challenge (as well as the real SETI data availabe via the SETI@IBMCloud project).

The ML4SETI Hackathon Challenge – Summer 2017 / 100 Participants!

- SETI Institute, IBM Watson, UC Berkeley, Galvanize, Nimbix, Skymind , The SETI League

- Signal classification into 7 categories : ”noise” + →
- 35k training signals per class (140k total)
- Judging based on lowest multinomial LogLoss score on previously unobserved test data set

- Team Effsubsee (1st place)
  - Wide ResNet (34x2) based on Zagoruyko, et al http://arxiv.org/abs/1605.07146)
  - NVIDIA TitanX: ~1 day training
- Team Signet (2nd place)
  - 201 layer densenet from Huang, et al. https://arxiv.org/abs/1608.06993
  - NVIDIA GTX 1080 Ti: ~2 days training



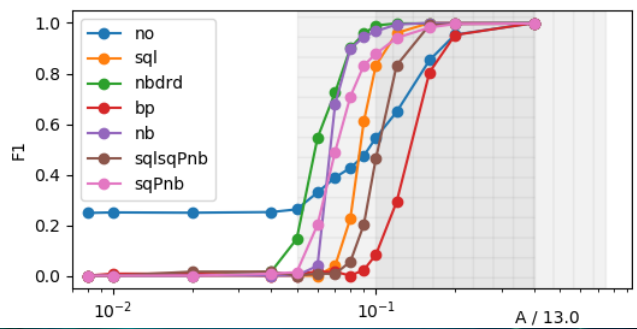
https://arxiv.org/abs/1803.08624

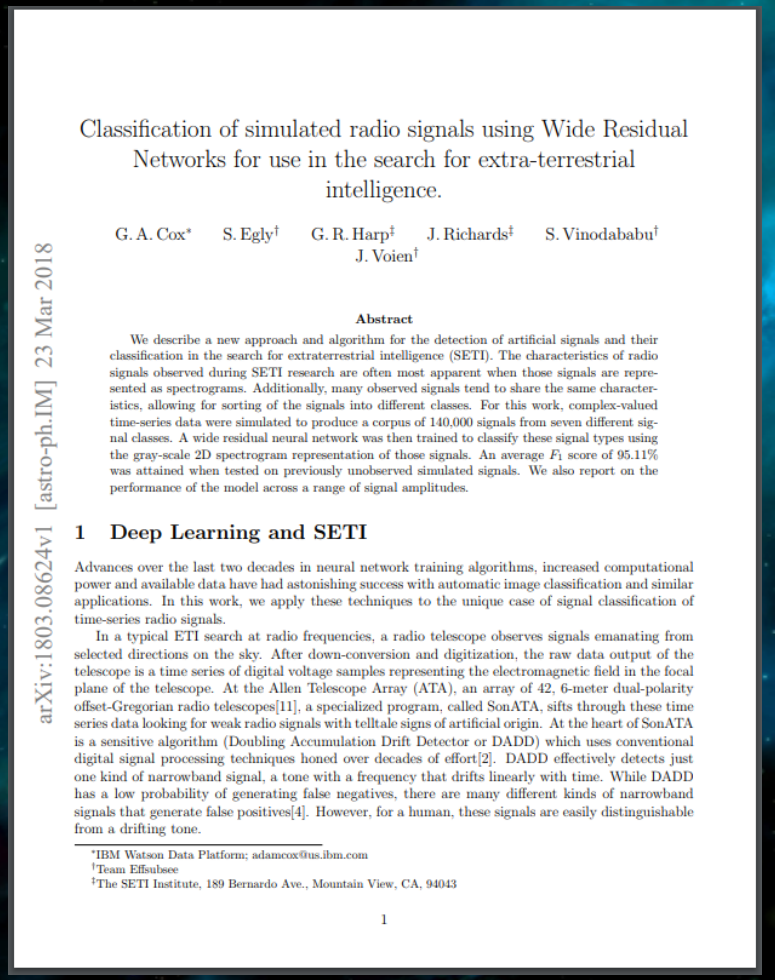
The ML4SETI Hackathon Challenge

Top Prize: Team Effsubsee using DL on Wide ResNet

Based on Zagoruyko, et al http://arxiv.org/abs/1605.07146

	N	precision	recall	F_1
brightpixel	385	0.991	0.857	0.919
narrowband	355	0.994	0.944	0.968
narrowbanddrd	348	0.969	0.977	0.973
noise	368	0.785	0.995	0.877
squarepulsednarrowband	385	0.975	0.925	0.949
squiggle	322	1.000	0.997	0.998
squigglesquarepulsednarrowband	332	1.000	0.970	0.984





arXiv:1803.08624v1 [astro-ph.IM] 23 Mar 2018

Classification of simulated radio signals using Wide Residual Networks for use in the search for extra-terrestrial intelligence.

G. A. Cox* S. Egly† G. R. Harp‡ J. Richards‡ S. Vinodababu† J. Voien†

Abstract

We describe a new approach and algorithm for the detection of artificial signals and their classification in the search for extraterrestrial intelligence (SETI). The characteristics of radio signals observed during SETI research are often most apparent when those signals are represented as spectrograms. Additionally, many observed signals tend to share the same characteristics, allowing for sorting of the signals into different classes. For this work, complex-valued time-series data were simulated to produce a corpus of 140,000 signals from seven different signal classes. A wide residual neural network was then trained to classify these signal types using the gray-scale 2D spectrogram representation of those signals. An average F_1 score of 95.11% was attained when tested on previously unobserved simulated signals. We also report on the performance of the model across a range of signal amplitudes.

1 Deep Learning and SETI

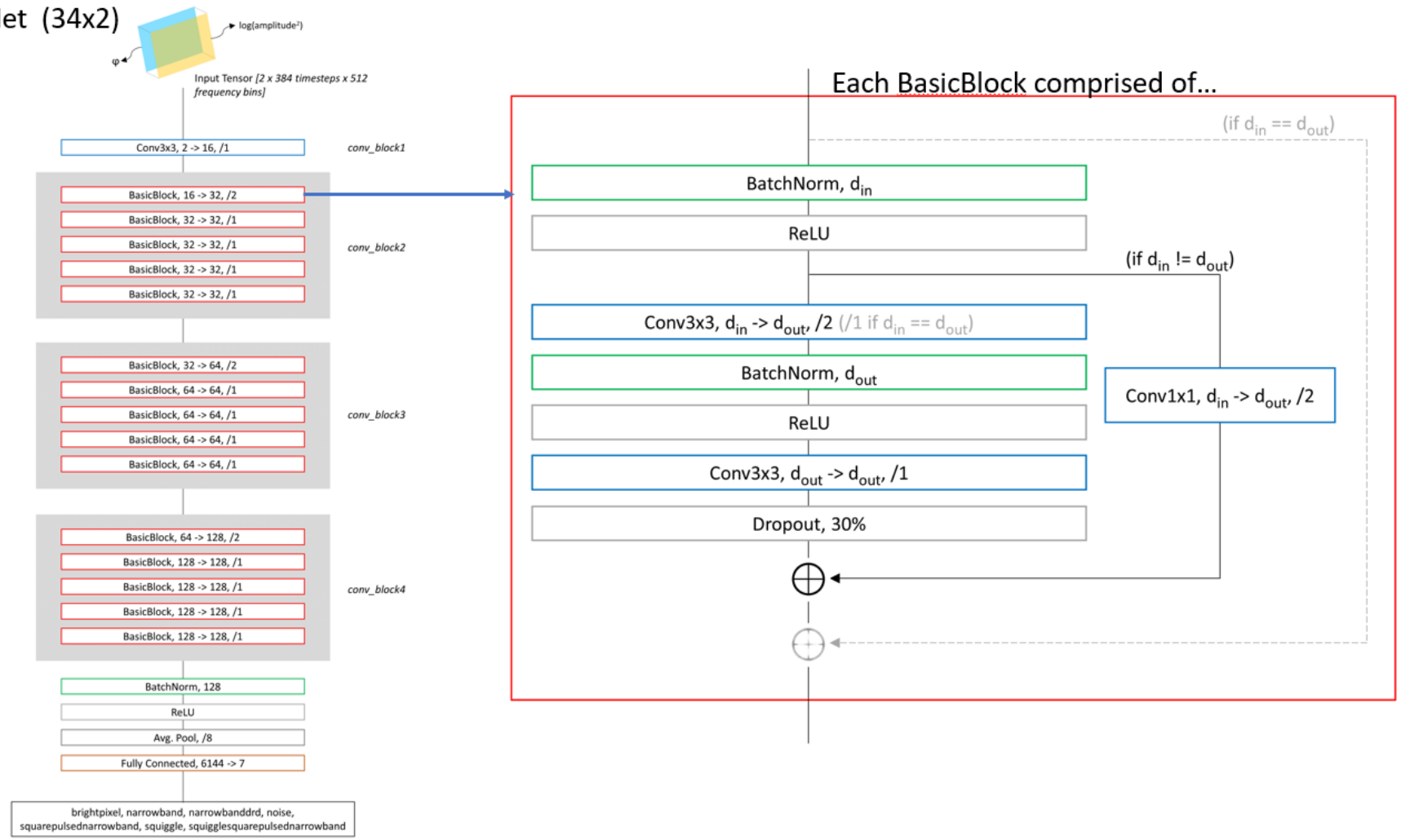
Advances over the last two decades in neural network training algorithms, increased computational power and available data have had astonishing success with automatic image classification and similar applications. In this work, we apply these techniques to the unique case of signal classification of time-series radio signals.

In a typical ETI search at radio frequencies, a radio telescope observes signals emanating from selected directions on the sky. After down-conversion and digitization, the raw data output of the telescope is a time series of digital voltage samples representing the electromagnetic field in the focal plane of the telescope. At the Allen Telescope Array (ATA), an array of 42, 6-meter dual-polarity offset-Gregorian radio telescopes[11], a specialized program, called SonATA, sifts through these time series data looking for weak radio signals with telltale signs of artificial origin. At the heart of SonATA is a sensitive algorithm (Doubling Accumulation Drift Detector or DADD) which uses conventional digital signal processing techniques honed over decades of effort[2]. DADD effectively detects just one kind of narrowband signal, a tone with a frequency that drifts linearly with time. While DADD has a low probability of generating false negatives, there are many different kinds of narrowband signals that generate false positives[4]. However, for a human, these signals are easily distinguishable from a drifting tone.

*IBM Watson Data Platform; adamcox@us.ibm.com
†Team Effsubsee
‡The SETI Institute, 189 Bernardo Ave., Mountain View, CA, 94043

1

Wide ResNet (34x2)



SETI INSTITUTE

NASA FRONTIER DEVELOPMENT LAB

AI for Space Science

A few examples from 2017…

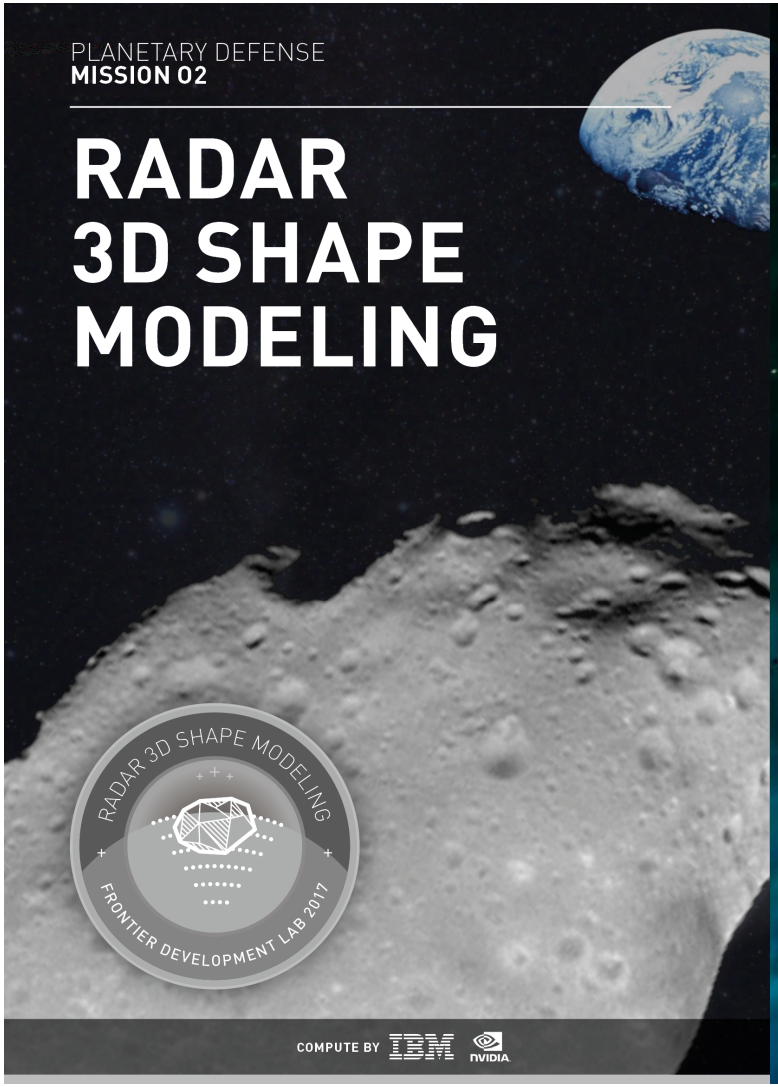
NASA FDL 2017

- Planetary Defense: Asteroid Shape Modeling
- Planetary Defense: Long Period Comets
- Space Weather: Solar Flare Prediction

- Teams of 6-8 researchers – AI developers + space scientists
- IBM equipped each team with…
  - Dual Xeon E5-2690v4 / 28 cores / 2.60 GHz / 128 GB RAM / 1.2TB SSD HD
  - GPU = 2 x Tesla P100 GPUs with 16GB
  - 100TB of shared cloud storage

PLANETARY DEFENSE
MISSION 02

RADAR 3D SHAPE MODELING



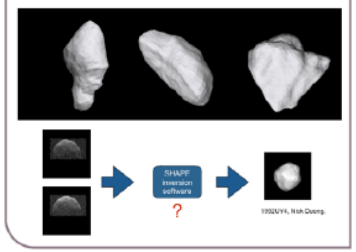
- The FDL team tackled the task of automating task of creating 3D shape models of NEOs from sparse radar data – critical for threat assessment and orbit fitting
- The process currently takes up to **four weeks** of manual interventions by experts using traditional software.
- The team demonstrated a DL model for automation that allows asteroids to be 3D shape generated in **several hours.**
- This result will hopefully allow researchers to render 3D models of the current backlog of radar imaged asteroids.

New Approaches For Asteroid Spin State and Shape Modeling From Delay-Doppler Radar Images

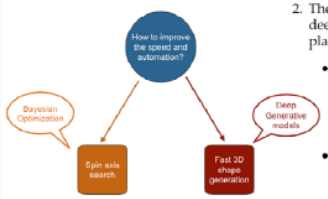
C. Raïssi, M. Lamé, O. Mosiane, C. Vassallo, M. W. Busch, A. H. Greenberg, L. A.M. Benner, S. Naidu, N. Duong

Motivation

- **Delay-Doppler radar imaging** is a powerful technique to characterize the trajectories, shapes, and spin states of near-Earth asteroids.
- **Reconstructing** objects' shapes and spins from delay-Doppler data is a **computationally intensive problem**.

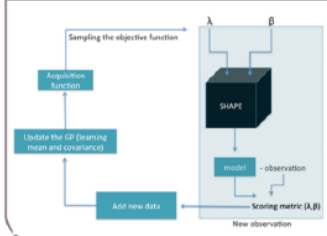


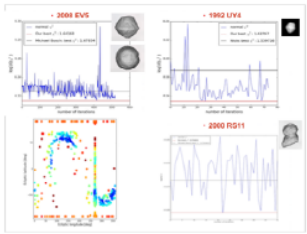
Contributions

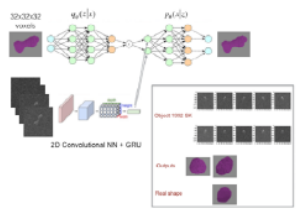


1. One of the most time-intensive steps of the shape modeling process: grid search to constrain the target's spin state. We have implemented a **Bayesian optimization routine** that uses SHAPE to **autonomously** search the space of spin-state parameters.
2. The shape modeling process is **further accelerated** using a deep ***"generative model"*** to complete (and in the future replace) the iterative fitting.
   - Deep generative models are implemented as feedforward **deep neural networks** which are a family of machine learning algorithms usually represented as direct acyclic graphs that are able to process tasks such as classification, regression or generation.
   - We have implemented and trained a **variational autoencoder** (VAE). **Preliminary experimental tests on** 29 **different asteroid shapes from human-guided SHAPE fits to Arecibo and Goldstone radar images** show very promising results.
   - Intuitively, it helps if the model first decides which asteroid shape to generate before it assigns a value to any specific voxel. This kind of decision is done through **latent variables**.

Results







Future Work

- Bayesian optimization can efficiently replace human supervision of SHAPE for asteroids in principal-axis rotation. It still needs to be tested for **asteroids with non-principal-axis rotation**.
- Additional development is required to produce a VAE that can produce the latent variable vector for an object's shape from **different series of delay-Doppler images**.
- Other deep generative models like GANs may also be useful, and should be explored.

What we need help with

1. High-resolution radar images of more **near-Earth asteroids**.
2. **Verified shapes** for more asteroids to train generative models.
3. **Lightcurve observations of radar targets** to constrain spin period and elongation.

Funding

This research was supported by the **NASA Frontier Development Laboratory** program.

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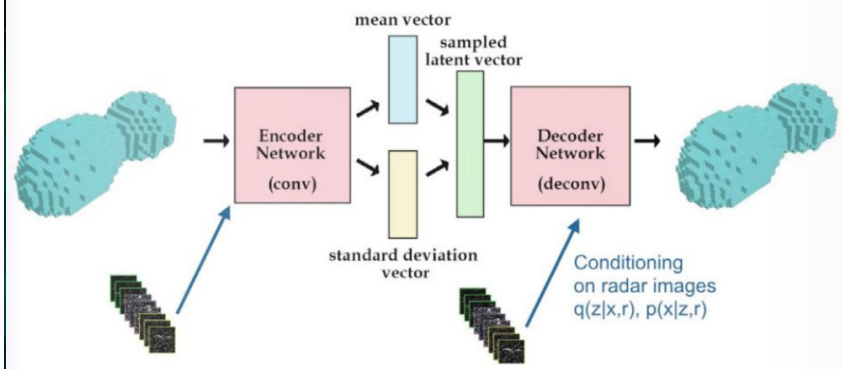
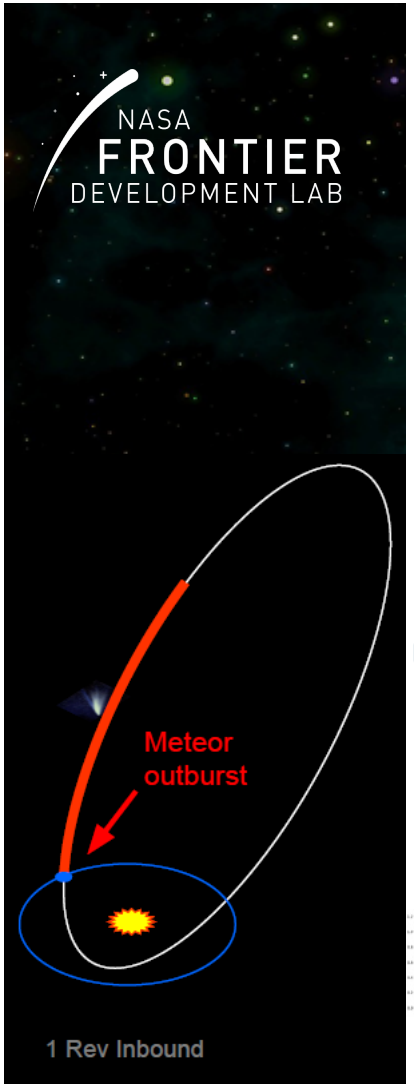
- mbusch@seti.org (SETI, CA, USA)

NASA FRONTIER DEVELOPMENT LAB



Diagrammatic representation of variational autoencoder, modified from a figure by Kevin Frans at http://kvfrans.com/variational-autoencoders-explained/



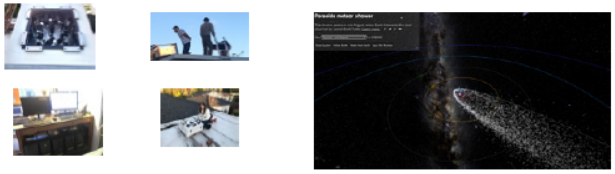
Planetary Defense: In Search of Long Period Comets with Deep Learning

Susana Zoghbi, Marcelo De Cicco, Antonio Ordonez, Andres P. Stapper, Jack Collison, Peter S. Gural, Sidha Ganju, Jose-Luis Galache, Peter Jenniskens

The Mission

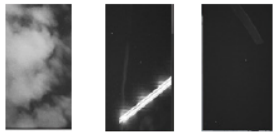
Provide more warning time for long period comet impacts by applying deep learning to meteor shower observations, whose trajectories enable dedicated searches along predicted orbits.

Monitoring the sky with CAMS

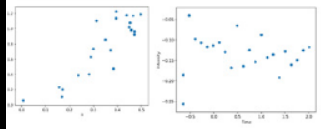


Meteors vs. Non Meteors

Non Meteors

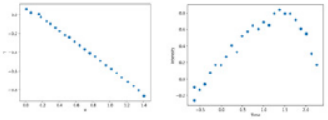


Clouds Planes Birds



Meteors

Small Bright Behind Clouds

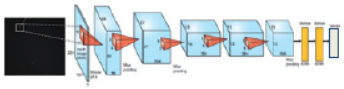


Motivation

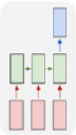
Any new comet on an impact trajectory with Earth would likely only be discovered 6-12 months before impact. 190 impact craters detected so far.

Methodology

Convolutional Neural Network



Long Short Term Memory Network



Inputs: XY position, time, and intensity

Results

Method	Input	Precision	Recall	F1
CNN	Images	88.3	90.3	89.5
RF	Tracklets	90.0	80.6	84.9
LSTM	Tracklets	90.0	89.1	89.6

Conclusions

- Improved and automated identification of meteors.
- Achieved above human level performance.
- Provide cleaner data to the subsequent process of identifying meteoroid orbits potentially associated with long-period comets that pass close to Earth's orbit.
- Models can be deployed on site.

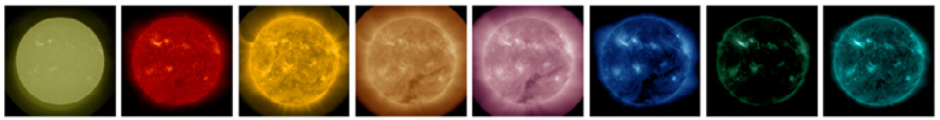
SPACE WEATHER
MISSION 02

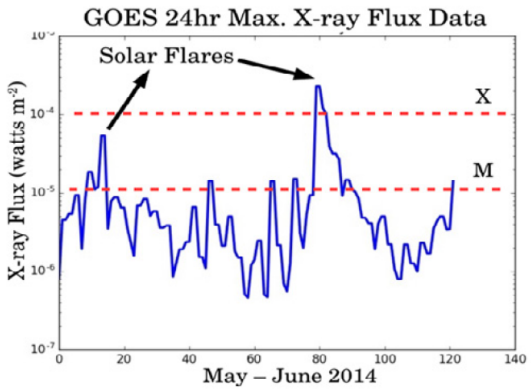
IBM LOCKHEED MARTIN kx

SOLAR STORM PREDICTION

COMPUTE BY IBM NVIDIA

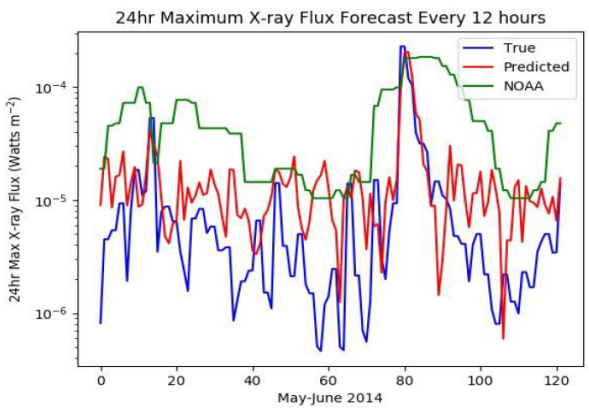
- Solar storm prediction is critical for protecting satellites and other technical infrastructure, as well as the lives of astronauts
- Current operational flare forecasting relies on human morphological analysis of active regions and the persistence of solar flare activity.
- The FDL team performed analyses of solar magnetic complexity and deployed convolutional neural networks to connect solar UV images taken by SDO/AIA into forecasts of maximum x-ray emissions.
- The technique has the potential to improve both the reliability and accuracy of solar flare predictions.

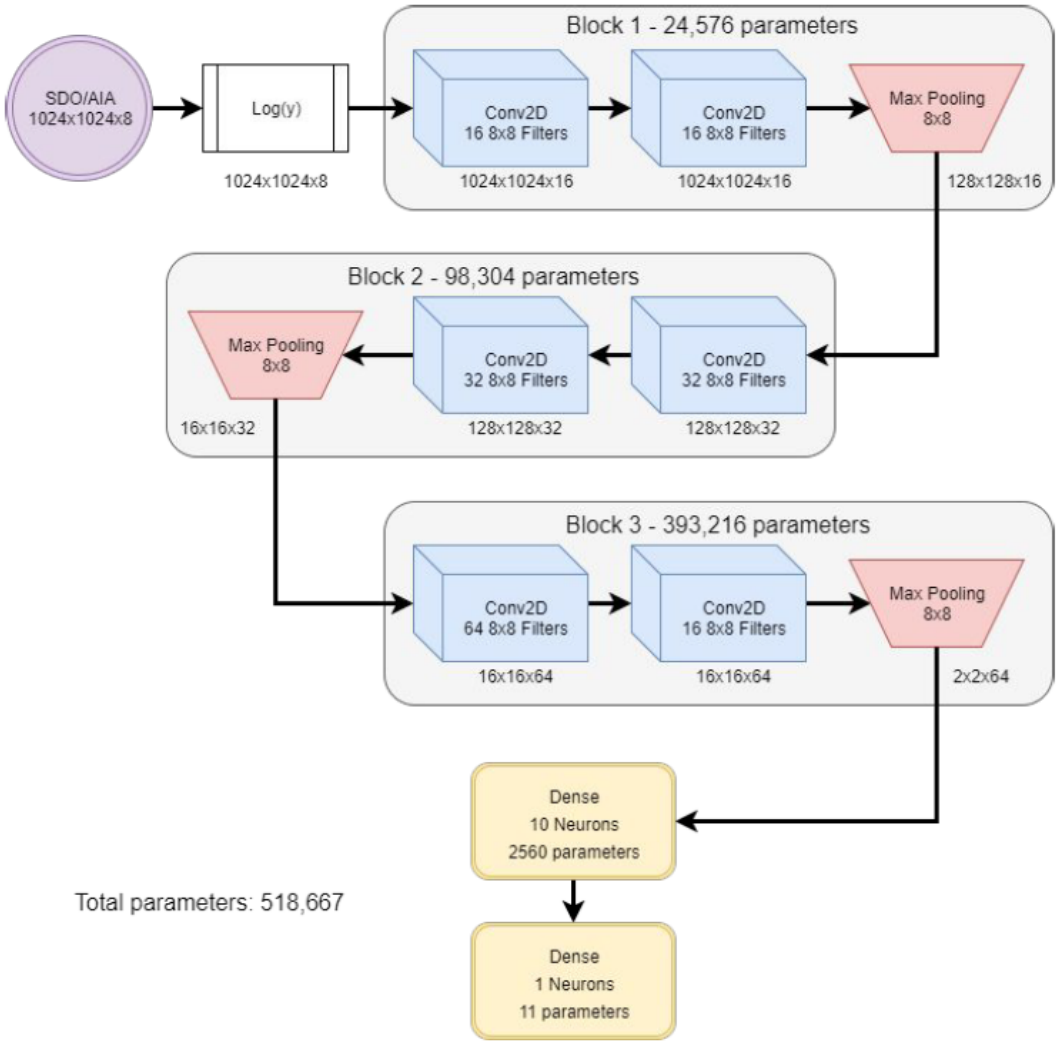




Stretch Goal:
Use AIA to forecast GOES X-ray flux **1 hr Ahead**

Can we use deep learning to connect AIA images with flare strength?





Total parameters: 518,667

FlareNet is able to produce an upper level of X-ray flux activity!

Want more details on FDL 2017 Implementations and Results?

Check out the NASA FDL 2017 Proceedings: bit.ly/FDL2017_Proceedings

CONFERENCES WHERE FDL'S RESULTS WERE SHARED

AI & Technology Conferences and Events

GPU Technology Conference
Date: October 26- 27, 2016
Location: Washington DC, USA
Title of talk: Defending our Planet with AI
Name of presenter: James Parr

Digital DNA
Date: June 6 - 7, 2017
Location: Belfast, Northern Ireland
Title of talk: Defending our Planet with AI
Name of presenter: James Parr

GPU Technology Conference
Date: October 10 - 12, 2017
Location: Munich, Germany
Title of talk: AI & Deep Learning
Name of presenter: Susana Zoghbi

Women in Machine Learning workshop
Date: December 4 & 7, 2017
Location: Long Beach, California, USA
Poster title: Planetary Defense: In Search of Long Period Comets with Deep Learning
Name of presenter: Susana Zoghbi

Neural Information Processing Systems (NIPS)
Date: December 4-9, 2017
Location: Long Beach, California, USA
Name of presenter: Sean McGregor [Barenet], Susana Zoghbi [Long period comets], Tim Seabrook [Crater detection game]

Space Science Conferences

5th IAA Planetary Defence Conference
Date: May 15 - 19, 2017
Location: Tokyo, Japan
Title of talk: Application of Machine Learning for Planetary Defense – Three Case Studies
Name of presenter: Frank Marchis

AAAI Futures Conference
Date: February 4 - 9, 2017
Location: San Francisco, California, USA
Title of talk: Defending our Planet with AI
Name of presenter: James Parr

LEAG (Lunar Exploration Analysis Group)
Date: October 10 - 12, 2017
Location: Columbia, Maryland, USA
Title of talk: AI & Space Sciences
Name of presenter: Sara Jennings

NewSpace Europe
Date: November 16 - 17, 2017
Location: Luxembourg
Title of talk: Artificial Intelligence and Space
Name of presenter: Sara Jennings & Jacek Czaja

AGU Fall Meeting
Date: December 12, 2017
Location: New Orleans, Louisiana, USA
Poster title: Modeling Geomagnetic Variations using a Machine Learning Framework
Name of presenter: Bala Poduval

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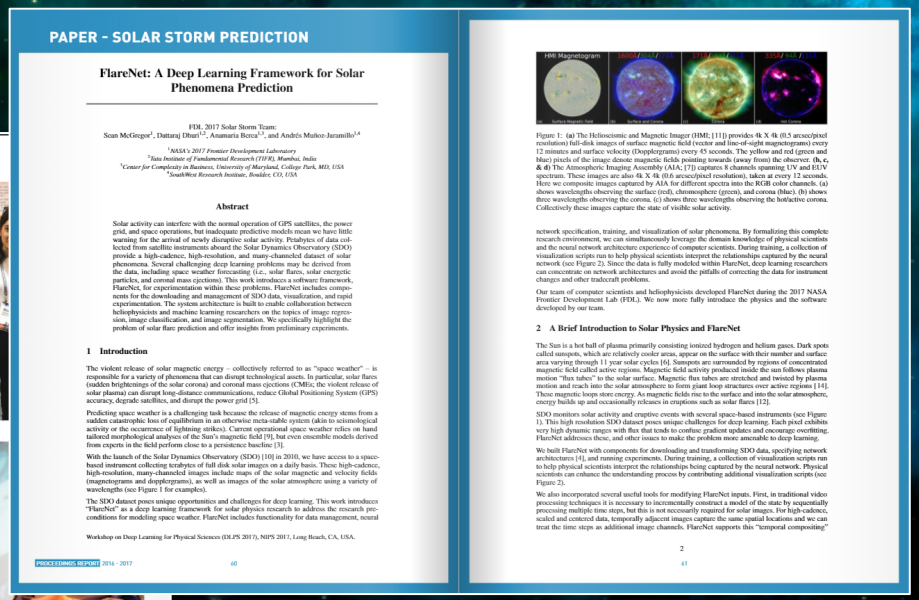
#NASAFDL18



PAPER - SOLAR STORM PREDICTION

FlareNet: A Deep Learning Framework for Solar Phenomena Prediction

FDL 2017 Solar Storm Team:
Sean McGregor[1], Dattaraj Dhuri[1,2], Anamaria Berea[1,3], and Andrés Muñoz-Jaramillo[1,4]

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[2] *Data Institute of Fundamental Research (TIFR), Mumbai, India*
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[4] *SouthWest Research Institute, Boulder, CO, USA*

Abstract

Solar activity can interfere with the normal operation of GPS satellites, the power grid, and space operations, but inadequate predictive models mean we have little warning for the arrival of newly disruptive solar activity. Petabytes of data collected from satellite instruments aboard the Solar Dynamics Observatory (SDO) provide a high-cadence, high-resolution, and many-channeled dataset of solar phenomena. Several challenging deep learning problems may be derived from the data, including space weather forecasting (i.e., solar flares, solar energetic particles, and coronal mass ejections). This work introduces a software framework, FlareNet, for experimentation within these problems. FlareNet includes components for the downloading and management of SDO data, visualization, and rapid experimentation. The system architecture is built to enable collaboration between heliophysicists and machine learning researchers on the topics of image regression, image classification, and image segmentation. We specifically highlight the problem of solar flare prediction and offer insights from preliminary experiments.

1 Introduction

The violent release of solar magnetic energy – collectively referred to as "space weather" – is responsible for a variety of phenomena that can disrupt technological assets. In particular, solar flares (sudden brightenings of the solar corona) and coronal mass ejections (CMEs; the violent release of solar plasma) can disrupt long-distance communications, reduce Global Positioning System (GPS) accuracy, degrade satellites, and disrupt the power grid [5].

Predicting space weather is a challenging task because the release of magnetic energy stems from a sudden catastrophic loss of equilibrium in an otherwise meta-stable system (akin to seismological activity or the occurrence of lightning strikes). Current operational space weather relies on hand tailored morphological analyses of the Sun's magnetic field [9], but even ensemble models derived from experts in the field perform close to a persistence baseline [3].

With the launch of the Solar Dynamics Observatory (SDO) [10] in 2010, we have access to a space-based instrument collecting terabytes of full disk solar images on a daily basis. These high-cadence, high-resolution, many-channeled images include maps of the solar magnetic and velocity fields (magnetograms and dopplergrams), as well as images of the solar atmosphere using a variety of wavelengths (see Figure 1 for examples).

The SDO dataset poses unique opportunities and challenges for deep learning. This work introduces "FlareNet" as a deep learning framework for solar physics research to address the research preconditions for modeling space weather. FlareNet includes functionality for data management, neural network specification, training, and visualization of solar phenomena. By formalizing this complete research environment, we can simultaneously leverage the domain knowledge of physical scientists and the neural network architecture experience of computer scientists. During training, a collection of visualization scripts run to help physical scientists interpret the relationships captured by the neural network (see Figure 2). Since the data is fully modeled within FlareNet, deep learning researchers can concentrate on network architectures and avoid the pitfalls of correcting the data for instrument changes and other tradecraft problems.

Our team of computer scientists and heliophysicists developed FlareNet during the 2017 NASA Frontier Development Lab (FDL). We now more fully introduce the physics and the software developed by our team.

2 A Brief Introduction to Solar Physics and FlareNet

The Sun is a hot ball of plasma primarily consisting ionized hydrogen and helium gases. Dark spots called sunspots, which are relatively cooler areas, appear on the surface with their number and surface area varying through 11 year solar cycles [6]. Sunspots are surrounded by regions of concentrated magnetic field called active regions. Magnetic field activity produced inside the sun follows plasma motion "flux tubes" to the solar surface. Magnetic flux tubes are stretched and twisted by plasma motion and reach into the solar atmosphere to form giant loop structures over active regions [14]. These magnetic loops store energy. As magnetic fields rise to the surface and into the solar atmosphere, energy builds up and occasionally releases in eruptions such as solar flares [12].

SDO monitors solar activity and eruptive events with several space-based instruments (see Figure 1). This high resolution SDO dataset poses unique challenges for deep learning. Each pixel exhibits very high dynamic ranges with flux that tends to confuse gradient updates and encourage overfitting. FlareNet addresses these, and other issues to make the problem more amenable to deep learning.

We built FlareNet with components for downloading and transforming SDO data, specifying network architectures [4], and running experiments. During training, a collection of visualization scripts run to help physical scientists interpret the relationships being captured by the neural network. Physical scientists can enhance the understanding process by contributing additional visualization scripts (see Figure 2).

We also incorporated several useful tools for modifying FlareNet inputs. First, in traditional video processing techniques it is necessary to incrementally construct a model of the state by sequentially processing multiple time steps, but this is not necessarily required for solar images. For high-cadence, scaled and centered data, temporally adjacent images capture the same spatial locations and we can treat the time steps as additional image channels. FlareNet supports this "temporal compositing"

Workshop on Deep Learning for Physical Sciences (DLPS 2017), NIPS 2017, Long Beach, CA, USA.

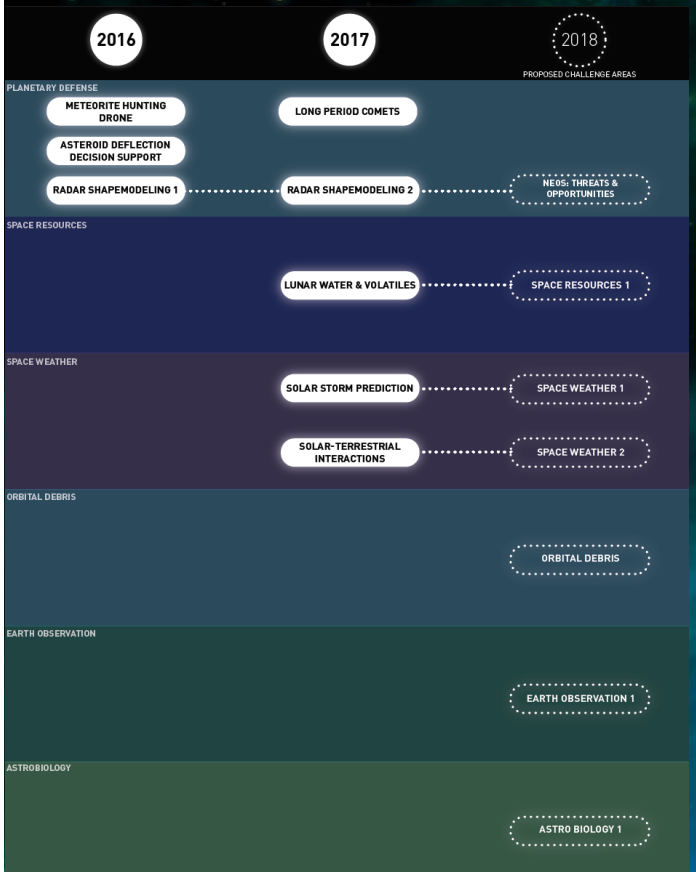
PROCEEDINGS REPORT 2016 - 2017 60 61

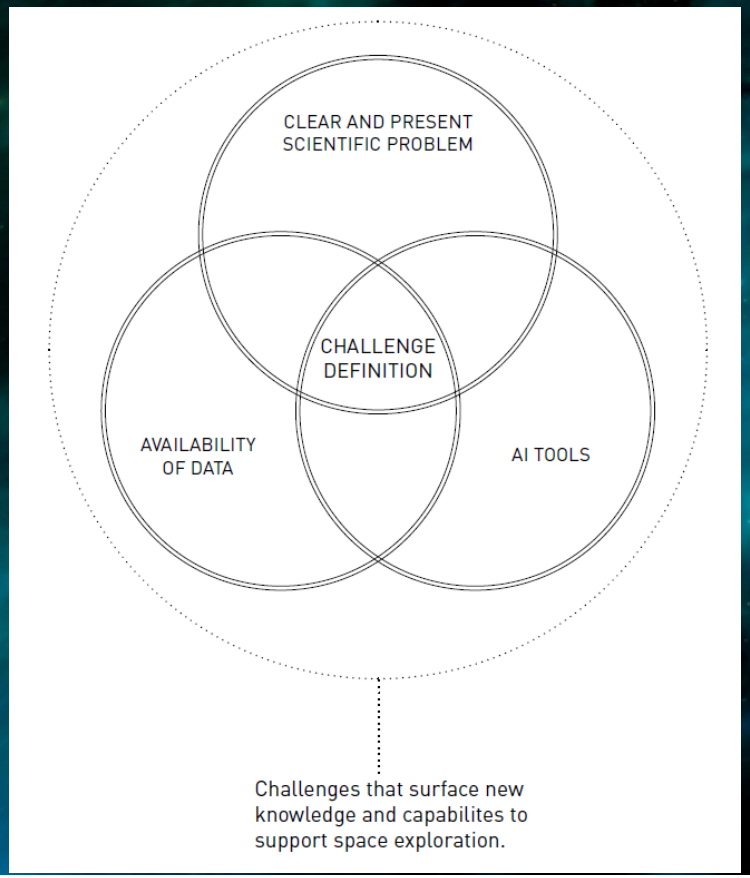
HMI Magnetogram

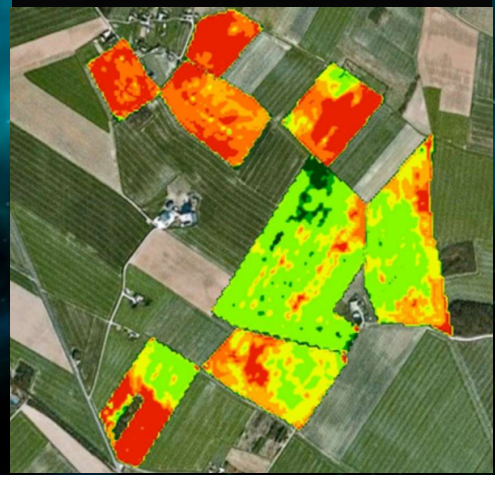
Figure 1: (a) The Helioseismic and Magnetic Imager (HMI; [11]) provides 4k X 4k (0.5 arcsec/pixel resolution) full-disk images of surface magnetic field (vector and line-of-sight magnetograms) every 12 minutes and surface velocity (Dopplergrams) every 45 seconds. The yellow and red (green and blue) pixels of the image denote magnetic fields pointing towards (away from) the observer. (**b, c, & d**) The Atmospheric Imaging Assembly (AIA; [7]) captures 8 channels spanning UV and EUV spectrum. These images are also 4k X 4k (0.6 arcsec/pixel resolution), taken at every 12 seconds. Here we composite images captured by AIA for different spectra into the RGB color channels. (a) shows wavelengths observing the surface (red), chromosphere (green), and corona (blue). (b) shows three wavelengths observing the corona. (c) shows three wavelengths observing the hot/active corona. Collectively these images capture the state of visible solar activity.

NASA FDL 2018 – Bigger and Better!

NASA FRONTIER DEVELOPMENT LAB



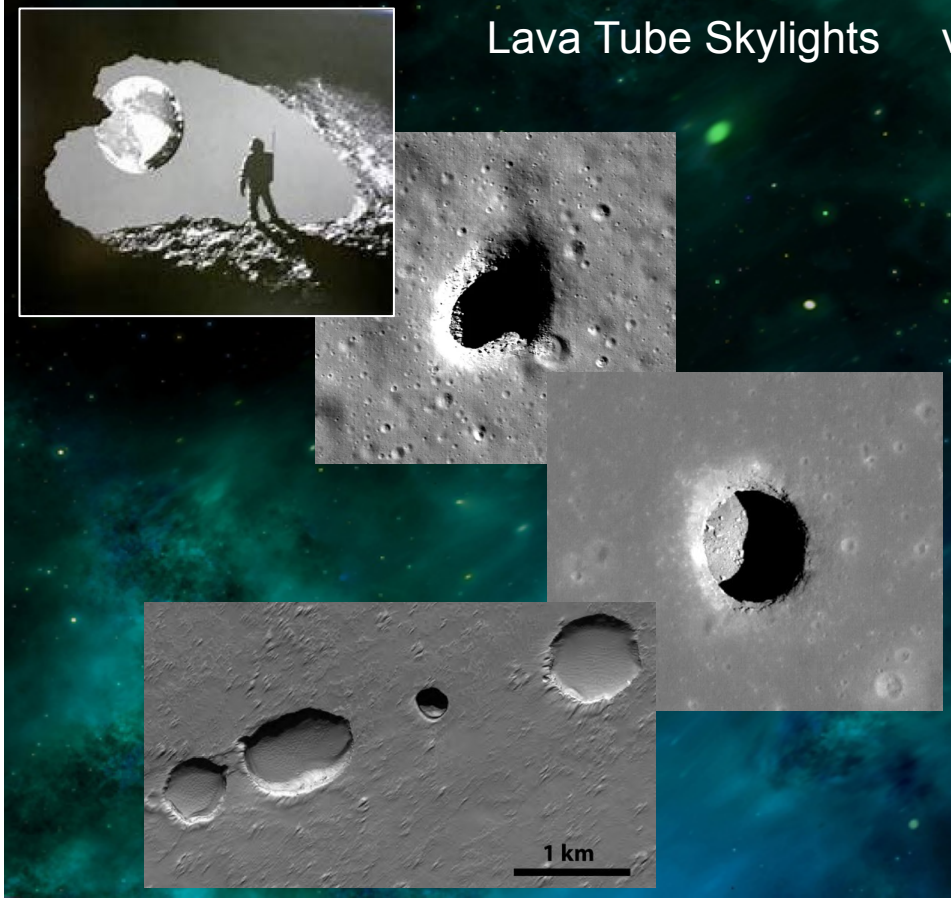




Example: Lunar Resources for Permanent Outposts

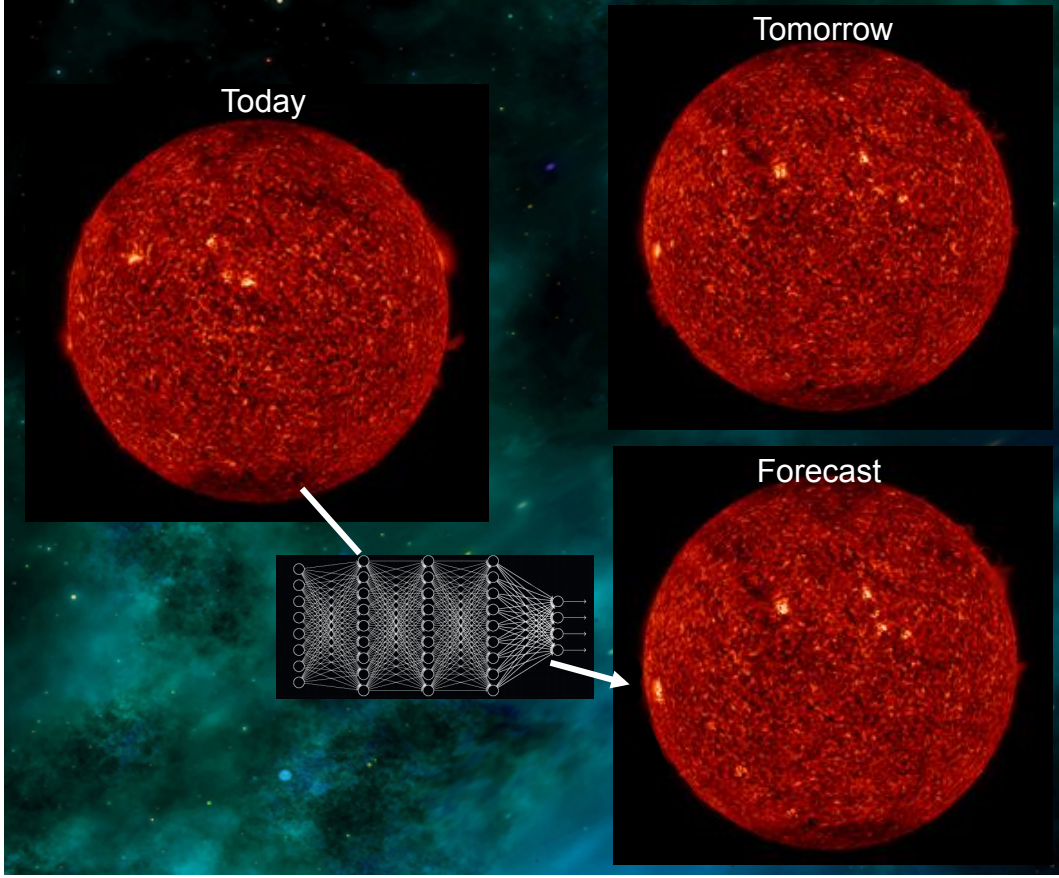
(e.g. Ice water in perma-shadows, ready-made shelters, etc.)

Lava Tube Skylights v.s. Craters



Example: The Sun Tomorrow, Today

24 hour forecast of the appearance of the Sun



- Solar Dynamics Observatory AIA instrument … 12 HD images of the Sun every 12 seconds since 2010.
- Use petabytes of SDO AIA images to build a neural net model to produce a forecast of what the sun will look like 24 hours into the future.
- The trained neural net model would ingest a time-series sequence of AIA images leading up to the present moment, and output an image of the sun as it is predicted to appear in 24 hours.

Looking ahead….

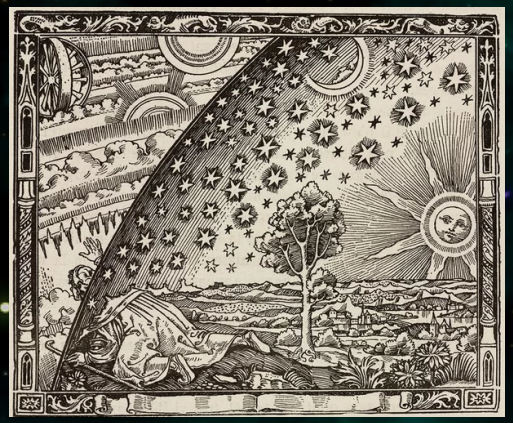
- SETI Institute supports NASA FDL and the application of AI across a wide range of space science problems
- This experience and investment is being internalized to "AI-enable" the core SETI mission
- Artificial Intelligence is critical to advancing the search for biosignatures and techno-hints
- To understand why, we must endure a few minutes of humiliation…

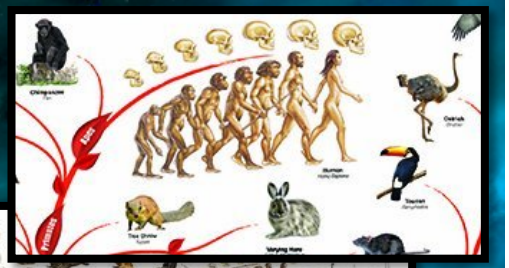
The Ego of Humankind

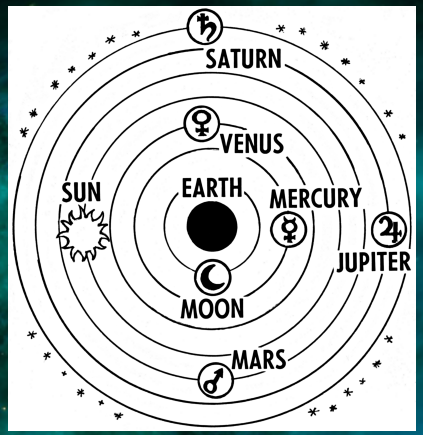
Science says:

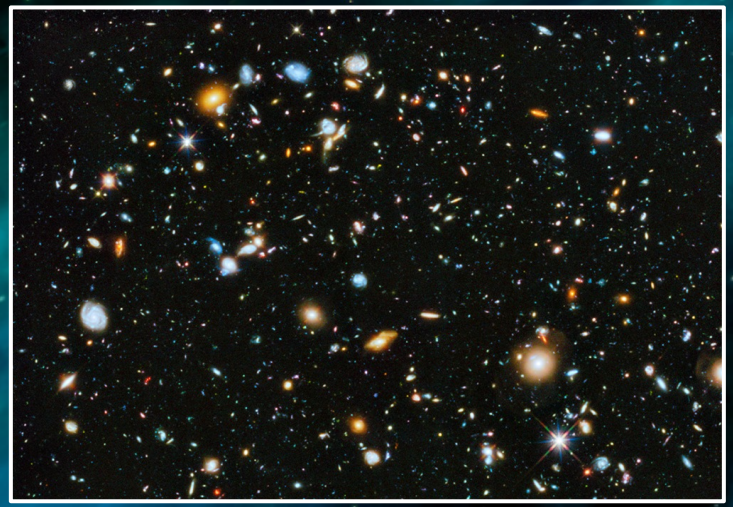
"Hey, h[illegible]s. gre[illegible] news....
it turns ou[illegible]at [illegible] ar[illegible]much more
important th[illegible]ou t[illegible]t you were!"

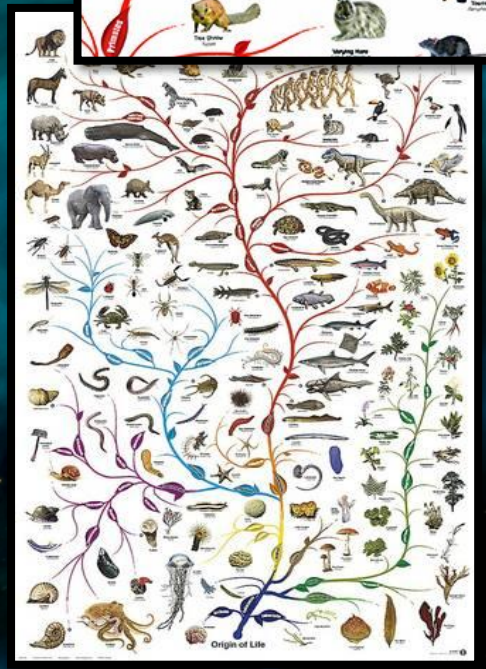
The Ego of Humankind

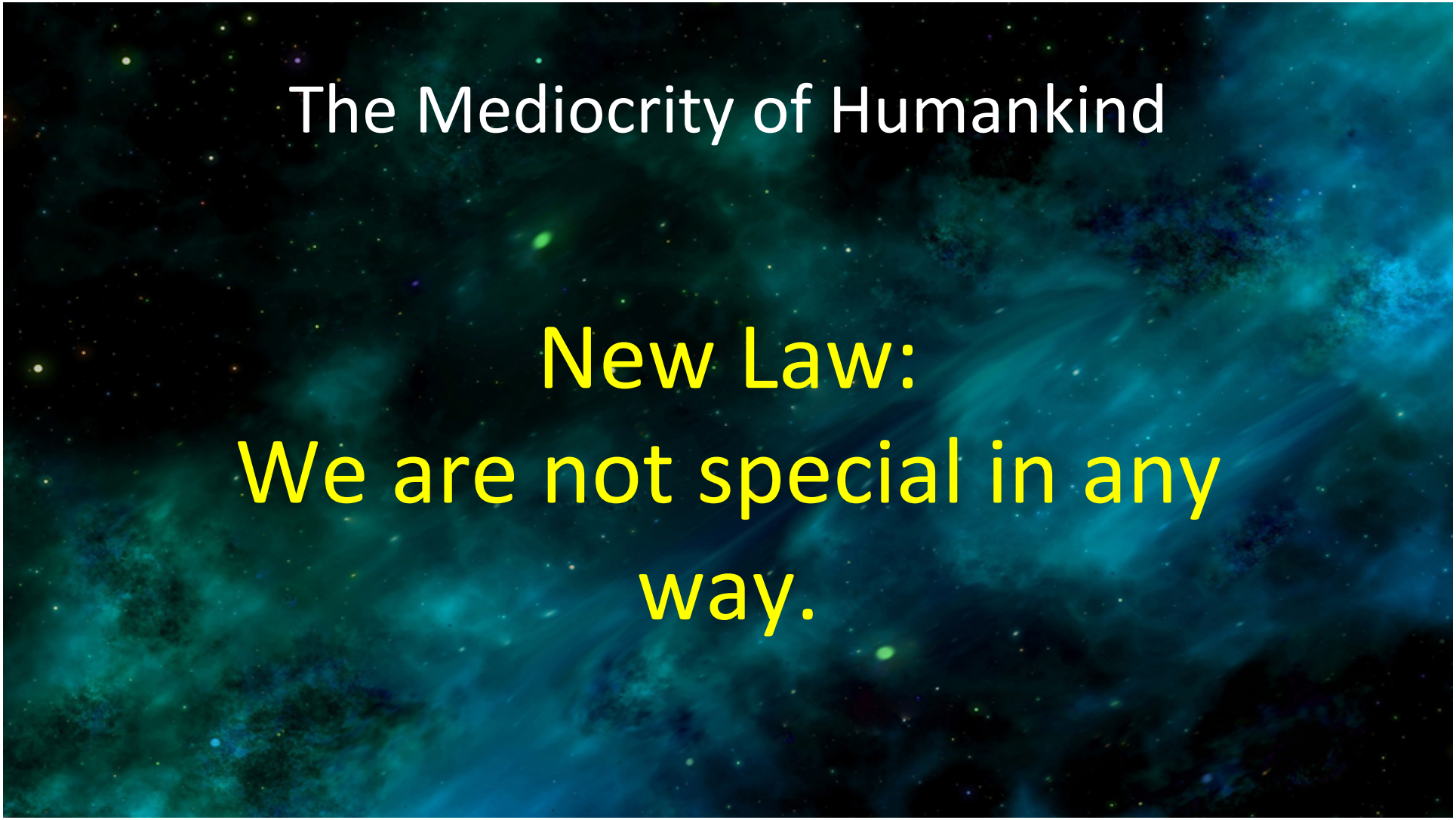










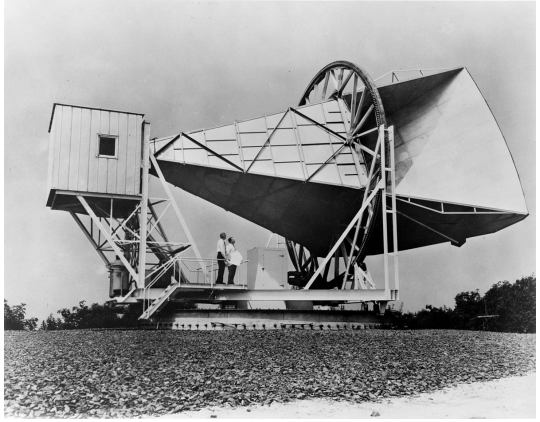

The Mediocrity of Humankind
New Law:
We are not special in any way.

Answering Fermi

WE ARE ~~SUPER~~ SMART.

WE ARE SUPER DUMB.

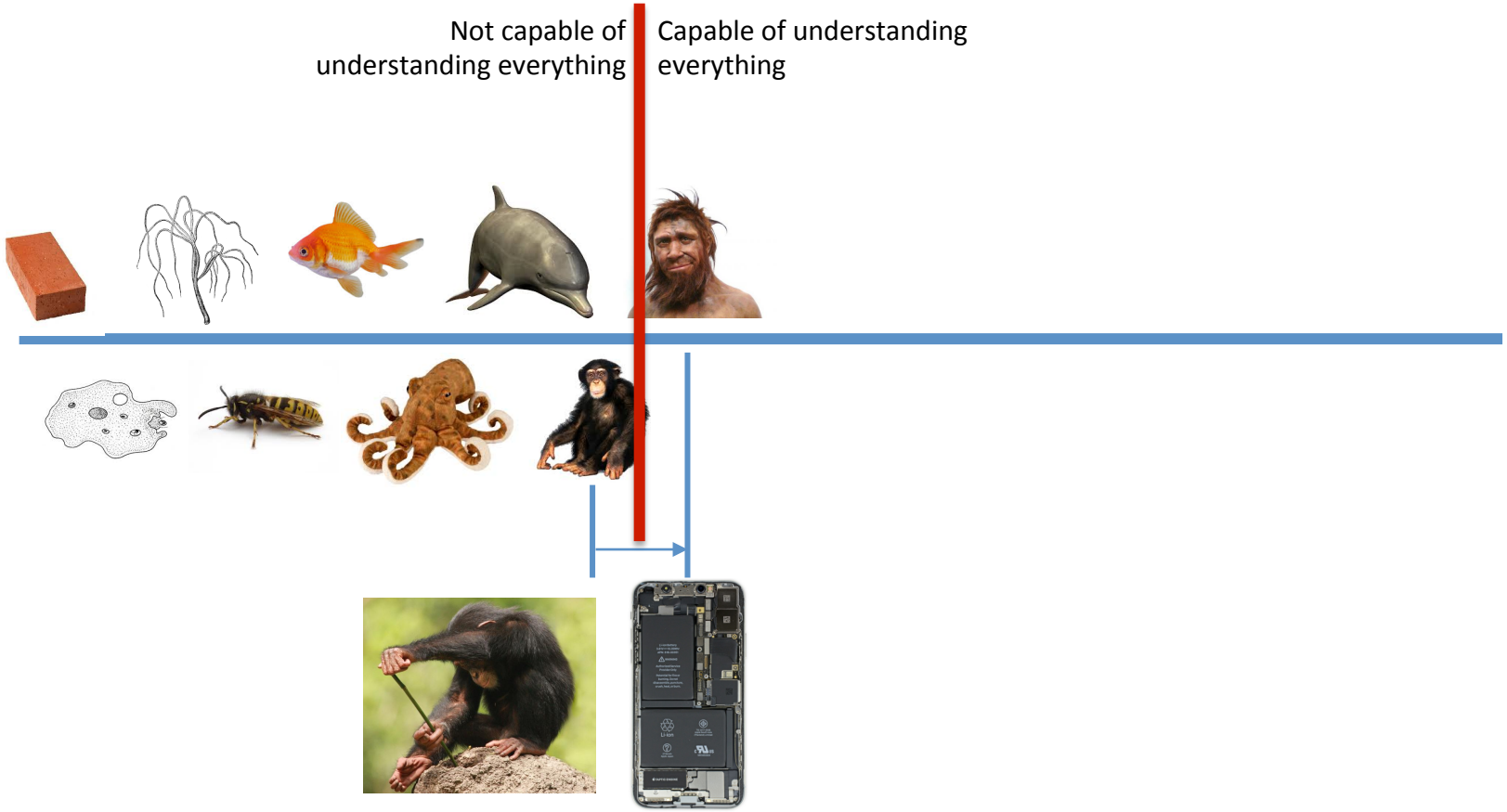
Exploring the notion that we are super dumb



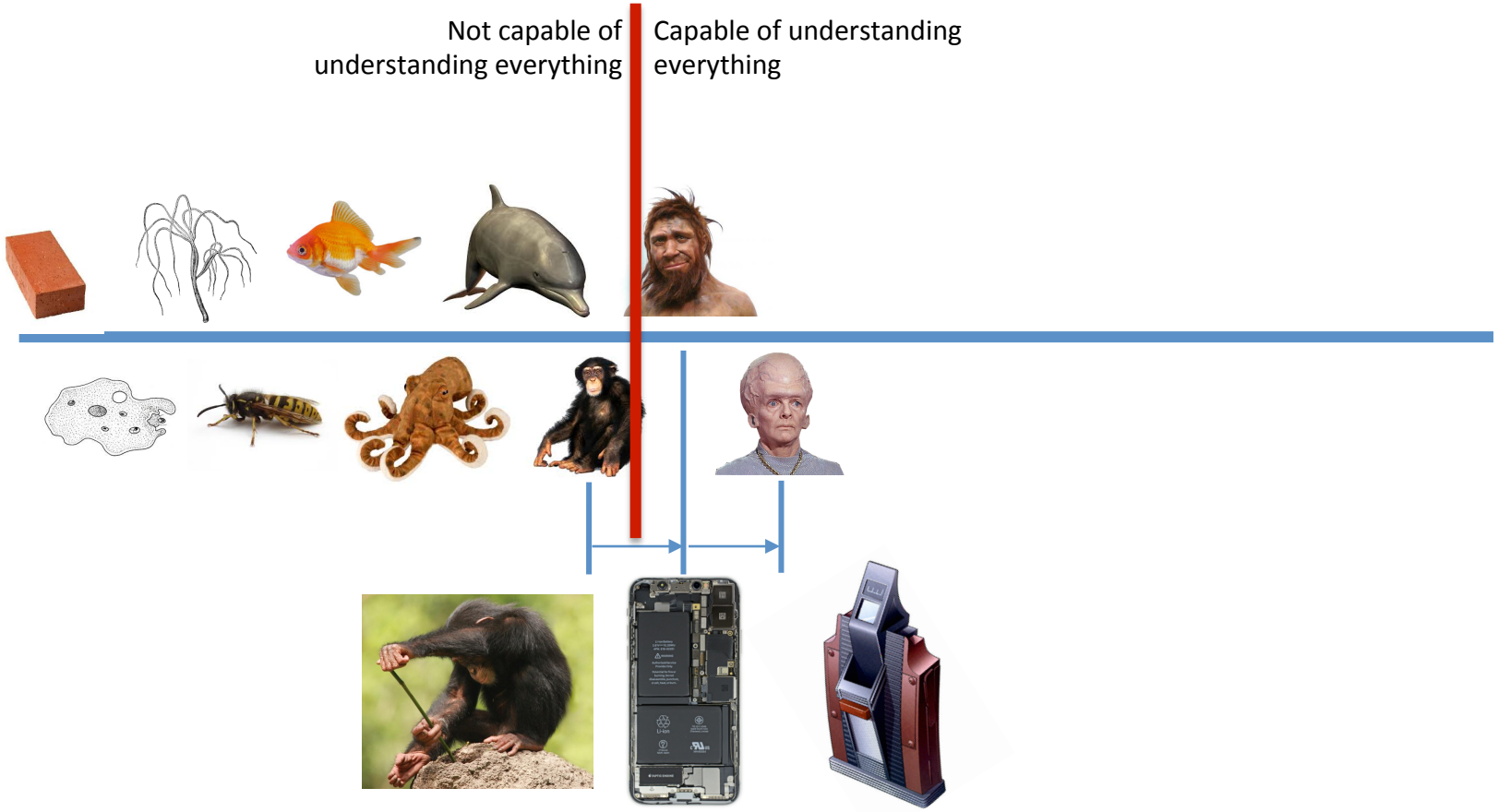
Exploring the notion that we are super dumb

It’s the law: We are not special

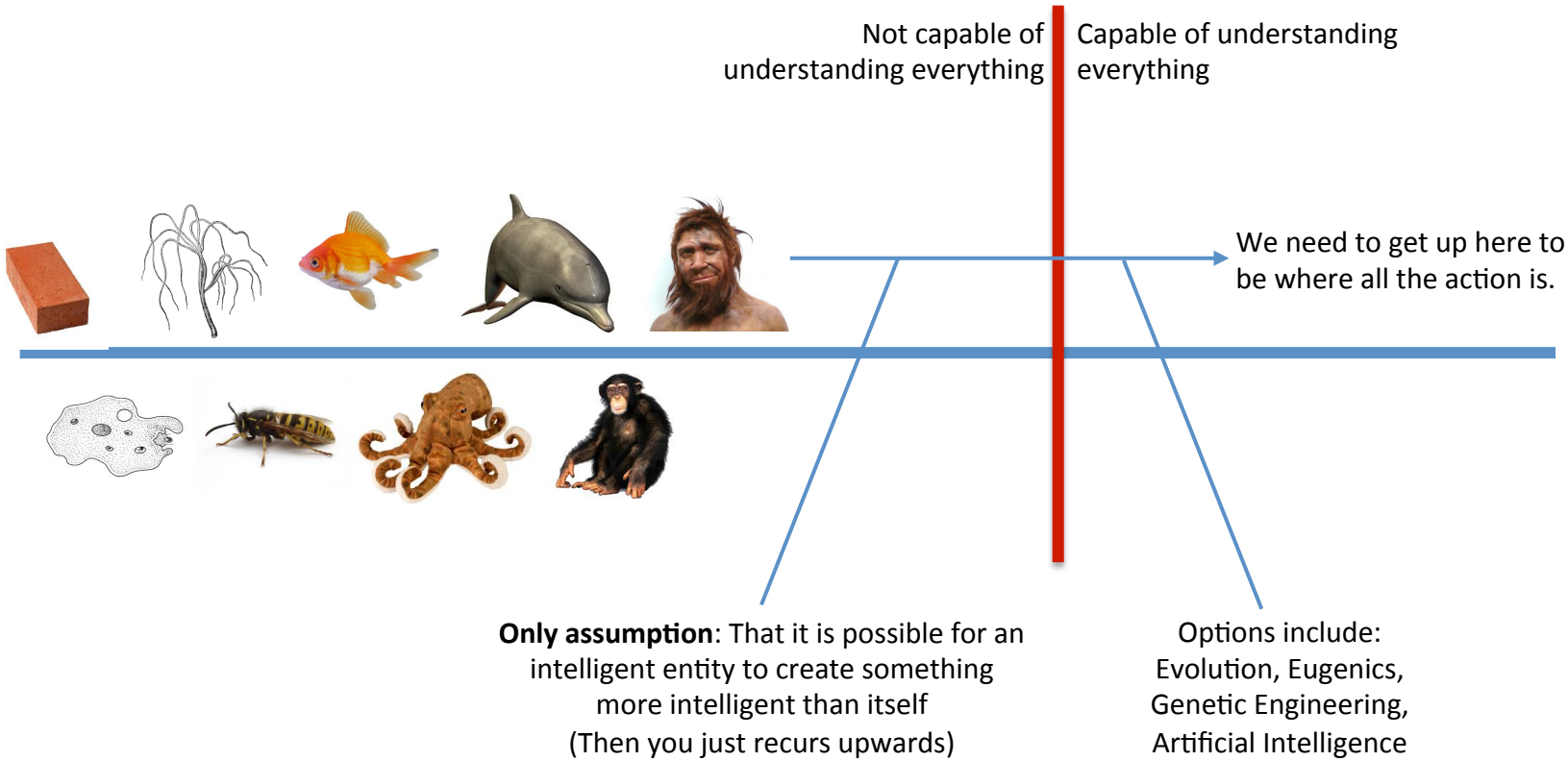
Exploring the notion that we are super dumb



Exploring the notion that we are super dumb



Exploring the notion that we are super dumb



Taking Stock of the Situation

- We are not special in any way.
- Compared to ET, it is highly probable that:
  - We are technological newborns, and oblivious to what ET is doing.
  - We will never understand what ET is doing, unless we enhance our intelligence.
- Artificial Intelligence is the fastest way to achieve the higher enlightenment needed to join the club.

… in the meantime …

- Artificial Intelligence may also be the best way to detect ET, even if we don't have a clue what is really going on.

Detecting ET when you are not special or intelligent

- Assume no intentional signals, and that ET will not dumb things down for us.
- Assume we can't comprehend what ET is doing.
- Assume that ET intelligence may not biological:
  - Looking for bio-signatures is a very important endeavor, but...
  - Bio-hints and the concept of "*habitable zones*" may have no bearing on where or how intelligence exists

- Strategy: Hope that ET's activities generate side-effects in our observable universe that can be remotely detected using our current technology and that they are somehow distinguishable from our definition of "*nature*"
- SETI = Looking for "techno-hint" anomalies.

The Anomaly Engine: AI and the Detection of Alien Intelligence

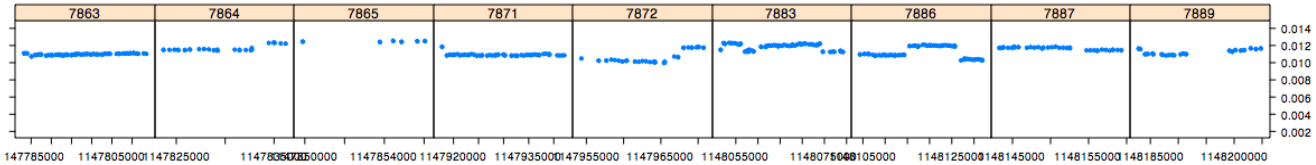
- Augmented SETI: Using AI to look for anomalies.
- Great strategy because:
  - We are not smart enough to comprehend what intelligence really looks like.
  - We are not special enough to have ET make things obvious for us.

- The all-or-nothing nature of "*traditional SETI*" is augmented with a win-win scenario:
  - Best case: Anomaly remains stubbornly unexplained and seems suspiciously intentional... growing consensus that something is afoot.
  - Worst case: Anomaly has whispers of ET, but the scientific community discovers a natural explanation. Examples: pulsars, KIC 8462852, quantized dispersion measures of FRBs

The Anomaly Engine: AI and the Detection of Alien Intelligence

Imaginary scenario : Anomalous correlations

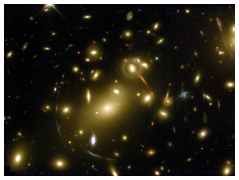
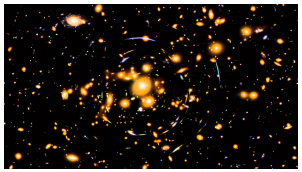
- Time series luminosity from millions of stars... they all look pretty normal



- Use AI to look for any patterns within the luminosity data

Imaginary scenario : Anomalous morphologies

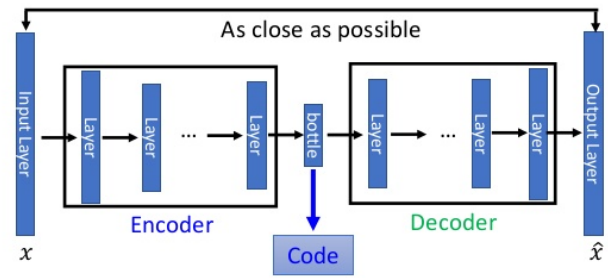
- Train a Deep Learning model to find all observable examples of gravitational lensing, and classify them based on similarity
- It finds lots of these...

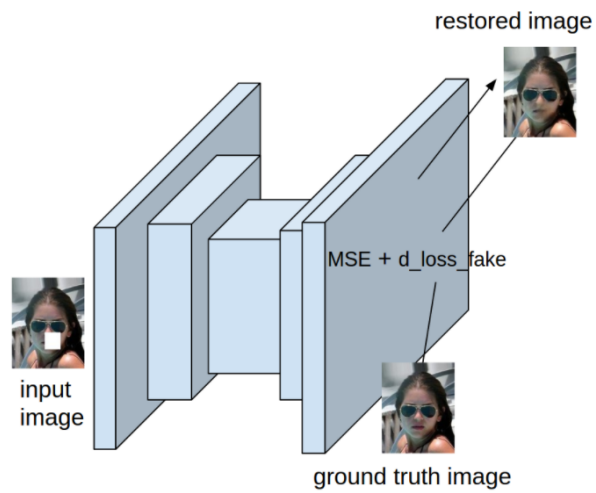




The AI Anomaly Engine: Examples and current research

- **Deep Learning Autoencoders**: popular choice for anomaly detection.
- Train an autoencoder that is able to reconstruct data of a certain domain.
- The model will do a good job of reconstructing "normal" data that was relatively common in its training, but will fail to reconstruct anomalous/outlier data.
- "Anomaly index" = the cost function: the difference between original data and the reconstructed data produced by the autoencoder.

- NN encoder + NN decoder = a deep network

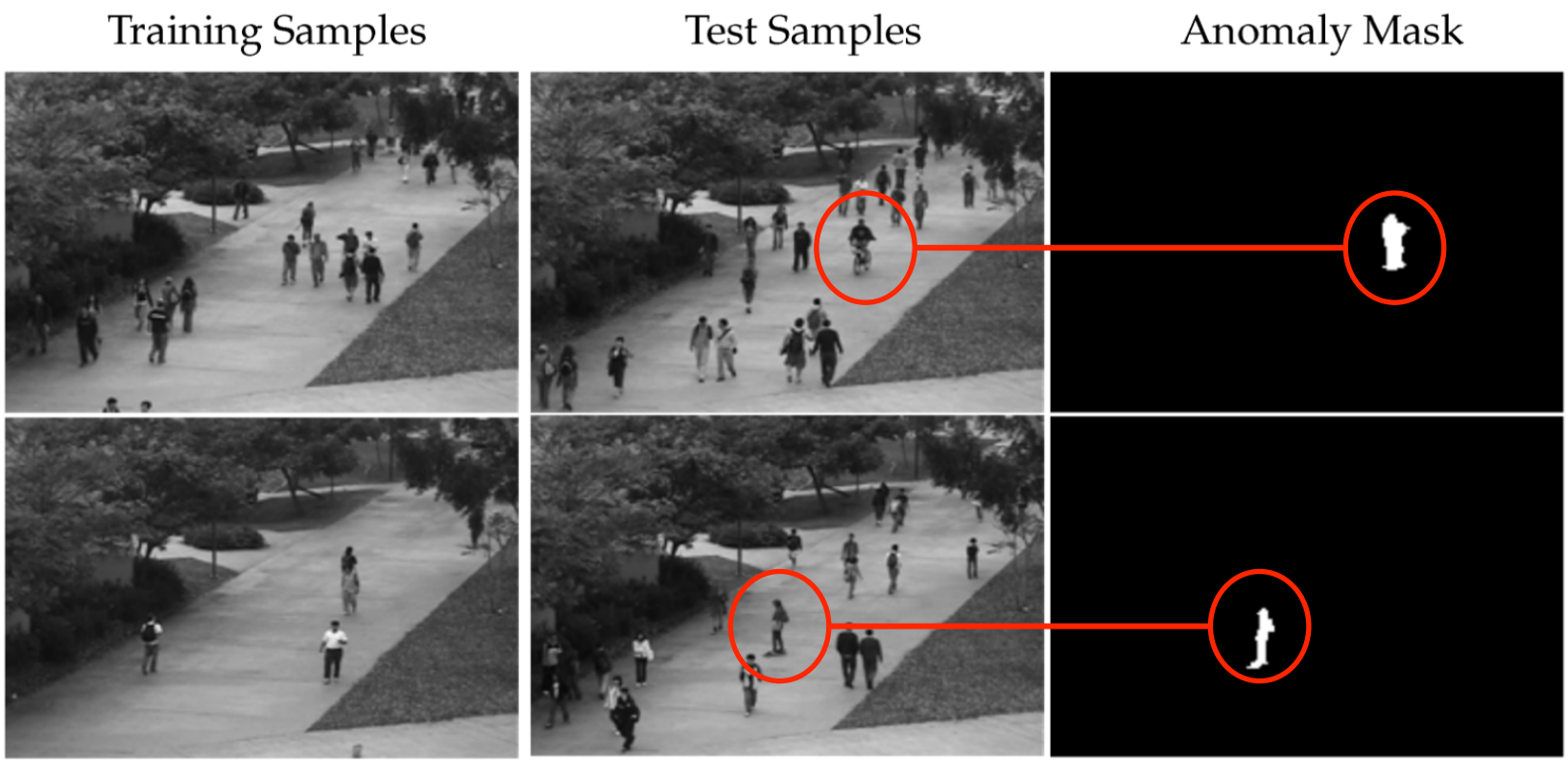




Example use: An autoencoder that is shown thousands of faces does a great job of denoising and repairing pictures of new faces it has never seen before.

Credits: Avery Allen, Wenchen Li. "Generative Adversarial Denoising Autoencoder for Face Completion", www.cc.gatech.edu/~hays/7476/projects/Avery_Wenchen

The AI Anomaly Engine: Examples and current research



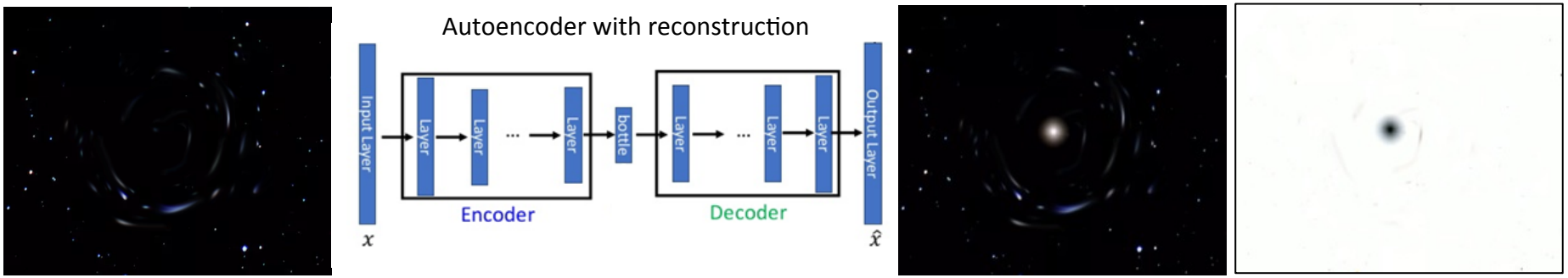
Credits: Kiran BR, Thomas DM, Parakkal R. An Overview of Deep Learning Based Methods for Unsupervised and Semi-Supervised Anomaly Detection in Videos. Journal of Imaging. 2018; 4(2):36.

The AI Anomaly Engine – Nearby black hole or ET manipulating gravity?

Step 1: Use known images of gravitational lensing to train a CNN to look for more examples (supervised learning).

Step 2: Use output of Step 1 to train a DL autocorrelation model to reconstruct images of gravitational lensing.

Step 3: Feed the same output of Step 1 into the DL autocorrelation model and "score" each image based on accuracy of the reconstruction… poor reconstruction means "something unusual"



Ground truth

Reconstructed image

Anomaly Mask
(image difference)

In Summary, the proposed hypothesis is...

- Without AI, we will be incapable of understanding the activities of the interstellar community.
- Nearer term, AI is also a powerful tool to cast a wide net to look for “techno-hint” anomalies that such a community exists.

- Anomaly-centric SETI is increasingly compelling due to AI:
  - Look for byproducts of technology we can’t understand.
  - Drive a SETI strategy that will generate new science even when ET turns out to not be answer... a win-win.

Join us!

AI Developers (you) + NVIDIA GPUs + Space Science Data =
"Are We Alone?"

www.frontierdevelopmentlab.org

www.seti.org