Poster #22 - Second AI and Data Science Workshop for Earth and Space Sciences

Time Series Analysis Methods for On-board Detection of Magnetic Field Boundaries by Europa Clipper

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Introduction

The **Plasma Instrument for Magnetic Sounding (PIMS)** on the Europa Clipper mission aims to characterize the properties of the Jovian plasma surrounding Europa, providing insight into Europa's cryovolcanic activity and its subsurface ocean.

Mode-Switching in PIMS

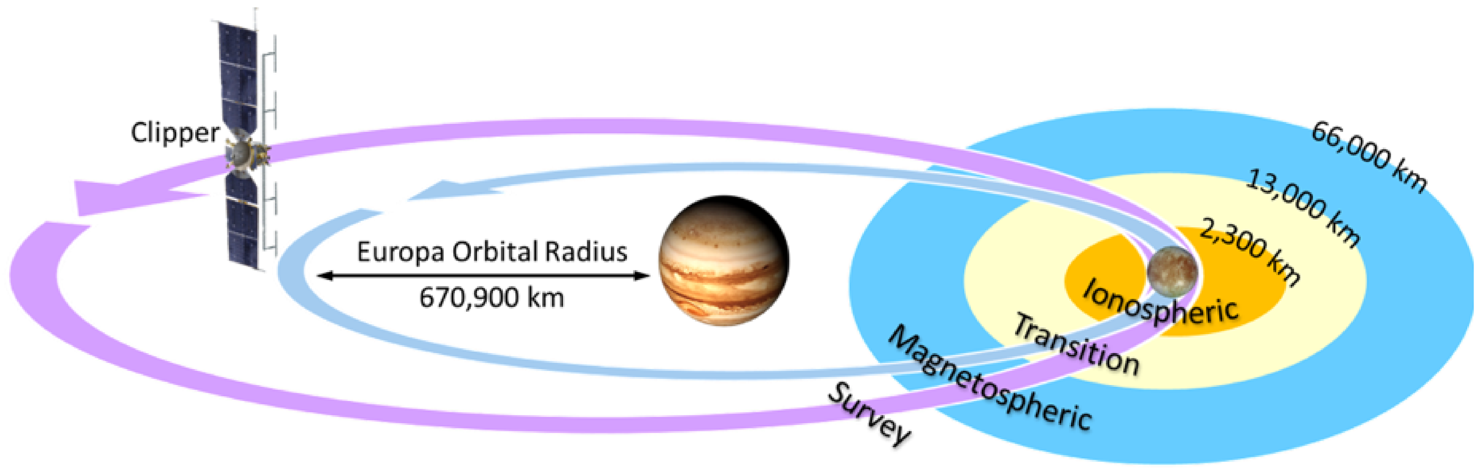

Figure 1: PIMS modes as currently planned.

PIMS operates in 4 different modes, depending on **prior estimates of the magnetic field boundaries** and the distance to Europa. To account for uncertainty in these estimates, PIMS spends significant amount of time in a **transition mode**.

The Key Question

Can we instead make PIMS **responsive**, and **switch modes automatically** based on its current observations?

Detecting Magnetic Field Boundaries

At each time step, PIMS counts the number of particles within energy 'bins':

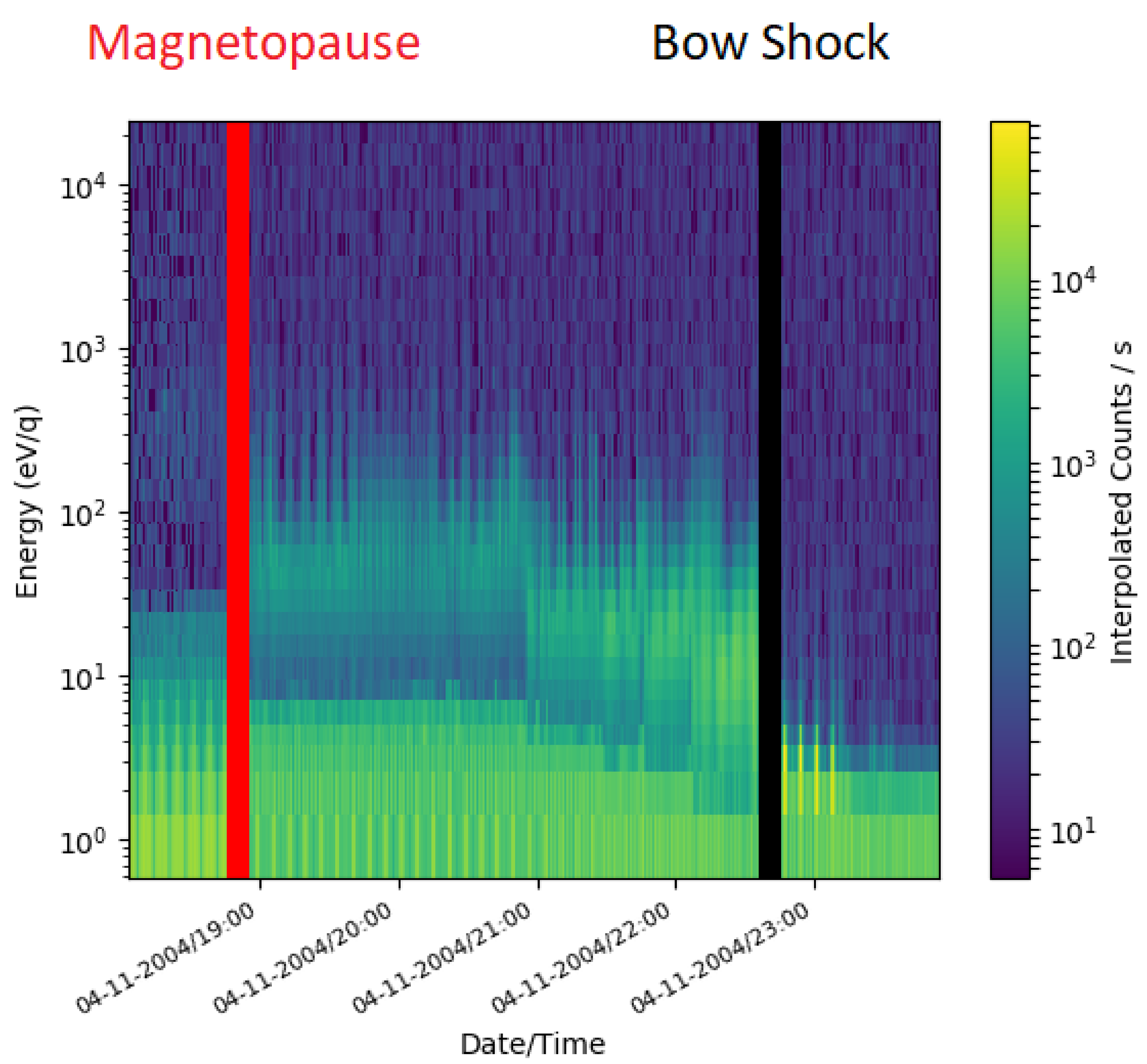

Figure 2: Magnetic field boundaries of Saturn as seen by an analogous instrument, the CAPS ELS on the Cassini mission.

We cast this as an **anomaly detection** problem over **multidimensional time series**.

To deal with the lack of knowledge about the true magnetic field boundaries around Europa, we investigate **unsupervised** methods.

We can evaluate these methods using labelled data from the Cassini mission.

Results on Cassini Data

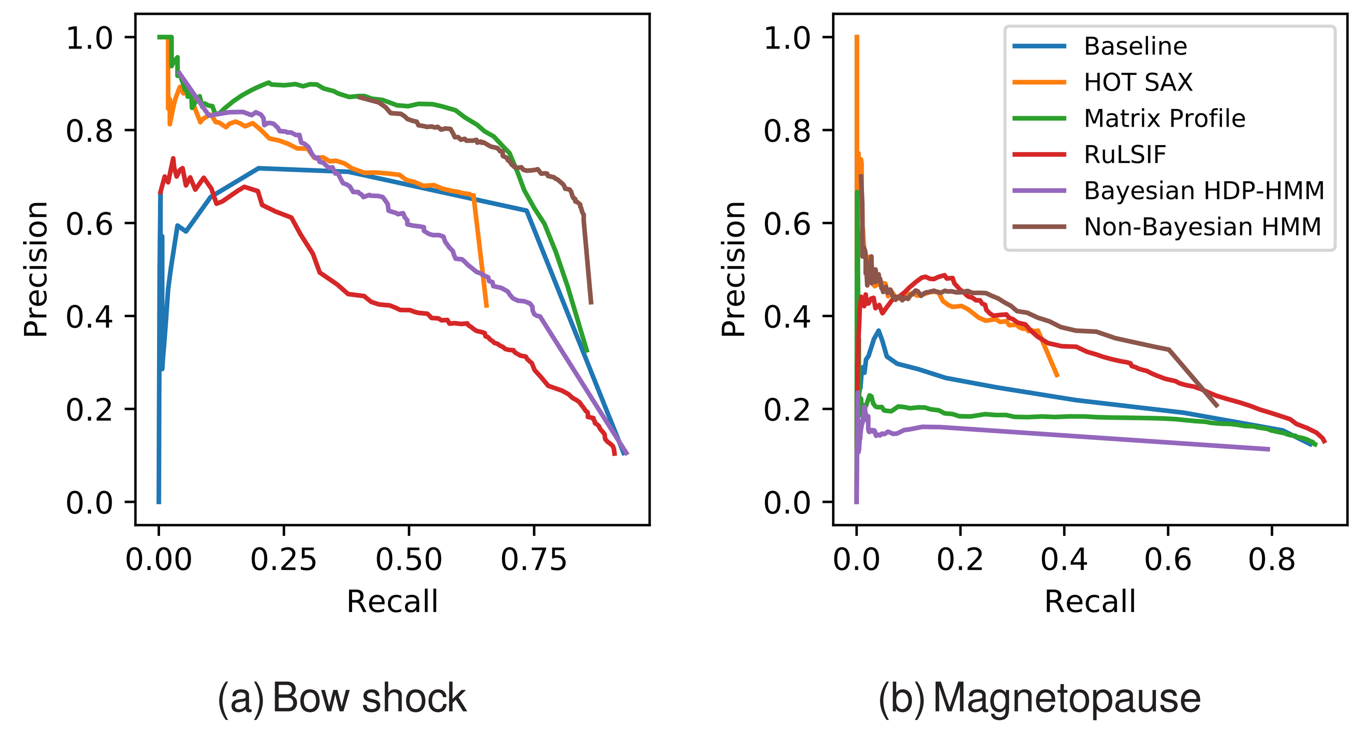

Figure 3: Test performance on around 2300 crossings spread across years 2005 to 2012. Parameters were optimized using 60 crossings from 2004.

Our Key Contributions

- We **evaluate** four unsupervised approaches to identify magnetic field transitions in CAPS data.
- We propose an **extension to the Matrix Profile** for anomaly detection in multidimensional time series.
- We show that **bow shock transitions** from CAPS data can be **detected best** by the **Multidimensional Matrix Profile** and the **non-Bayesian HMM**.
- We find that all four approaches **struggle to identify magnetopause transitions** from CAPS data. Significant differences between spacecraft orbits across years limits the generalizability of parameters optimized on a single year: **online adaptation may be beneficial**.

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For more information, please see the full paper at https://kdd-milets.github.io/milets2020/papers/MiLeTS2020_paper_11.pdf.

GPU Saturation Testing with Variable Applications and Storage Platforms

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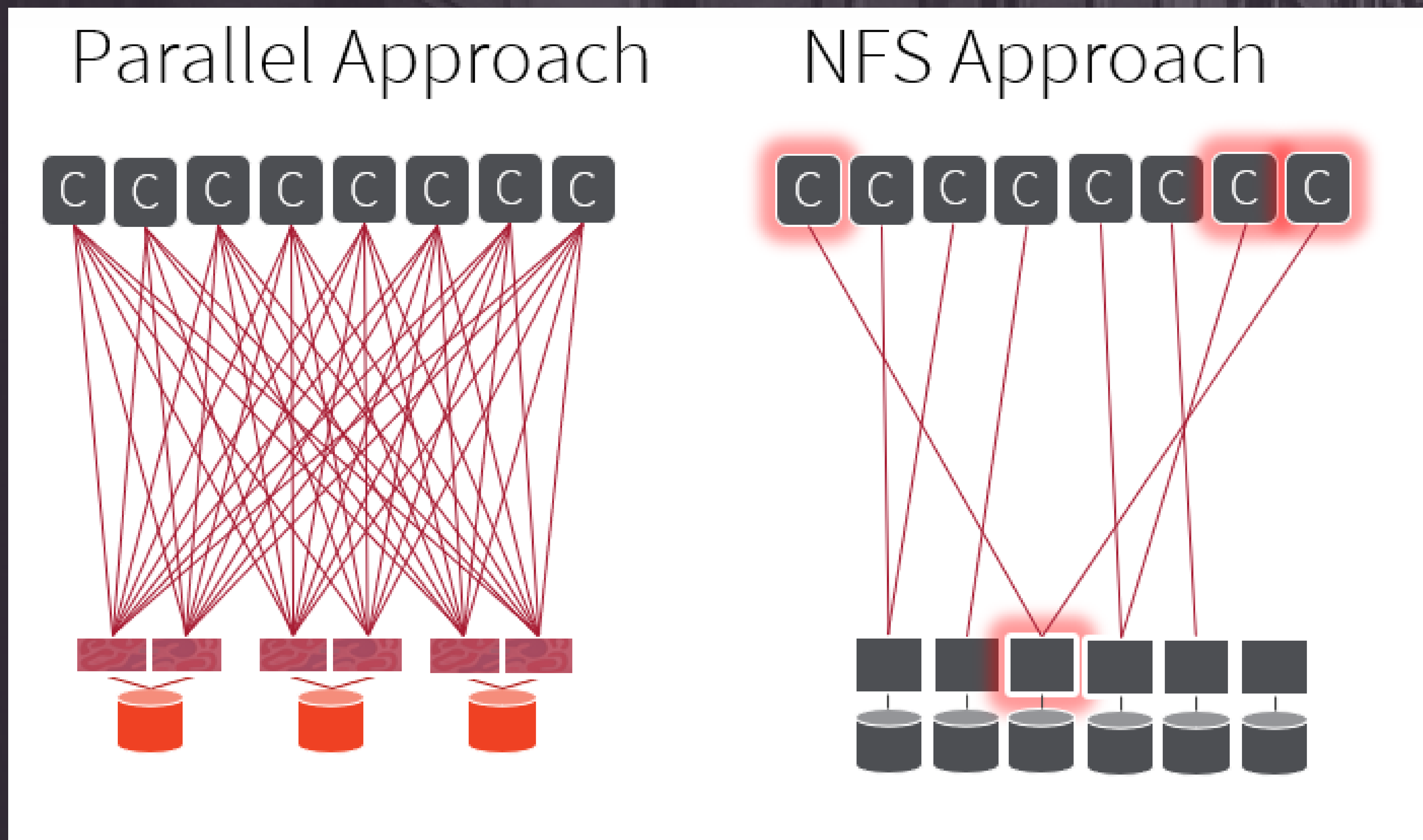
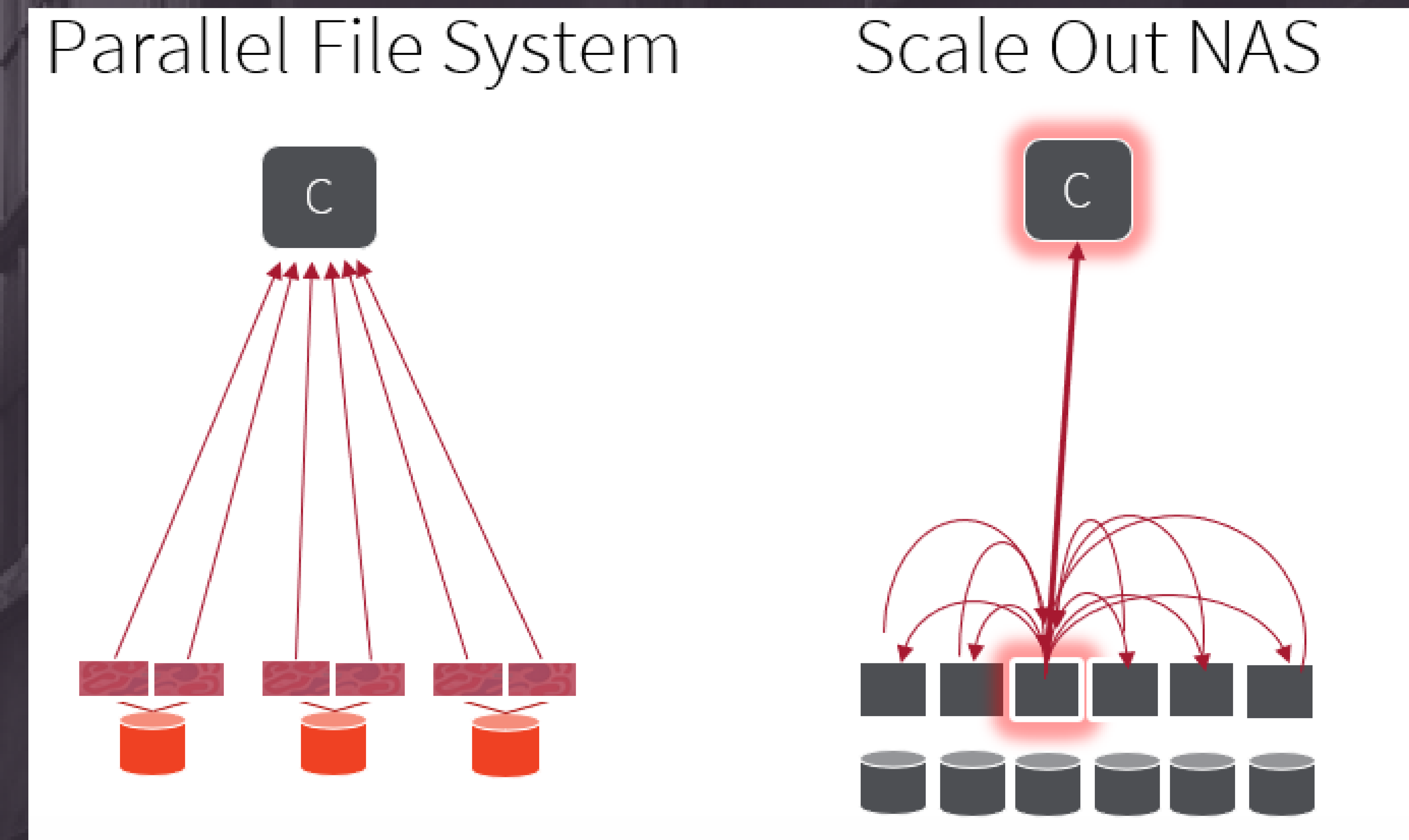


Even, granular balanced I/O from each application to all servers eliminates hot spots

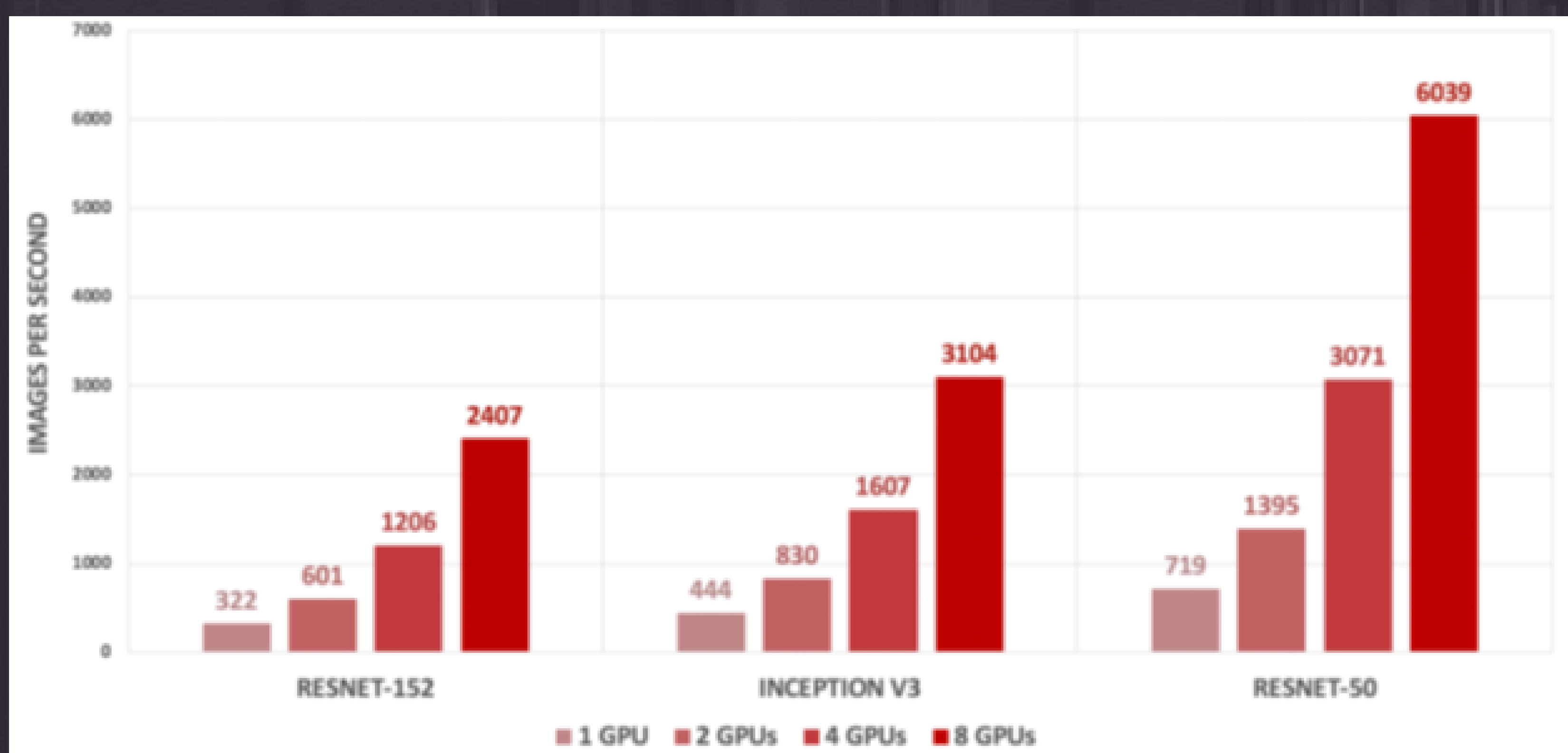
Uneven workloads and 1:1 client server relationship creates hot spots in storage and slows down applications

By design, the GPU architecture provides facilities for massive processing concurrency. Some GPU based applications distribute over 96 nodes simultaneously, touching 1500 GPUs. These application profiles necessitate parallel data paths that deliver data with high-throughput, low-latency and massive concurrency, directly to GPU memory.



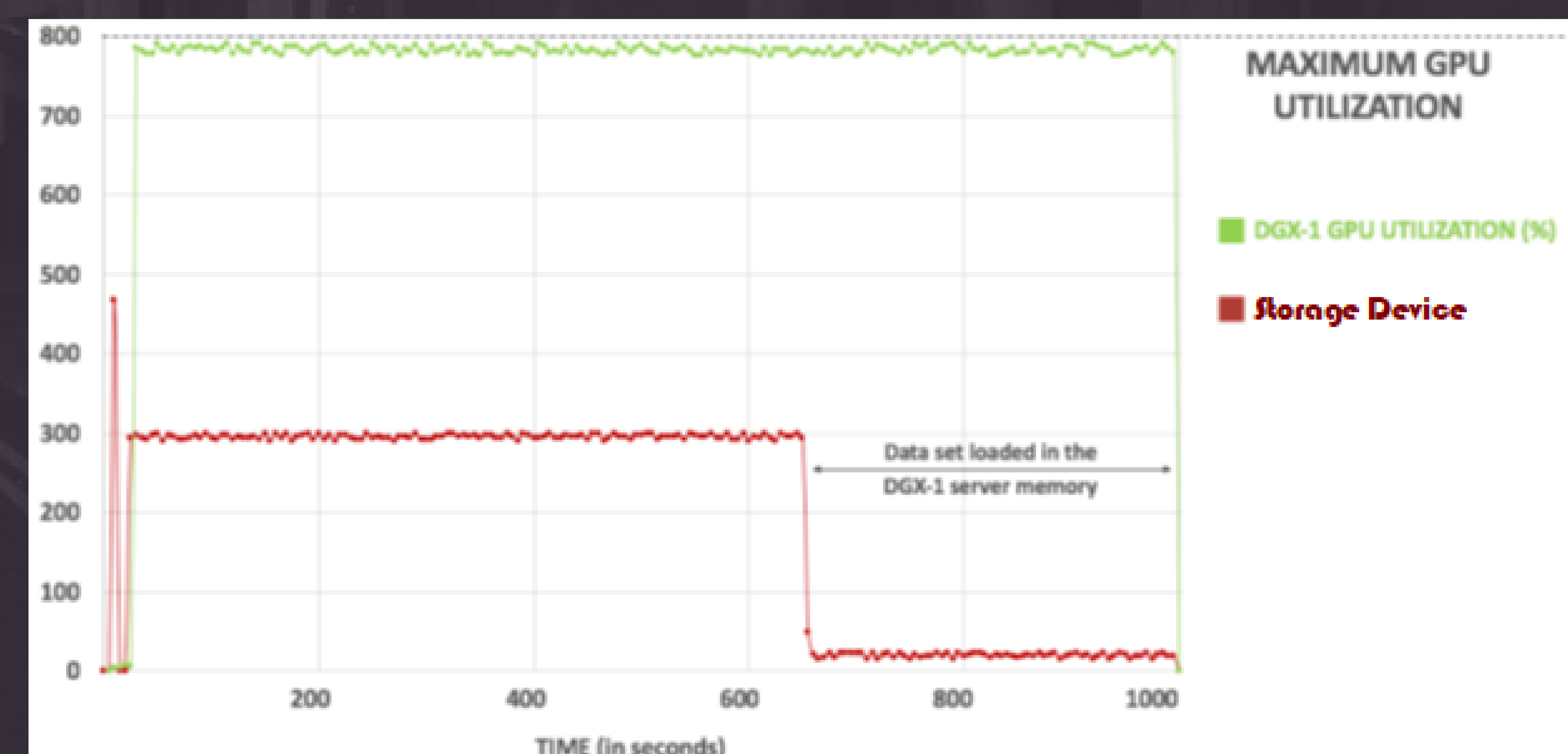
Clients read in parallel data directly from servers that hold the data for low latency high throughput reads

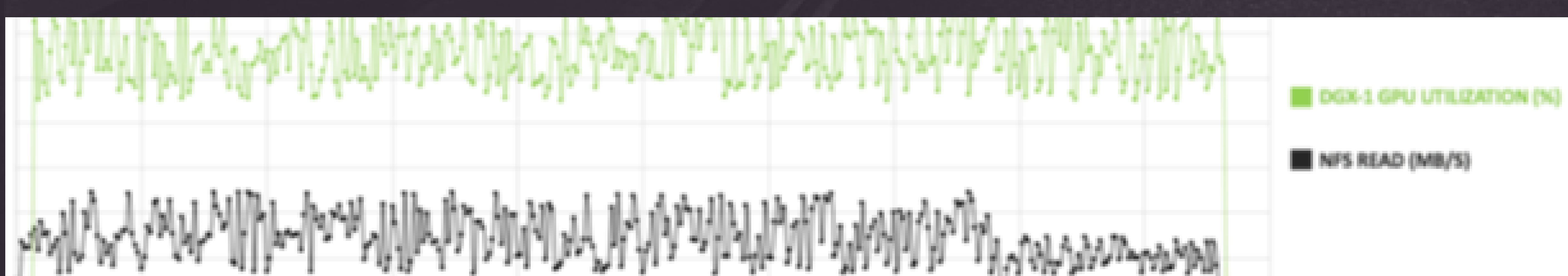
Client only reads from **one** server and must wait for all the data to be retrieved from all peer servers



The graph on the left, demonstrates training application performance with resnet-50, resnet-152 and inceptionV3 models using different numbers of GPUs on a single DGX- 1 server. The resnet-152 and inceptionV3 tests were executed with the NVIDIA TensorFlow 18.03-py2 dockerfile and a data set from the ImageNet Large Scale Visual Recognition Challenge 2012 (ILSVRC2012). The resnet-50 test was executed with the NVIDIA TensorFlow 18.09-py3 dockerfile and same data set

Illustrated to the right, is the GPU utilization and read activity from the ai-configured storage appliance. The GPUs achieve maximum utilization by using the storage appliance to deliver a steady stream of data through the training process. The application takes 933 seconds to complete. At approximately 660 seconds, the data set is fully loaded into the DGX-1 server and the application no longer needs to read the data from the storage appliance.





Illustrated to the left is the GPU utilization and read activity from the same application accessing data on NFS storage. The GPUs never achieve maximum utilization, and the NFS storage fails to deliver a steady stream of data to the application. The training application takes nearly 2000 seconds to complete.

Supporting Global Knowledge Sharing using Cross Language Information Retrieval

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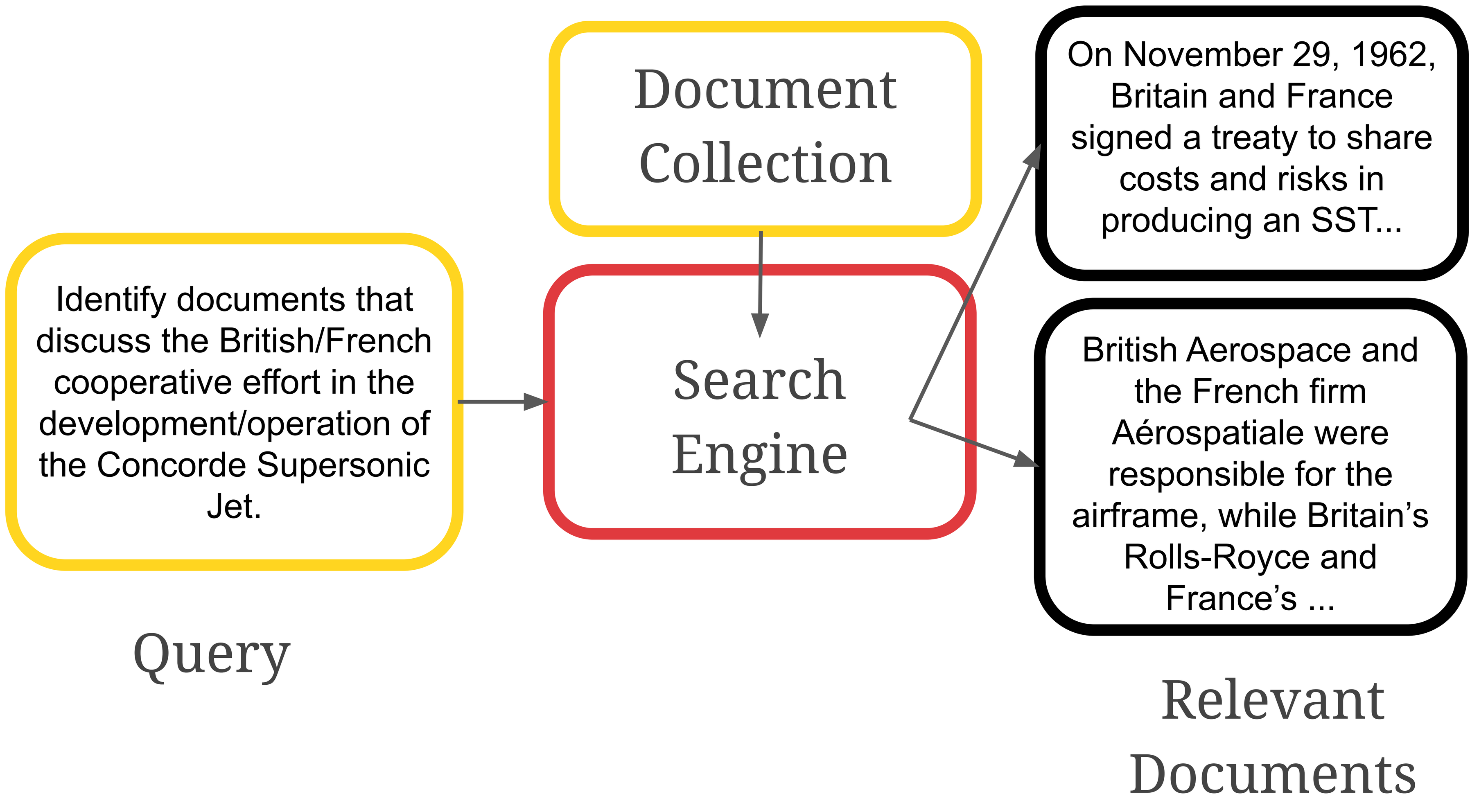
Information Retrieval

Information retrieval is searching for the relevant documents in a large collection of documents using a query input by the user. The aim of the search engine is to return documents relevant to the query.

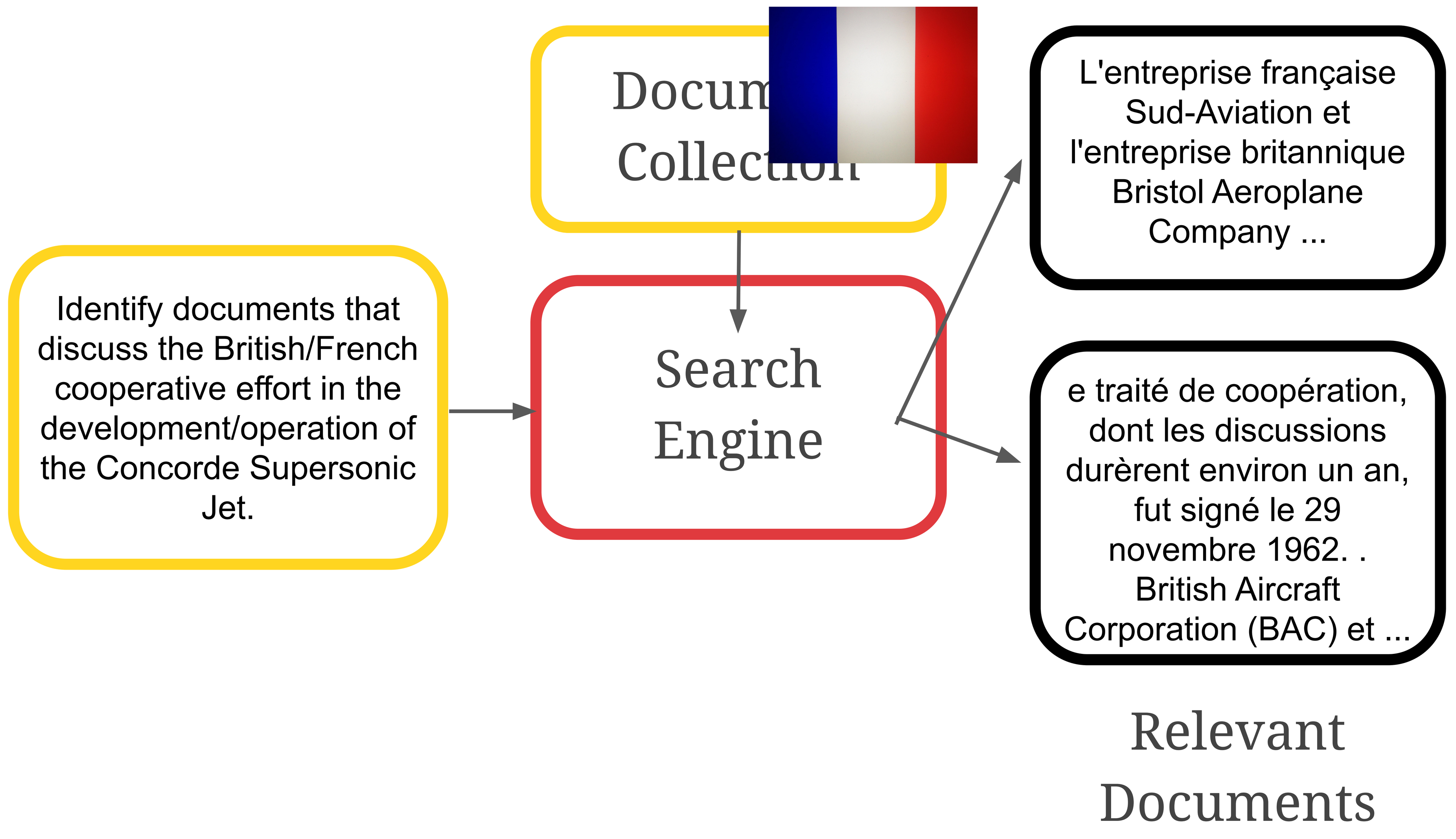


Possible Applications

- Chinese technical publications might be of value to NASA engineers working on similar problems.
- Understanding the global reaction to NASA's activities would benefit from systems that could process Hindi and French as easily as English.
- Allowing search in the oral history archives. The interviews in the Shuttle-MIR oral history collection were conducted in English; people who could speak only Russian simply weren't interviewed,

Cross Language Information Retrieval (CLIR)

CLIR is a special case of Information retrieval in which the language of the documents differs from the language of the query.



CLIR Architecture

- Documents or queries are translated into compatible representations using machine translation or dictionaries.
- Search engines can handle ambiguity and translation errors well using multiple translation variants.
- Ranking based on embeddings (dense vector representations) of terms, sentences or segments.
- Ensemble methods can improve robustness.

CLIR vs. Monolingual IR

System	Mean Average Precision
Monolingual IR (Russian queries) BM25	0.345
Cross-Language IR (English queries) Document translation + BM25	0.336
Cross-Language IR (English queries) Document translation + embeddings	**0.434**

Table 1. Comparison of the monolingual and crosslingual retrieval on the Russian 2003 and 2004 collections. Documents are in Russian, queries are either in Russian or English.

Beyond CLIR

- "Documents" might be speech or video.
- Text might be printed or handwritten.
- Content or queries may include several languages.
- Queries might be structured or simple.
- Information need might be narrow or broad.
- Summaries of relevant documents might be needed.
- Summaries and documents may need translation.
- How quickly can we build systems?

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SCAN ME

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Retrieval results were provided by the participants of the 2021 Johns Hopkins HLTCOE Mini-SCALE workshop.

Solar Flare Prediction using Convolutional Neural Nets (37)

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Abstract [1]

During my time with the Space Weather Lab at George Mason University (GMU), most of our research was focused on Active Regions (AR) on the Sun's surface. Recent work with Goddard's Heliophysics Lab has opened my field to the uses of Artificial Intelligence (AI) and Artificial Neural Networks (ANN). ARs are one of the last natural phenomena that we don't fully understand what governs its movements and actions. This problem was a great fit to use an ANN algorithm to determine and decipher the qualities of the images that indicate activity when formulas and simulations fail. Knowledge of the Sun's surface and ARs are critical because, at any moment, a harmful Coronal Mass Ejection (CME) can be released causing worldwide failure of the electric grid. Fortunately, most events correlate, so when a strong solar flare occurs in an active region, it is an excellent indicator that a CME will have a stronger possibility to release from that same region. Dr. Jie Zhang, a solar physic professor and advisor at GMU, and I have recently looked at the old question of can we predict solar flares from magnetogram images of the ARs using AI? We decided that using an ANN was the most efficient approach in the fact we would be dealing with larger datasets. We attempted to train the ANN with the AR images so that when the trained ANN is presented with unknown AR images, it could correctly predict if that region will have a solar flare within 24 hours. In a combined effort with GMU's computer science department, we have now matured our ANN to a Convolution Neural Network (CNN) that is optimized for image classification. CNN is still an ANN, but it has the added feature of convolution layers that mathematical takes into account the surrounding pixels as a feature of the ANN. Convolutional layers are an excellent technique used to find structures in images using only pixel data. Our research data is the magnetogram images from Helioseismic and Magnetic Imager (HMI) on the Solar Dynamic Observatory (SDO) sliced to a square region containing the full AR. Our data is from 2010 to 2014, which consists of around 1000 images. The images are from the last solar maximum to get a more significant distribution of ARs that erupted with a solar flare within 24 hrs, and this was done by connecting them with archived flare. We are now looking toward using object detection algorithms like YOLO (you only look once) to take the entire magnetogram image of Sun to detect ARs and automatically slice them to a shape the CNN can read and predict. Our end goal is the addition of these two powerful AI techniques to produce a program that can be used by scientists and satellites to predict the release of a CME on behalf of humanity. I hope to present a proof of concept that can be used to observe the Sun's surface, and when an AR forms, the object detector will find it, and the CNN determines if a solar flare will occur within 24 hrs.

The Introduction [2]

In 1925 Cecilia Payne-Gaposchkin proposed her doctoral thesis that the stars are composed of mostly hydrogen and helium. Ever since then we have continued to learn more about our host star from the fact that is our source of life-giving energy and also the biggest, most dangerous nuclear bomb for the next 4 light-years.

The Sun continuously produces streams of charged particles into the surrounding space, which is a reason why space is dangerous. When the Sun has a lot of activity in its active regions it is likely to release a solar flare and a Coronal Mass Ejection (CME). The CME is a concentrated pressure wave of charged particles from the sun due to actions of the surface and has been known to cause problems on Earth and in our solar system. A large CME hit Earth on March 9th in 1989 causing a large geomagnetic storm shutting down some cities' power grids, like Quebec, and completely jamming worldwide communication channels like radio. It was reported that an X15 (very big) solar flare was reported on March 6th just 3 days before the incident. But, this is simply a bad day compared to the ferocity of the Carrington Event on 1859 from September 1st to the 2nd. The Carrington Event is the largest geomagnetic storm on record. Electrical grids were very small then, but the telegraph systems all over there world failed, and many telegraph workers reported that they were electrocuted at work by the event. Richard Carrington reported that a 'white light flare' came from the Sun several hours before the event. It is understood that a geomagnetic storm like the 1859 Carrington Event today would destroy electrical grids, cause widespread blackouts, and cost trillions of dollars. In 2012 a powerful CME, similar to the Carrington Event, was released but missed the Earth by nine days. In this introduction, I wanted to simply state the background and importance of this work which has led me to attempt to predict solar flare occurrences on the Sun. An accurate prediction can give us more time to be better prepared to handle it when it does.

Definitions

Active regions - Regions on the Sun's surface that have very strong magnetic fields. They have a tendency the form sunspots, seen as the darker region in Figure 1. Active regions sometimes come in contact with another polar opposite active region and will produce solar phenomena like flares and CMEs.

Charged Particles - are atomic particles or ions with an electric charge. They are released by the trillions by the Sun producing the solar wind. They can disrupt or destroy unprotected electrical equipment.

Coronal Mass Ejection (CME) - is a significant release of plasma, charged particles, and magnetic flux from the Sun's surface seen in Figure 2. They are often seen to follow the appearance of solar flares, but a CME will not always that be released with every solar flare.

Geomagnetic Storms - are a major disturbance of Earth's magnetosphere that occurs when there is a very strong exchange of energy from the solar wind to Earth's atmosphere. Can be seen on Earth as Auroras in Figure 3

Solar Flare - is a sudden bright flash of light on the Sun's surface, seen as the bright spot in Figure 2. It is found primarily seen in active regions. A solar flare can be accompanied by a CME.

Figure 1 (Magnetogram Image of AR and Solar disc)

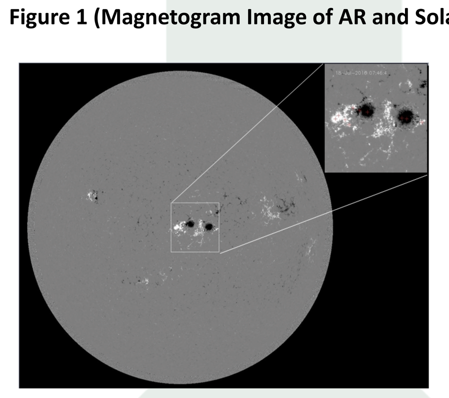


Figure 2 (Release of Solar Flare and CME)

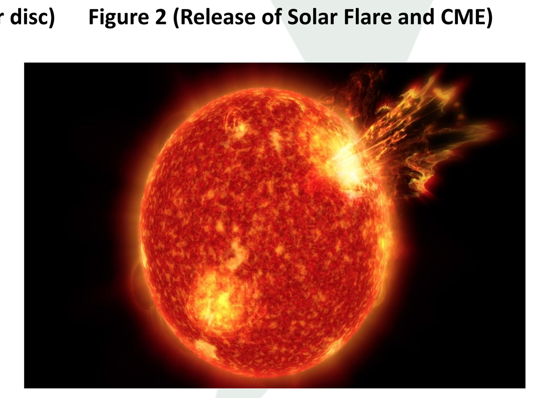


Figure 3 (Aurora from Geomagnetic storms)

Methods and Results [3]

The method I am using to predict a solar flare occurrence from an active region is the AI algorithm known as Artificial Neural Networks (ANN) and in particularly Convolutional Neural Networks (CNN). A CNN has all of the same functions and structures as ANNs except the addition of a convolutional layer that pools a set of incoming data to come up with results that take into account the values of close proximity inputs. This can be done by simply finding the sum or the average of pieces of the incoming inputs. CNNs are known to work very well with image data that is in the matrix-like form similar to pictures from a camera.

The CNN architecture I am using started with the VGG-16 architecture, seen in Figure 5, which is a very successful CNN algorithm used by the Visual Geometric Group out of Oxford who got a 95.2% model score on the very large ImageNet set of images. VGG-16 had a normal 224 x 224 input but I needed 256 x 256, so I made an hourglass-like residual layer structure to start the network, an example is seen in Figure 4 added to the front of Figure 5. I did this to strengthen the starting heat map of features and output to the smaller 224 x 224 image size when added to the beginning of the VGG 16 model. I also removed Max-pooling and used average pooling due to the way the numeric data was presented. I used the activation function ReLu for every layer but the last which I used the softmax function to help classify. My loss function was a simple Binary crossentropy with no reduction type and my optimizer was Adam with a learning rate of 0.0001, amsgrad = True, beta 1 = 0.9, beta 2 = 0.9999, and epsilon = 0.00001.

Figure 4 (Hourglass ANN architecture)

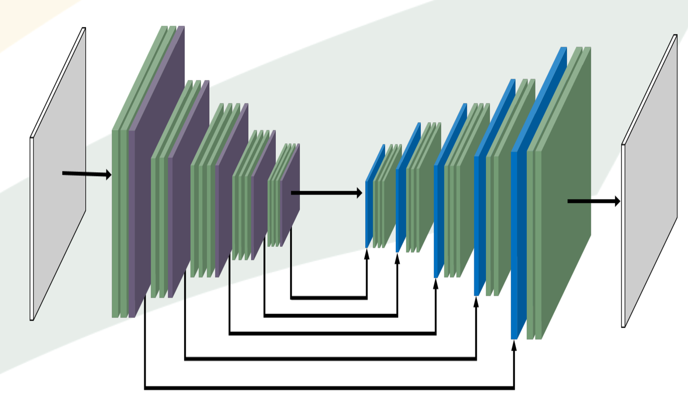
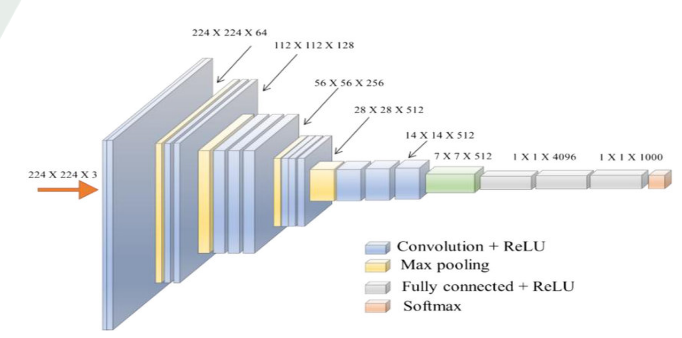


Figure 5(VGG-16 ANN architecture)



Training the Model

The data used to train the model was 1070 images of the Sun's active regions, like in Figure 1, with the dimensions of 256x256x1. The images are HMI Magnetogram, like in Figure 1, were taken from the Solar Dynamic Observatory (SDO) from 2010 to 2014 around the last solar maximum. There were 70 images of active regions that created a solar flare within 24hrs, and 1000 images of active regions that did not. I also used 22,000 epochs with an image batch size of 32. My goal was simply to produce a 0 meaning that no flare will be produced or a 1 meaning that a solar flare will be released.

The Hardware that is used to train the following CNN is two NVIDIA Quadro RTX 4000 GPU for a total of almost 5,000 Cuda cores. The software programs used the create and train the CNN architecture are TensorFlow 2 and Keras in python 3.7 on the Ubuntu 18.04 operating system.

From the trained CNN model I produce the visual results of a confusion matrix (Figure 6), a normalized confusion matrix (Figure 7), and a ROC curve (Figure 9), and for the quantitative model parameters produced are Sensitivity, Specificity, Precision, Negative Predictive Value, Accuracy, AUC (area under the curve), and the Appleman Skill Score (Equation 1). The calculations are shown in Figure 8 and the calculated values are shown in Table 1. I converted some to a percentage for discussion purposes.

Figure 6 (Confusion Matrix)

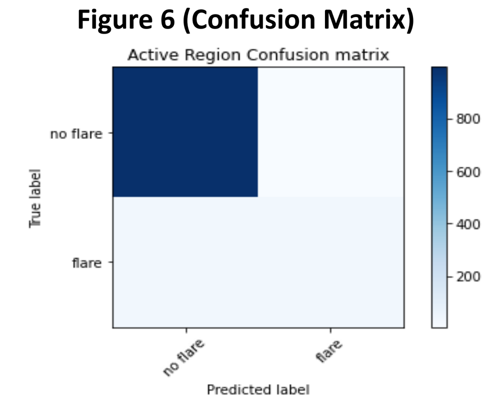


Figure 7 (Normalized Confusion Matrix)

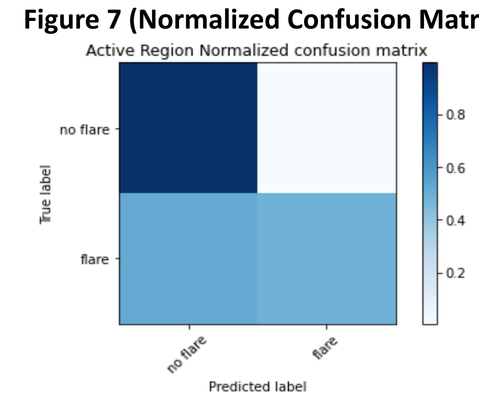


Figure 9(ROC Curve)

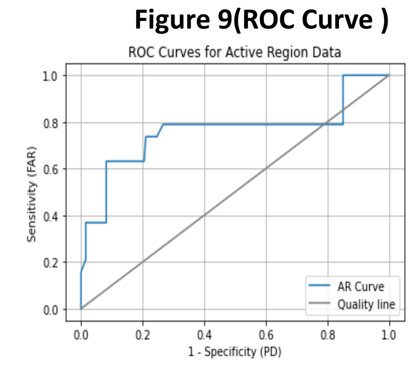


Figure 8 (Confusion Matrix labels and Equations)

Actual Class \ Predicted Class	Positive	Negative	
Positive	True Positive (TP)	False Negative (FN) Type II Error	Sensitivity $\frac{TP}{(TP+FN)}$
Negative	False Positive (FP) Type I Error	True Negative (TN)	Specificity $\frac{TN}{(TN+FP)}$
	Precision $\frac{TP}{(TP+FP)}$	Negative Predictive Value $\frac{TN}{(TN+FN)}$	Accuracy $\frac{TP+TN}{(TP+TN+FP+FN)}$

Table 1 (Calculated Vales from CNN Model)

Model Score	92.21%
Sensitivity	48.57%
Specificity	99.40%
Precision	85%
Negative_Preditive	96.50%
Accuracy	96.07%
Applemen Skill Score	-0.03%
AUC	.761

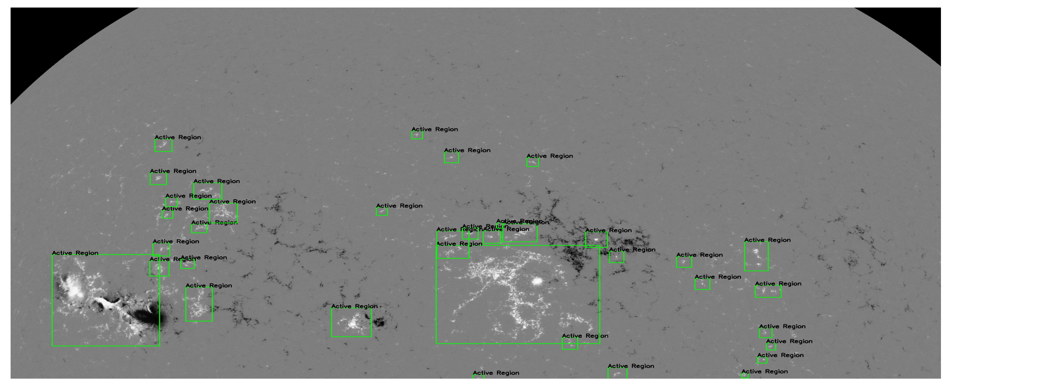
Equation 1 : $$Appleman's\ Skill\ Score = \frac{\frac{(TN+TP)}{total\ images} - (TN+FP)/total\ images}{1-(TN+FP)/total\ images}$$

Methods and Results (continued..)

Picking Active regions from the Sun's disc.

I attempted to make an object detection model that can detect and classify active regions on the sun, but most, if not all, of the activity of the Sun, will have an active region present. What I did instead is use the python module OpenCV to create a sudo-edge detector. I used Canny edge detection, gaussian blurs, and threshold adjustments for the program to detect ARs on the surface against the seeming blank surface background the magnetogram produces. When an AR is detected a bounding box is put around it, seen in Figure 10, and this bounding box is what will in the future slice to a specific size image and feed into the train CNN. I believe this only worked because of simplistic magnetogram images and would work poorly for any other solar image of wavelength.

Figure 10 (AR detections on the Solar Disc)



Discussion and Conclusion [4]

Discussion

The model performed well with a respectable model score of 92.2%, but this does not mean that the CNN can predict the occurrence of solar flares at that efficiency. First, in discussing the convolution matrix in Figure 6 it is easy to see that the data is completely skewed by the overwhelming higher percentage of non-solar flare making active regions by the fully blue true positive and every other box being almost blank. For the normalized confusion matrix seen in Figure 7, we can see the distribution of squares better, but we are also able to see the poor classifying for active regions that will produce a solar flare from the false positive and true negative beginning about the same color. This says that it was around a 50/50 split of the trained CNN model being able to determine if the region that is going to have a solar flare will have a solar flare. Just from the confusion matrixes, we can say that the CNN is good at determining that an active region won't have a solar flare, but we are likely to get quite a lot of false positives before getting a true solar flare.

The ROC curve, in Figure 9, agrees with the result of getting very many false positives with the slope line closer to a lower specificity on the x-axis. The ROC curve's AUC shows positive predictability with .761 that represents moderate model performance.

All calculated predictive values, except specificity and Appleman's skill score, are very good but are taken with the same grain of sand the great model score is. This is because the model was very good a predicting the non-flare bearing active regions that make up more than 90% of the data. The specificity of 45% on the other hand shows the truth of not being able to identify the flare bearing active regions results very well, and this reiterates the runaway false positive problem above.

The Appleman's skill score was my most sought after metric to truly quantify how well my model worked. In the 2016 paper titled A COMPARISON OF FLARE FORECASTING METHODS, G.Bares et al. were able able to get a state-of-the-art model with an Appleman's skill score of 0.19. simply meaning they were able to predict more solar flares than not. My Appleman's skill score was -0.03, basically zero, because of the 50/50 tie between false positives and true negatives of flare bearing active regions. This result doubles down on the fact that we will get detect a similar amount of false positives of flare-bearing active regions as actual solar flare events.

Conclusion

In conclusion, it is no simple feat to predict solar flares. Although there were many positive results in this proof of concept the algorithm is far from being a great predictor of the occurrences of solar flares. The two biggest problems are that there is such a big difference in the quantity of data for each class, and the classic problem of we need more data. The positive progress of both of these problems of both these problems, it will create a better predictive model. But, the model we created model still has the strong ability to tell that an active region is not going to have a solar flare. This model may not have certainty in that a possible active region may have a solar flare, but due to the vast amounts of false positives, it will likely not miss the actual AR that will birth a solar flare. Much like the algorithm to find fraudulent credit card activity, it is better to find the problem and be wrong about that finding than to miss the problem entirely. One of the many false positives this trained CNN would detect could be the real thing, and that may be the difference in readiness for a Carrington-like solar event.

References [5]

(1) G.Barnes et al. (2016) A COMPARISON OF FLARE FORECASTING METHODS. I. RESULTS FROM THE"ALL-CLEAR"WORKSHOP
(2) Karen Simonyan∗& Andrew Zisserman, (2015), VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION
(3) Nushaine Ferdinand (May 29, 2020), Using Hourglass Networks To Understand Human Poses

Acknowledgements [6]

I would like the thank all the great staff of GMU's Physic's department, College of Science Research Club, Robotic Lab, The Space Weather Lab, along with the great staff at NASA Goddard's Heliophysic lab. I would like to particularly thank Jie Zhang for his idea to do this work, Barbara Thompson for her help and support with AI, and Suman Dhakal for the hard task of getting and labelling the data.

National Aeronautics and Space Administration

Automated Data Accountability for the Mars Science Laboratory

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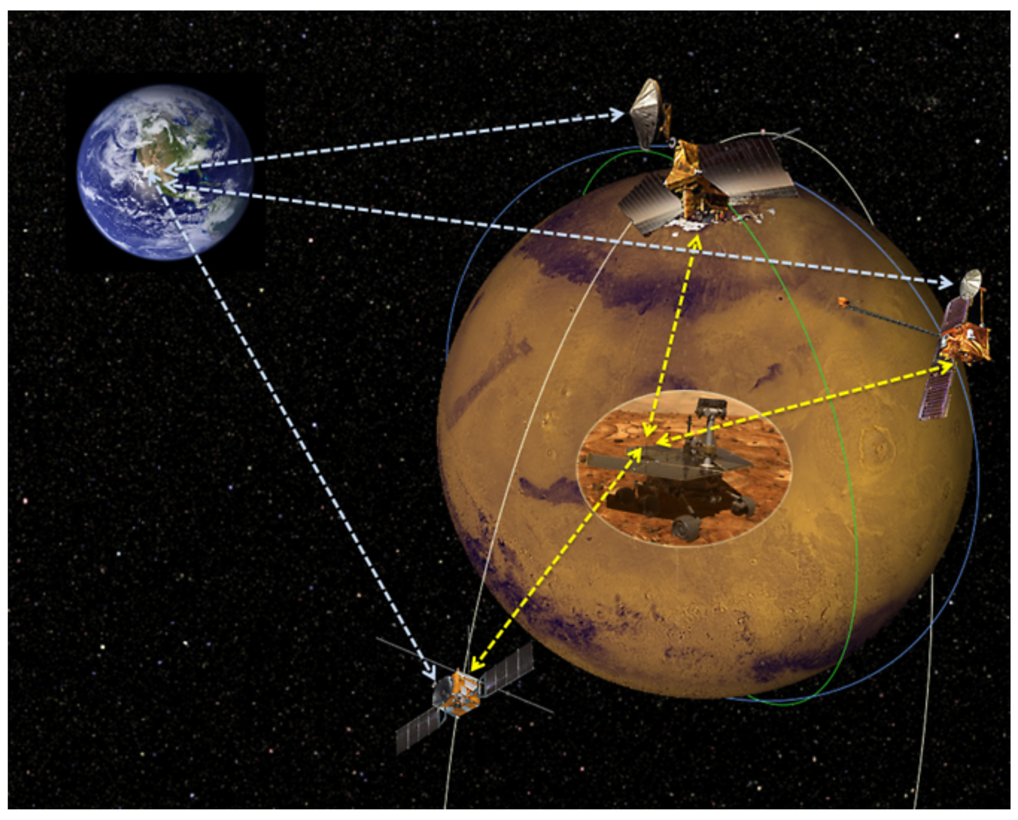
Ryan Alimo (393K), Dariush Divsalar (332B)

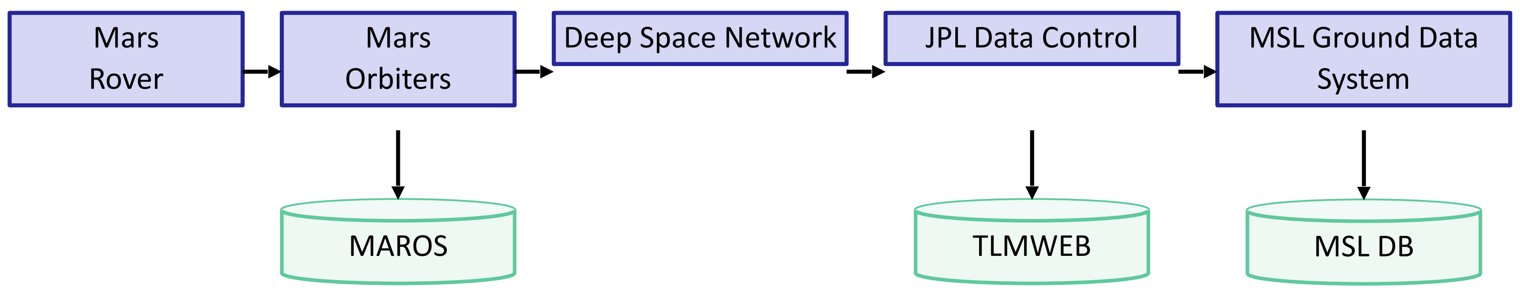
Introduction

Data Accountability is the process of ensuring that all data sent from a spacecraft is received and processed successfully on the ground and also identifying where in the pipeline data becomes missing if it not received. The Mars Science Laboratory (MSL) currently relies on Ground Data Systems Analysts (GDSA) to determine whether or not all data has been accounted for. When data is missing, it can take several hours to determine the root cause of the issue. There have been previous attempts to automate the data accountability process, but they are unreliable for operational use. This paper presents machine learning based approaches to automate and optimize the detection of volume loss from the downlink process of telemetry data from the Mars Curiosity Rover.



MSL Downlink Process

During the downlink process, data is transferred from the rover to one of the Mars orbiters. The orbiter then sends the data to one of the Deep Space Network Stations. The station sends the data to the Jet Propulsion Laboratory, where it is received by Data Control and stored in the Telemetry Data System (TDS). Finally, the MSL Ground Data System (GDS) software processes the data from the TDS and stores it in the MSL Database.



Approach

Data Collection

A data pipeline accumulates information about each downlink at various locations in the MSL Downlink Process. We gather data from three data sources: MAROS, which contains metadata from one of the orbiters; TLMWeb, which contains metadata from JPL Data Control, and the MSL Database, which contains metadata after the downlink has been processed by GDS software.

Signal Processing

A signal processor combines the raw metadata from these three separate sources and computes the relevant features. Expert GDSAs evaluated the computed features for each transmission to label each downlink as complete or incomplete. Our labelled dataset consists of approximately 9000 downlinks.

Machine Learning

With our well-labelled dataset, we trained both supervised learning models to classify each downlink as Complete or Incomplete. We also applied unsupervised learning techniques to identify anomalies in the data. These anomalies are equivalent to Incomplete passes labelled by the supervised learning algorithms. Our dataset is imbalanced; only about 10% of passes are Incomplete or anomalous, so detecting these can be difficult but is important for the GDSA team.

Hyperparameter Optimization

To further increase the accuracy of our models, we applied hyperparameter optimization while training. The Variational Autoencoder (VAE) had the highest recall of incomplete passes. Since our dataset is imbalanced, identifying these anomalies is more difficult and this recall is a better metric than overall accuracy. We chose to retrain the VAE with various hyperparameter optimization algorithms.

Accuracy of Trained Models

Machine Learning Algorithm	Recall of Incomplete Passes	Overall Accuracy
Adversarial Autoencoder	62%	67%
Variational Autoencoder	**80%**	**77%**
Linear Regression	38%	92%
Support Vector Machine	68%	85%
Gaussian Naïve Bayes	27%	97%
Deep Neural Network	50%	91%

Results of the trained machine learning models without hyperparameter optimization

Optimization Algorithm	Recall of Incomplete Passes	Overall Accuracy
Random Search	91%	83%
Tree Parzen Estimator	96%	87%
Hyper NOMAD	92%	85%
Delta-DOGS	94%	79%
Delta-MADS	**97%**	**88%**

Results of different optimization algorithms applied while training the Variational Autoencoder

Infusion and Explainability

The most accurate model was delivered to the MSL GDSA team. The model was infused into their software and is used to perform their daily operations. When a pass is labelled as Incomplete, the GDSAs need to know why. To answer this question, we determine which feature is the most anomalous by computing the error of each feature. Then an error message tells the GDSA which feature is anomalous and and the value of the feature. This error message provides the GDSA enough information to respond to the issue.

Sol 2696					
	46960	TGO_MSL_2020_066_03	Complete		350.273
	36960	MRO_MSL_2020_066_04	Complete		316.189
	46961	TGO_MSL_2020_067_02	Complete		185.804
	36961	MRO_MSL_2020_067_01	Incomplete	The data volume difference between the orbiter and TDS is 0.13 MB	397.564
	36961	MRO_MSL_2020_067_01	Complete		397.654
Sol 2697					
	46970	TGO_MSL_2020_067_03	Complete		391.194
	36970	MRO_MSL_2020_067_02	Complete		467.631

The MSL GDSA Report Summary Dashboard displays the status of each downlink as computed by the trained model. An error message explains where the data was lost.

National Aeronautics and Space Administration
Jet Propulsion Laboratory
California Institute of Technology
Pasadena, California

www.nasa.gov

Poster #39

A Systems Engineer's Virtual Assistant (SEVA)

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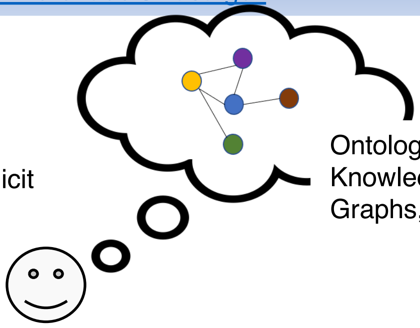
Mission

Our goal is to develop a virtual assistant system to help and interact with **one** engineer in their daily lives, while gradually accumulating that specific engineer's years of explicit and implicit knowledge and experience (lessons learned).



Ontology, Knowledge Base, Graphs, etc.

Systems Engineer

- Question-Answering
- Explainable System
- Dynamic Information
- Time & Scheduling
- Hypothetical Scenarios
- Capturing Experience

Personal Assistant

Information Assimilation

Documents (*Eg*: SE Handbook, Lessons Learned, etc.)

Motivation

- NASA currently lacks any personal assistant systems that are designed do trivial information management for systems engineers that deals with multitude of projects and disciplines.
- Although there exists knowledge engines and ontologies for the Systems Engineering domain such as MBSE, IMCE, and OpenCaesar, generic commonsense acquisition from raw text is rarely discussed; we aim to address this challenge.

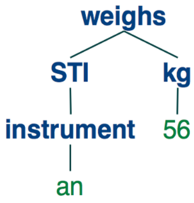
Our Current Goal

Extract knowledge from text to automatically construct knowledge graphs.

Open Information Extraction

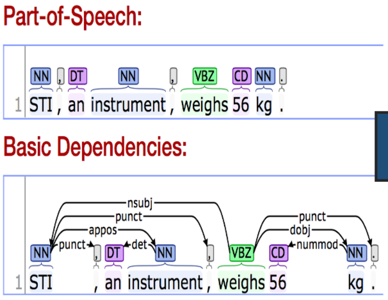
Sentence: STI, an instrument, weighs 56 kg

Dependency Parse Tree



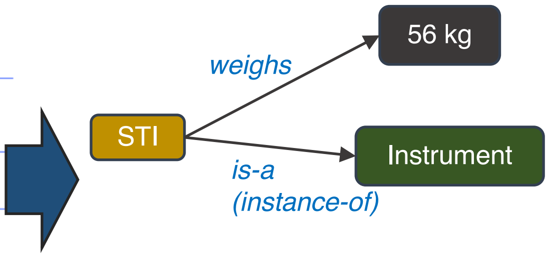
Part-of-Speech:

Basic Dependencies:



Tools: Stanford OpenIE, OpenIE by AI2, NLTK, Stanford CoreNLP, POS Tagger

Entities and Relations



Knowledge Graph (KG) Construction
+
Entity Linking

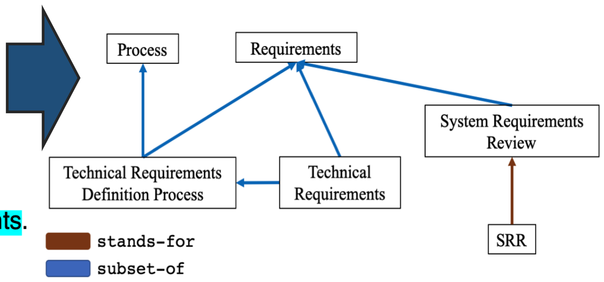
Concept Recognition

- **Concepts** are Systems Engineering domain-specific entities. Eg: '*Technology Readiness Level*', '*Project Manager*', '*Technology Maturity*', etc.
- **Goal**: Learn how to extract such entities from text.

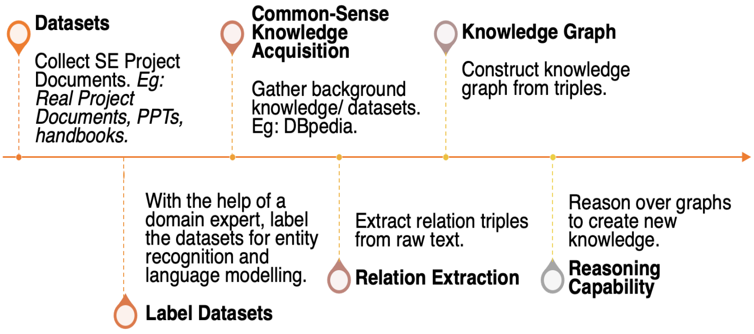
SEG is the art and science of developing an operable system capable of meeting requirements within often opposed constraints.

Abbreviation | System Concept | Operation Concept | SE Term

Sample KG Snippet



Future Work: Scalable + End-to-end



Conclusion

- SEVA: A framework to assist Systems Engineers in their daily activities.
- Commonsense knowledge acquisition and retaining lesson learned.
- From raw text to KGs (Entities and-Relations) using NLP.

Publications/Code/References: https://github.com/jitinkrishnan/NASA-SE

Poster #40

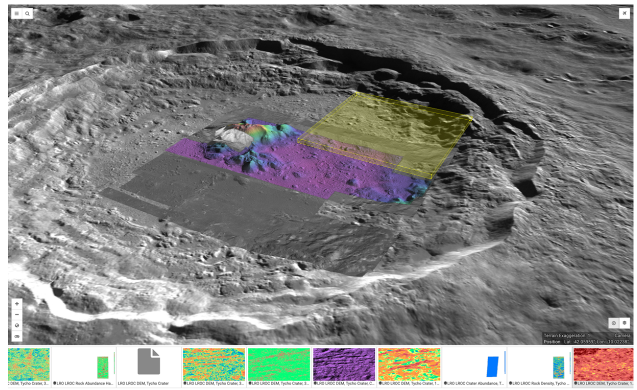
AI and Data Science Using NASA's Solar System Treks

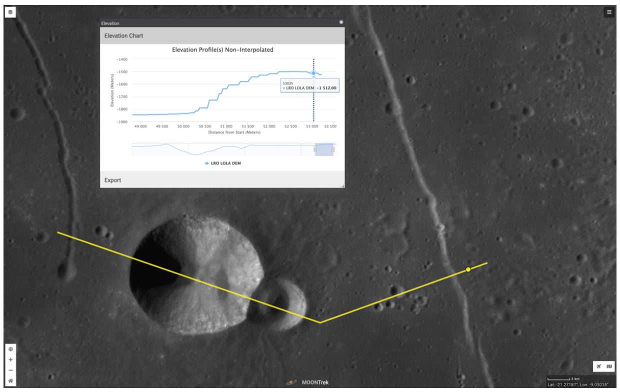
Emily Law, Catherine Suh & Solar System Treks Development Team[1]

Emily.S.Law@jpl.nasa.gov | trek@jpl.nasa.gov

NASA Jet Propulsion Laboratory, California Institute of Technology

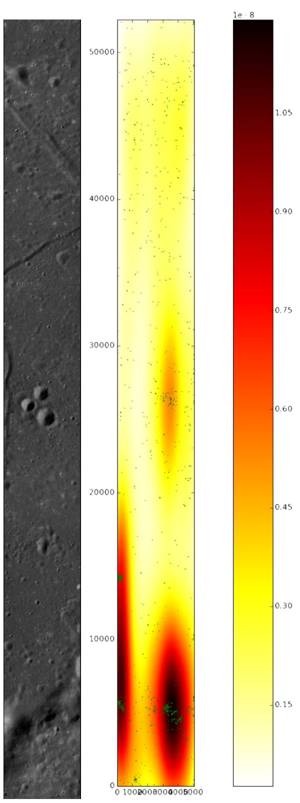
NASA's Solar System Treks program of lunar and planetary mapping and modeling produces a suite of interactive visualization and AI/data science analysis tools (https://trek.nasa.gov). These tools enable mission planners, planetary scientists, and engineers to access mapped data products derived from big data returned from a wide range of instruments aboard a variety of past and current missions, for a growing number of planetary bodies.

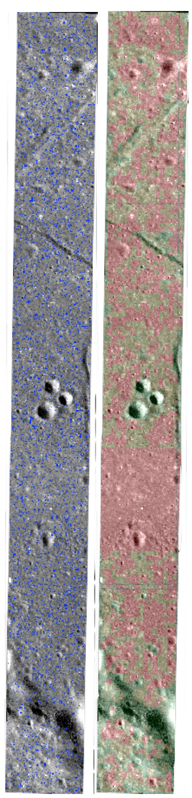


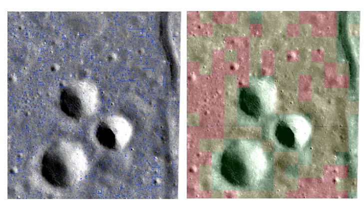


The portals provide easy-to-use tools for browsing, data layering and feature search, including detailed information on the source of each assembled data product. Interactive maps, include the ability to overlay a growing range of data sets. They allow users to easily find and access the geospatial products that are available. Data products can be viewed in 2D and 3D, in VR and can be easily integrated by stacking and blending together rendering optimal visualization. Data sets can be plotted and compared against each other. Standard gaming and 3D mouse controllers allow users to maneuver first-person visualizations of flying across planetary surfaces.

The portals provide a set of advanced analysis tools that employed AI and data science methods. The tools facilitate measurement and study of terrain including distance, height, and depth of surface features. They allow users to perform analyses such as lighting and local hazard assessments including slope, surface roughness and crater/boulder distribution, rockfall distribution, surface electrostatic potential, line of sight calculation and optimal traverse path determination. These tools facilitate a wide range of activities including the planning, design, development, test and operations associated with lunar sortie missions; robotic (and potentially crewed) operations on the surface; planning tasks in the areas of landing site evaluation and selection; design and placement of landers and other stationary assets; design of rovers and other mobile assets; developing terrain-relative navigation (TRN) capabilities; deorbit/impact site visualization; and assessment and planning of science traverses.

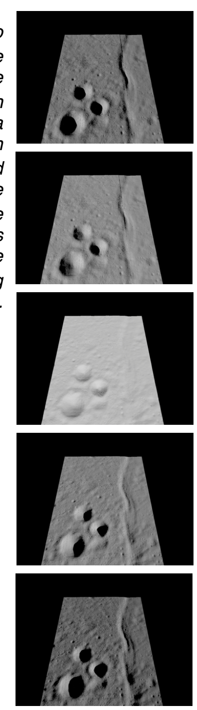




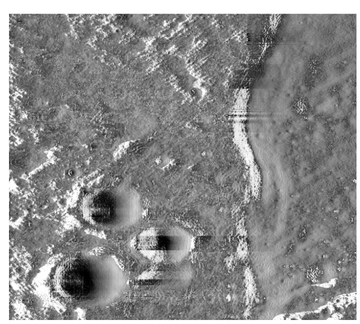


The images to the left and above are output from the crater detector and rock detector tools, respectively, with hazard maps to the right of the images on which the detection algorithms were run. These algorithms use neural networks and traditional image processing for detection and recognition.

The five images to the right are snippets from the lighting tool which takes a region of a Digital Elevation Model (DEM) and computes the amount of wattage for every pixel as a function of time with a ray tracing algorithm.



The image to the right is the result of calculating the potential static charge, or the static charge resulting from solar comic rays, per pixel over a given region of a Digital Elevation Model (DEM).



Nine portals are publicly available (https://trek.nasa.gov) to explore the Moon, Mars, Vesta, Ceres, Titan, Saturn's Icy Moons, Mercury, Bennu and Ryugu with more portals in development and planning stages. Contact trek@jpl.nasa.gov with any questions or concerns.

1 Eddie Arevalo, Bach Bui, George Chang, Aaron Curtis, Natalie Gallegos, Richard Kim, Emily Law, Heather Lethcoe, Shan Malhotra, Mike Rueckert, Syed Sadaqathullah, Catherine Suh, Quoc Vu

Data Ordering Genetic Optimization (DOGO) – A Data-Driven Quality Estimate for Every Observation

Dr. Lukas Mandrake, Masha Liukis, Steven Lu, and James Montgomery
Jet Propulsion Laboratory, California Institute of Technology

Poster ID 41, Second AI and Data Science Workshop for Earth and Space Sciences, February 11th, 2021

1. Quality Flags

- Space-based data sets (e.g., OCO-2, OCO-3) often contain quality flags.
- Guide users to find data to use for their analyses.
- Quality flags are great utility, but have drawbacks:
    - One-time optimization – not customized for your analysis
    - Assumes data is good or bad – data quality is not Yes/No; throw away too much data

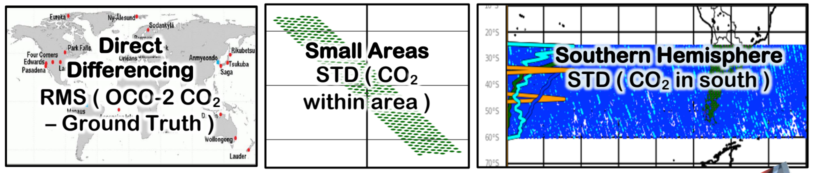
2. Instead of Flags, Order the Data

- No good or bad decisions, cutoffs, and lost data
- User specifies how much data from best to worst
- Tunable filter specific for every analysis
- Specify filtration strategy by a single threshold value
- Reproducible results, more comparable findings

3. Data Driven – Data Ordering Genetic Optimization

Turn the objections into statistical metrics to optimize

- Minimize MEAN(MONTHLY(STDEV(CO2))) in south
- Minimize MEAN(STDEV(CO2)) at small spatial scales
- Minimize RMS(CO2 – ground_truth_CO2)



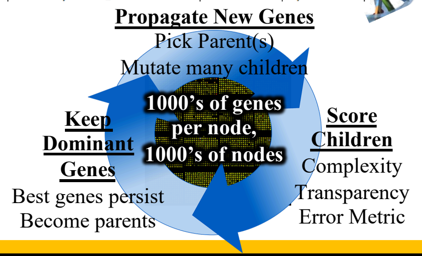
Gene = Data Quality Flag

- Define the gene
- Judge the gene
- Gene metrics

Field	Lower Limit (> or =)	Upper Limit (< or =)
Outcome flag (not in lite file)	N/A	2
Preprocessors/h2o_ratio	0.700	1.030
Preprocessors/co2_ratio	0.995	1.025
Preprocessors/dp_apb	-15.00	5.00
Retrieval/dp	-5.00	10.0
Retrieval/aod_ice	N/A	0.050
Retrieval/Aod_sulfate	N/A	0.400
Retrieval/Aod_dust*	0.001	0.30
Retrieval/Co2_grad_del	-70.0	70.0
Retrieval/albedo_2	0.10	N/A

Genetic Optimization

- Optimize a function
- Large compute resources
- Handle poorly behaved data that may be noisy



4. Results - Warn Levels

Every Observation Gets Its Judgement

- DOGO produces optimal quality flags for every 10% data accepted
- Each observation is examined: how many quality flags would reject it? 0 rejection => Warn Level 0
- Warn Levels are officially delivered to OCO-2 & OCO-3 user community
- Warn Levels are explainable

5. Future Work

- Expand DOGO to support more missions
- Simplify DOGO interface for easy use

6. Acknowledgement

The authors want to thank the OCO-2 & OCO-3 missions and Multi-Mission Ground System and Services (MGSS) for the continuous support of DOGO development.

Contact: lukas.mandrake@jpl.nasa.gov and you.lu@jpl.nasa.gov

Content-based Classification of Mars Imagery for the PDS Image Atlas

Poster ID 42

Steven Lu[1], Kiri Wagstaff[1], Emily Dunkel[1], Kevin Grimes[1], Brandon Zhao[2], Jesse Cai[3], Shoshanna B. Cole[4], Gary Doran[1], Raymond Francis[1], Jake Lee[1], and Lukas Mandrake[1]

[1]Jet Propulsion Laboratory, California Institute of Technology, [2]Duke University, [3]California Institute of Technology, [4]Space Science Institute

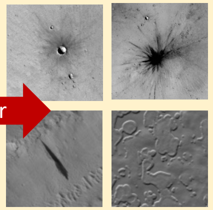
Contributions

1. Train machine learning classifiers to recognize image content
2. Classifier calibration for reliable posterior probabilities
3. Enable users to search millions of Mars images for content of interest
4. Deploy classifiers at the NASA Planetary Data System archive

Earth images

transfer

HiRISE Orbital Images



- Eight classes (e.g., crater, slope streak, etc.)
- Dynamic landmarking
- 10K labeled images
- Transfer learning

Calibration	Test Acc. (0.9 thresh.)	Calibration Error
Before	94%	0.056
After	**97%**	**0.022**

Data: https://doi.org/10.5281/zenodo.4002935

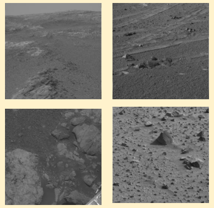
MSL Rover Images

- 19 classes (e.g. float rock)
- 3K labeled images
- Transfer learning
- Active learning experiments

Calibration	Test Acc. (0.9 thresh.)	Calibration Error
Before	87%	0.142
After	**90%**	**0.080**

Data: https://doi.org/10.5281/zenodo.4033453

MER Rover Images



- 25 classes
- 3K labeled images
- Multi-label transfer learning
- Classifier chain

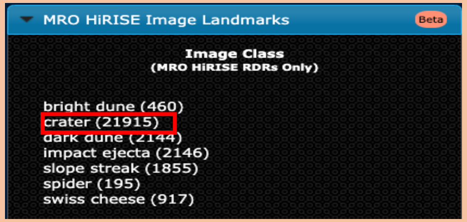
Calibration	Avg. Prec. (0.9 thresh.)	Avg. Recall (0.9 thresh.)	Avg. ECE
Before	89%	**53%**	0.031
After	**95%**	45%	**0.015**

Data: https://doi.org/10.5281/zenodo.4302760

NASA Deployment

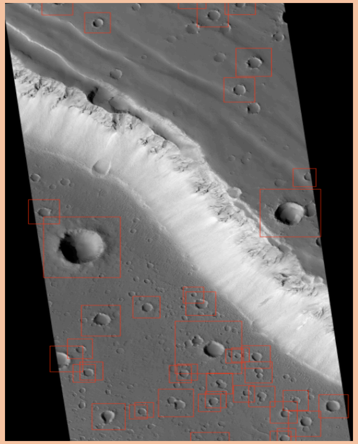
- Classified 1.1M images
- Access via PDS Image Atlas: https://pds-imaging.jpl.nasa.gov/search/

(1) Select class of interest

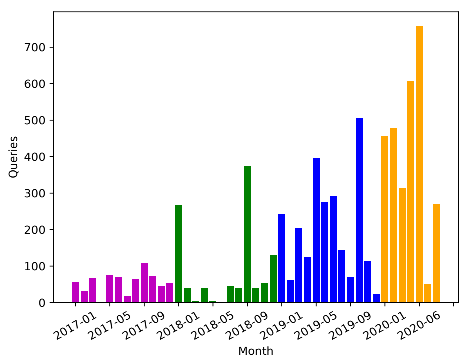


(2) Select from matches

(3) Classified content



Increasing usage over time



Next Steps

1. Characterize use cases for further Image Atlas improvements
2. Use tree-based multi-label learning approach to improve the performance of minority classes for MER classifier
3. Use label shift adaptation to adapt to new environments for MSL classifier
4. Create a classifier for Lunar Reconnaissance Orbiter (LRO)

Second AI and Data Science Workshop for Earth and Space Sciences, Feb. 2021.

Contact: you.lu@jpl.nasa.gov and kiri.wagstaff@jpl.nasa.gov

Thank you: Michael McAuley, Anil Natha, the Planetary Data System, and the Zooniverse labeling platform.

Auto-Calibration and High-Fidelity Virtual Observations of Remote Sensing Solar Telescopes with Deep Learning

Valentina Salvatelli (1,2), Brad Neuberg (1,2), Luiz F. G. dos Santos (3,4), Souvik Bose (5, 6), Mark Cheung (7), Miho Janvier (8), Meng Jin (2,7), Yarin Gal (9), Atılım Güneş Baydin (9, 10)

(1) Frontier Development Lab, (2) SETI Institute, (3) The Catholic University of America, (4) NASA - Goddard Space Flight Center, (5) Rosseland Center for Solar Physics, University of Oslo, (6) Institute of Theoretical Astrophysics, University of Oslo, (7) Lockheed Martin Solar & Astrophysics Laboratory (LMSAL), (8) Universite Paris-Saclay, CNRS, Institut d'astrophysique spatiale, (9) Department of Computer Science, University of Oxford, (10) Department of Engineering Science, University of Oxford

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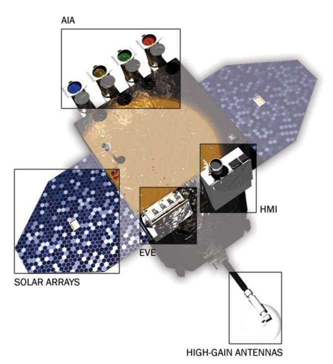
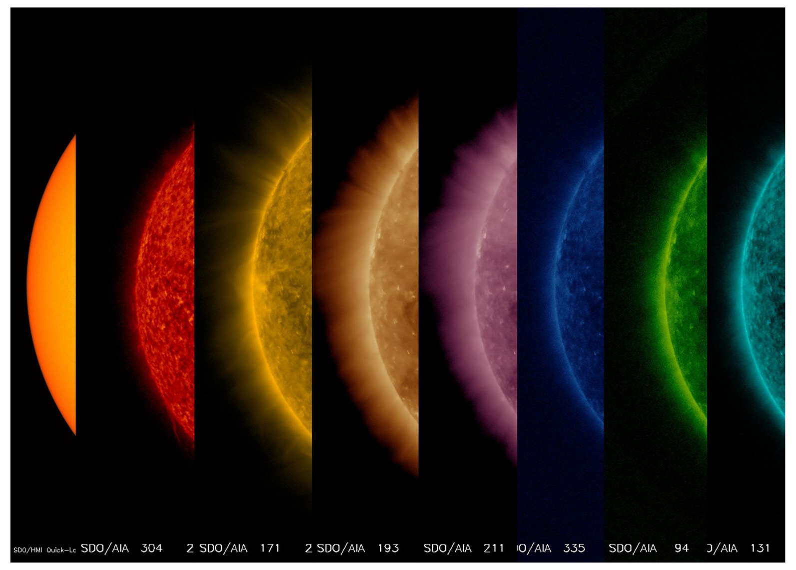
BACKGROUND

The **Solar Dynamics Observatory (SDO)** [1] is a mission designed to understand the causes of solar variability and its impact on Earth. SDO has been constantly monitoring the Sun 24x7 since 2010, with a 12 second cadence and 4k x 4k resolution, generating **terabytes** of observational data every day.



The **Atmospheric Imaging Assembly (AIA)** [2], one of SDO's instruments, has been collecting full-disk images of the solar atmosphere in 2 UV channels and in 7 extreme UV (EUV) channels with a high temporal and spatial resolution.



We experimented on how deep learning techniques applied to AIA multi-channel image data can be used to enhance the capabilities of present and future heliophysics missions, particularly in deep-space.

The results refer to two separate experiments: **A - automatic correction of the instrument degradation ; B - synthesis of virtual observations (aimed at reducing telemetry, and potentially hardware, needs of future missions).**

DATA

We used pre-processed images from the SDOML dataset [3]
- downsampled to 512x512
- temporally aligned and spatially co-registered
- identical resolution (4.8 arcsec)
- corrected for instrumental degradation and exposure

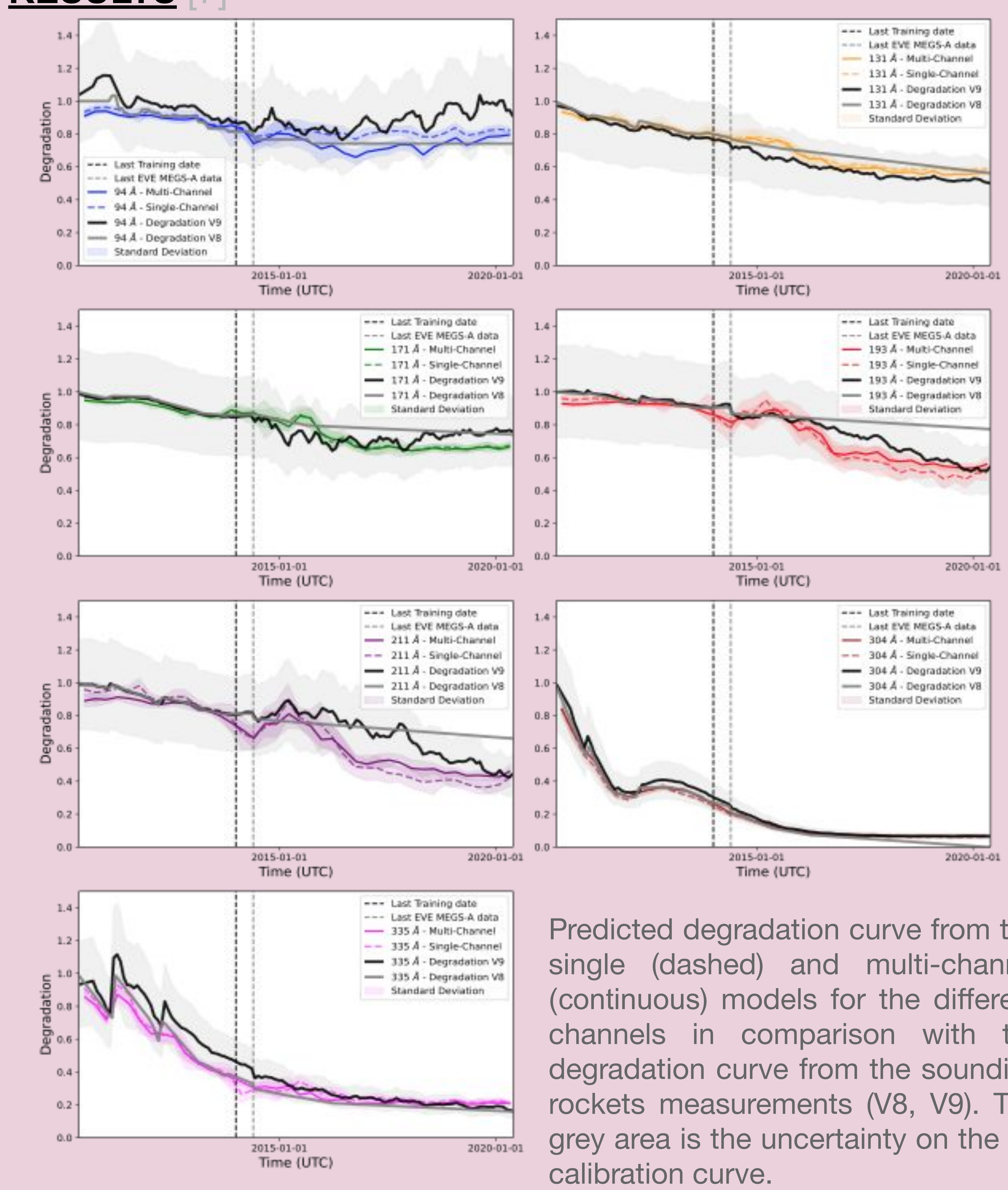
In both the experiments we
- split in train/test according to the month (to avoid solar cycle bias)
- span over several years of data

COMMON IDEA

How the spatial features in the solar corona appear at different wavelengths is determined by physics. A neural network can learn the correlation between these features from previous images and use that for future predictions.

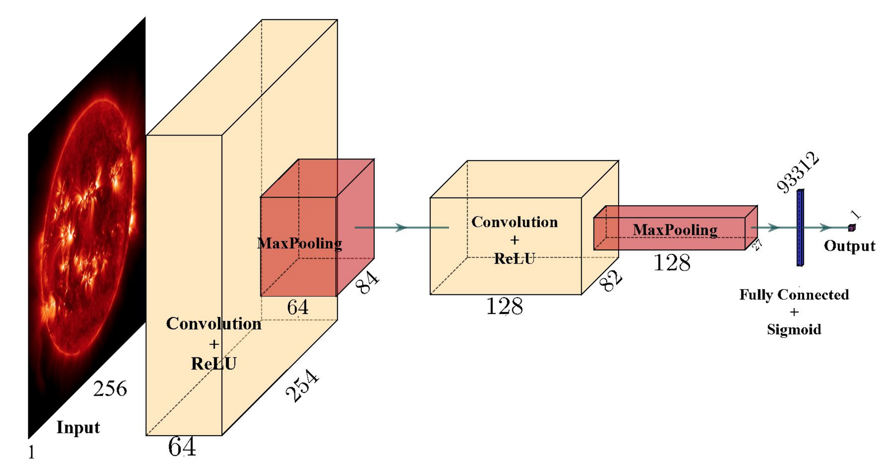
Auto-calibration of the CCD sensitivity (A)

RESULTS [7]

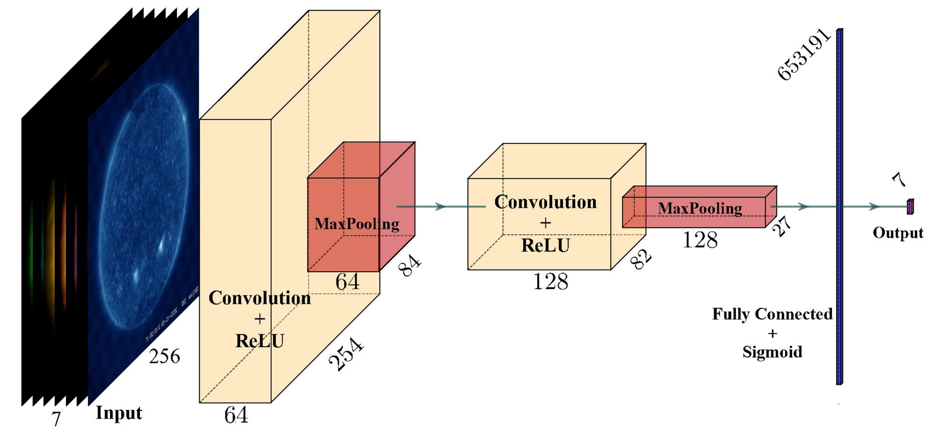


Predicted degradation curve from the single (dashed) and multi-channel (continuous) models for the different channels in comparison with the degradation curve from the sounding rockets measurements (V8, V9). The grey area is the uncertainty on the V9 calibration curve.

CNN - SINGLE INPUT CHANNEL



CNN - MULTIPLE INPUT CHANNEL



		Tolerances				
		0.05	5%	10%	15%	20%
Model	Baseline	51%	27%	43%	56%	66%
	Single Channel	78%	50%	73%	85%	92%
	Multi Channel	85%	53%	77%	89%	94%

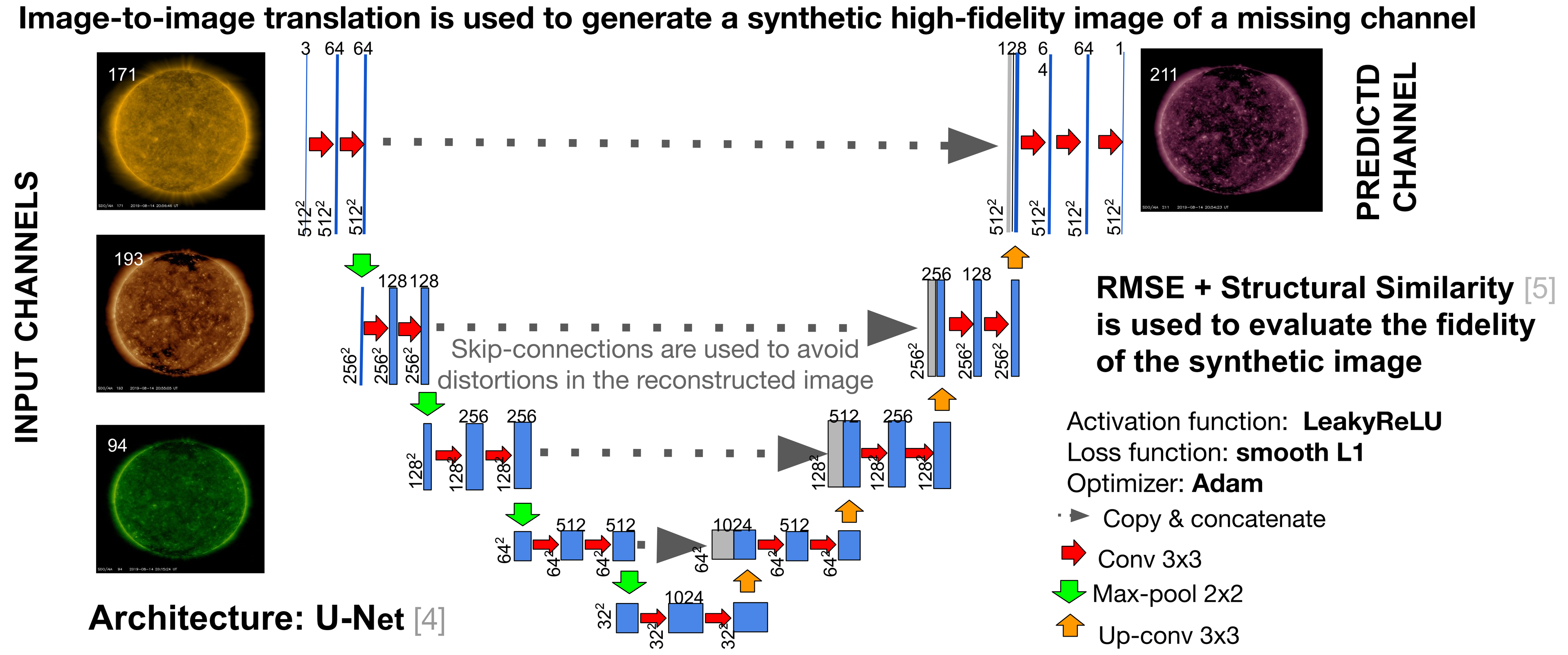
Results on the test set for the different approaches. The baseline is a non-machine learning method based on quiet areas of the Sun. Tolerance x% means the prediction is considered successful if the calibration error is within x.

APPLICATIONS

- ★ Enabling future HSO missions to auto-calibrate their EUV instruments without using sounding rockets.
- ★ Enabling Sun observatories from vantage points in deep-space (where sounding rocket calibration is not an option)

Synthesis of Virtual Observations (B)

Image-to-image translation is used to generate a synthetic high-fidelity image of a missing channel



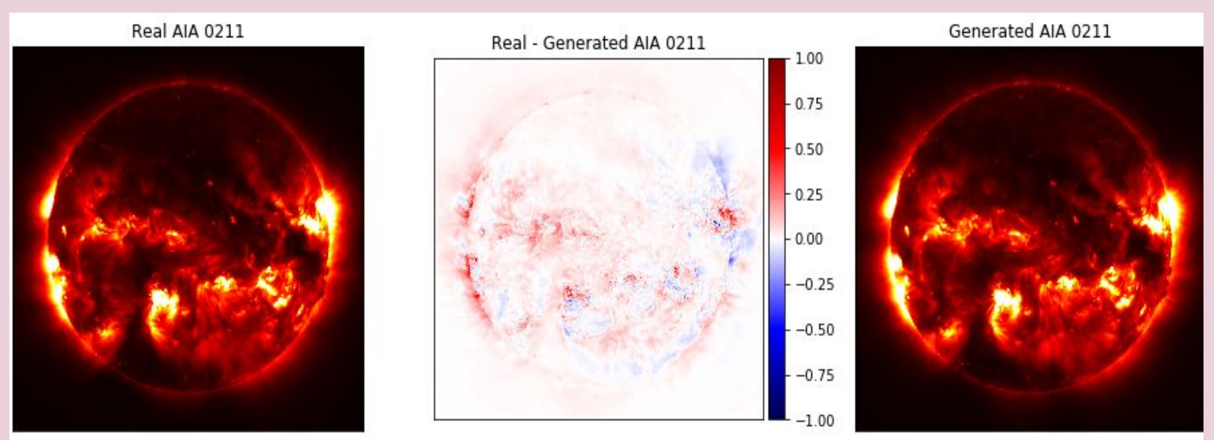
Architecture: U-Net [4]

RMSE + Structural Similarity [5] **is used to evaluate the fidelity of the synthetic image**

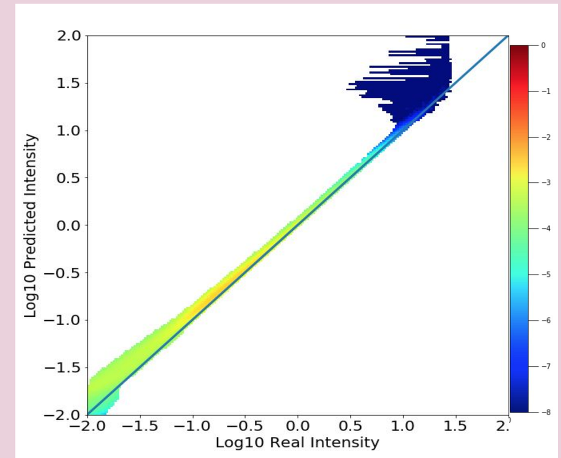
Activation function: **LeakyReLU**
Loss function: **smooth L1**
Optimizer: **Adam**

- Copy & concatenate
- Conv 3x3
- Max-pool 2x2
- Up-conv 3x3

RESULTS [6]



(Middle) Difference in units of data number/s/pixel between the real image (left) and the image reconstructed via **U-Net** (right).



Joint PDF at 90% c.l. for the test set on U-Net. Dark blue are extremely rare and saturated data points.

APPLICATIONS

- ★ Reduction of **telemetry needs,** through the use of alternate data sources and later resynthesis.
- ★ Improved **reliability** against instrument channel failures.
- ★ **Enhanced** observational **capabilities**

[1] William Pesnell, Barbara Thompson, and Phillip Chamberlin. **The Solar Dynamics Observatory**. solphys, 275:3–15, 11 2012. [2] J. R. Lemen et al. **The Atmospheric Imaging Assembly (AIA) on the Solar Dynamics Observatory (SDO)**. Solar Physics, 275:17–40, January 2012.
[3] Richard Galvez & al. **A Machine-learning Data Set Prepared from the NASA Solar Dynamics Observatory Mission.** The Astrophysical Journal Supplement Series, 242(1):7, May 2019. [4] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. **U-Net: Convolutional Networks for Biomedical Image Segmentation**. LNCS. 9351. 234-241. 10.1007/978-3-319-24574-4_28, May 2015. [5] Zhou Wang et al. **Image Quality Assessment: From Error Visibility to Structural Similarity.** IEEE Transactions On Image Processing, 13(4):600–612, 2004. [6] Valentina Salvatelli, Souvik Bose, Brad Neuberg, Luiz F. G. dos Santos et al. **Using U-Nets to Create High-Fidelity Virtual Observations of the Solar Corona,** NeurIPS 2019 Workshop ML4PS, arXiv:1911.04006 [7] Luiz F. G. dos Santos, Souvik Bose, Valentina Salvatelli, Brad Neuberg et al. **Multi-Channel Auto-Calibration for the Atmospheric Imaging Assembly using Machine Learning** arXiv:2012.14023, to appear on A&A.

Compressed Image Artifact Removal: Improving Instrument Data Quality After Lossy Compression

Daniel da Silva[1,2], Alex Barrie[1,3], Barbara Thompson[1], Ayris Narock[1,4], Michael Kirk[1,5]
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NASA AI Conference 2021
Session 3: Mission Operations, Engineering, and Cross-Cutting Capabilities
Poster #44

Background

Satellite instruments are collecting more data then ever before, outpacing advances in the telemetry infrastructure that enable their transmission.

A common trade-off in missions is **choosing to trade data quality for increased downlink volume**. Two methods of doing this are decreasing temporal / spatial / spectral resolution, and lossy compression.

Lossy compression is dangerous, but **image quality is extensively studied in computer vision / AI.** Specifically, around the following tasks:

- Denoising
- Flagging Image Quality
- Inpainting and object removal

Using **supervised learning** and a set of before/after training examples of the compression effect, models can be trained to remove the compression artifacts and noise in general.

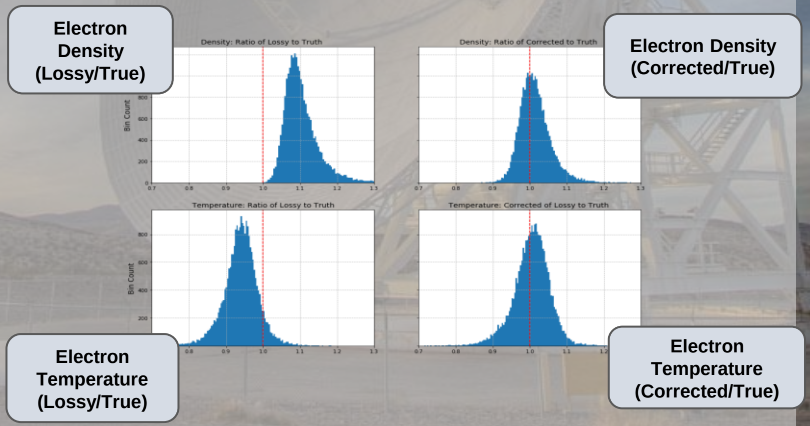
Often, a training dataset is available through **dual downlink of paired high-quality and lossy-quality data**. In practice, one must wait for the mission to collect enough data.

Instrument Case Study (MMS/FPI)

Particle instrument that during beginning of mission had lossy quality issues. Later-on it operated for period with no issues: this **allowed us to created side-by-side training dataset of compressing effect**.

Designed, trained and tested neural network to correct compression noise. Before/after results below.

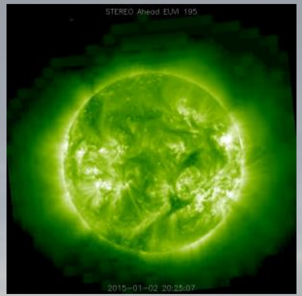
We used a **multi-layer perceptron neural network operating on patches** (tiles) of the image. To support the scientific community, we provided an interpretation of the reconstruction using basis functions theory.



Next Steps

We plan to start **designing other improvement pipelines**, starting with STEREO's operational space weather imagers EUVI and COR2.

Though at lower time resolution, versions of these images without quality issues are available to create a training set.



Lossy compression introduces artifacts in outer areas of solar image

This task, aiming to repair imagery rather particle data, has many more dimensions and different types of compression noise.

Having high-quality, high-resolution solar imagery will boost the national space weather forecasting capability, leading the path for other applications.

Support for research and engineering done for this work came from the MMS and STEREO missions. For full text open-access publication on the MMS/FPI instrument compression artifact removal, see: https://doi.org/10.1029/2019JA027181

Best practices in sharing enhanced data products and machine learning algorithms: learnings from NASA Frontier Development Lab

James Parr, Madhulika Guhathakurtha, Bill Diamond

ARTIFICIAL INTELLIGENCE RESEARCH FOR SPACE SCIENCE, EXPLORATION AND ALL HUMANKIND

http://fdl.ai

BACKGROUND

Advances in computing and machine learning (ML) are revolutionizing how we do science, opening up avenues of research that would have been impossible a few years ago.
However …

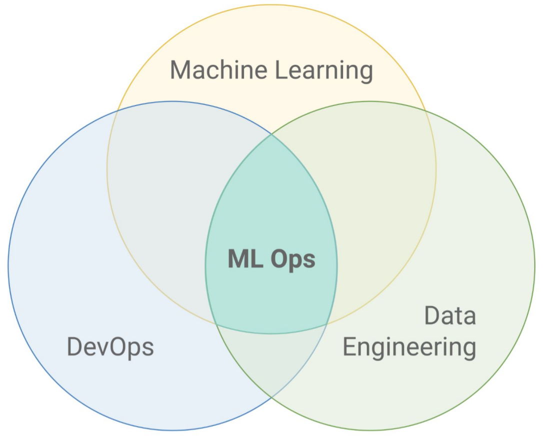
The **opportunity cost** to apply machine learning effectively can be high. 'Garbage in, garbage out" applies equally ML and, if applied blindly, complex ML workflows can **seriously exacerbate flaws in data**. Finally, ML is sometimes regarded as a 'dark art' by non-practitioners and **explaining *why* ML works can be difficult.**
However …

During five years of FDL, we have learned the formula to overcome these problems:

AI-ready data

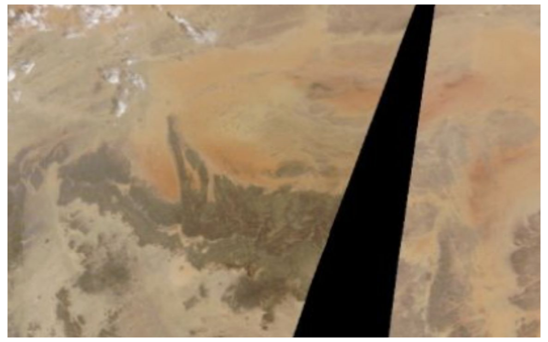
Common language and quality standards

A validated framework of *MLOps* tools



AI Ready Data

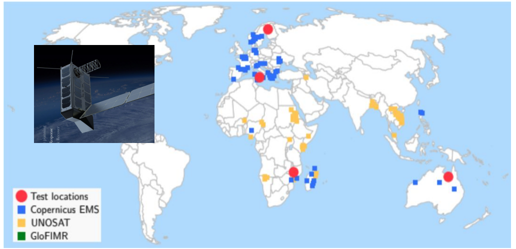
ML algorithms are great at finding 'features' in data and using them to make predictions. However, they can also be misled by flaws.



Automatic Swath Filler
This image adjustment tool developed as part of FDL automatically reduces the effect of missing imagery data.

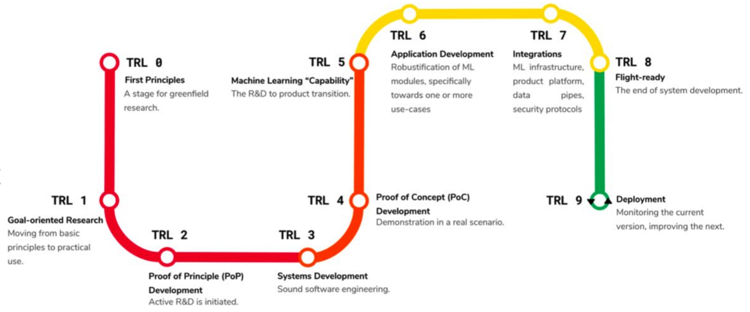
ML systems can be rigid in how they accept data, which must be transformed into the right format. Supervised ML also requires labelled data with balanced properties.

WorldFloods
The WorldFloods dataset contains carefully chosen and balanced Earth observation images , designed to train ML models to recognise floodwater.



Common Standards

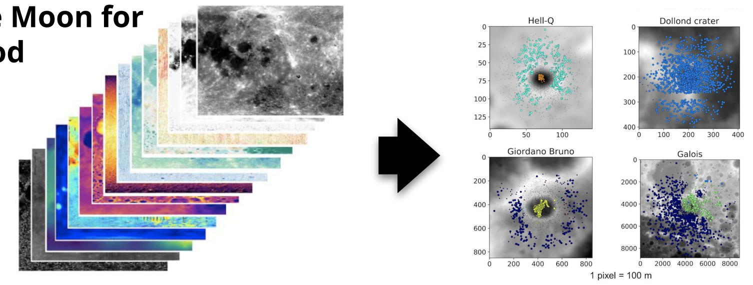
We have collaborated on a new 'ML Technology Readiness Level' that encourages development of robust, reliable and responsible ML systems.



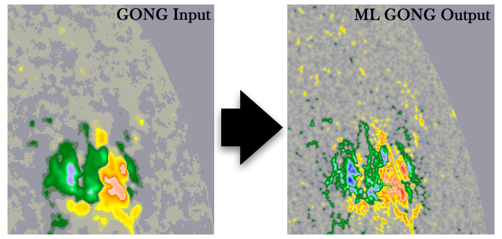
Advantages of AI

ML systems also have the power to fuse vast amounts of data into multi-dimensional stacks, and automatically decide which features are most important to the science.

The Moon for Good



ML techniques like 'super-resolution' can encode prior knowledge of physics or data properties and use these to make predictions from sparse or incomplete data



ML-Enhanced SDO
Upscaled (super resolution) of the solar magnetic field to create 40 years of data at contemporary resolutions.

MLOps and Open, Reproducible Science

Scientific culture is moving to expose all steps in the investigation process - conception, investigation, experiment and reporting. We are developing a platform that supports these 'open science' goals to share data, algorithms, code and documentation.

SPACEML

The SpaceML.org platform is offered as a repository of all FDL outputs, and as a resource to the scientific and ML community.

FDL FRONTIER DEVELOPMENT LAB

FRONTIER DEVELOPMENT LAB 2018: ASTROBIOLOGY TEAM 2

From Biohints to Confirmed Evidence of Life: Possible Metabolisms Within Extraterrestrial Environmental Substrates

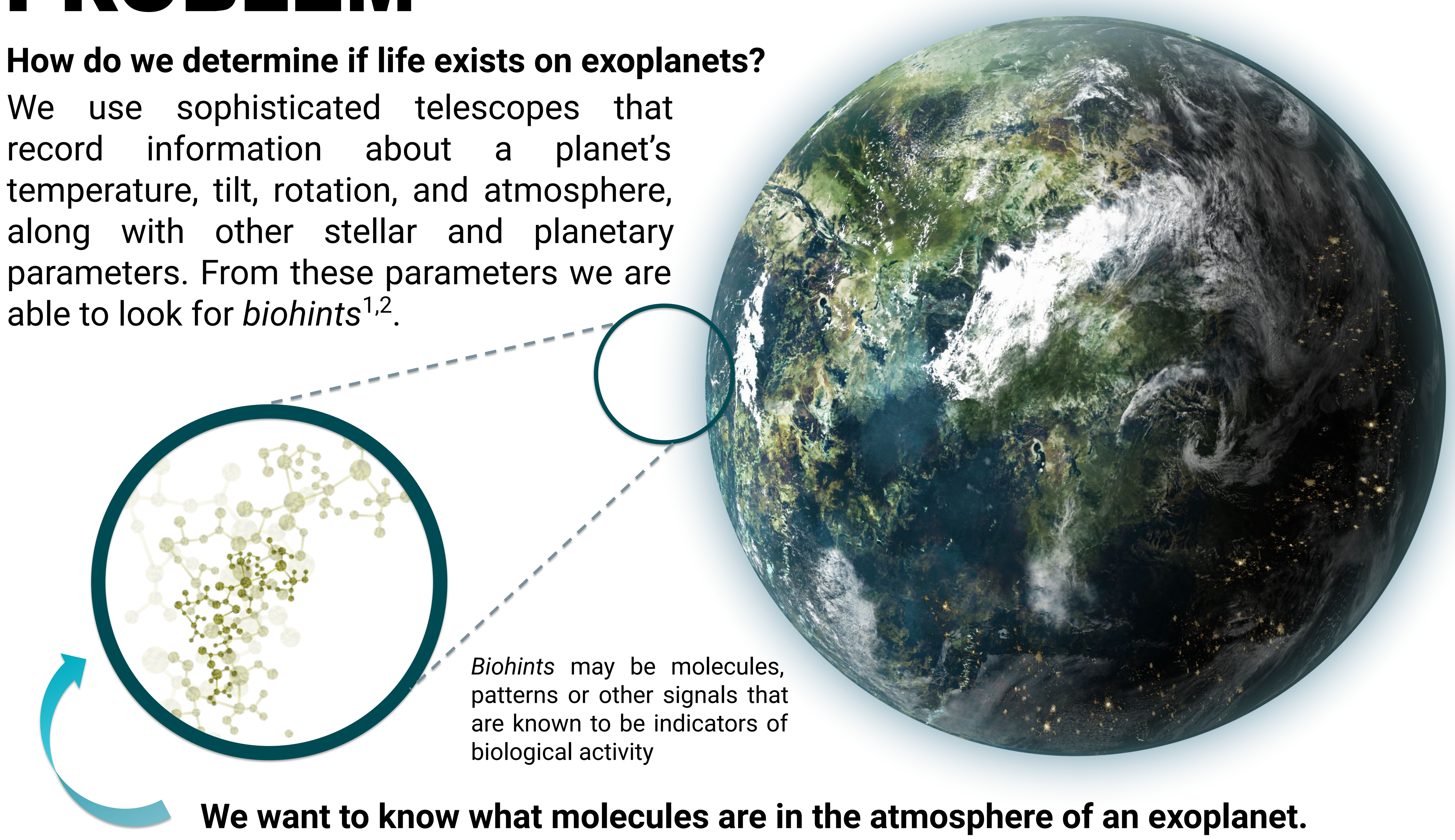
Frank Soboczenski[3], Michael D. Himes[1], Molly D. O'Beirne[2], Simònè Zorzan[4], Atılım Güneş Baydin[5], Adam Cobb[5], Yarin Gal, Massimo Mascaro, Daniel Angerhausen[7], Geronimo Villanueva, Shawn D. Domagal-Goldman[6] and Giada N. Arney[6]

Google Cloud

PROBLEM

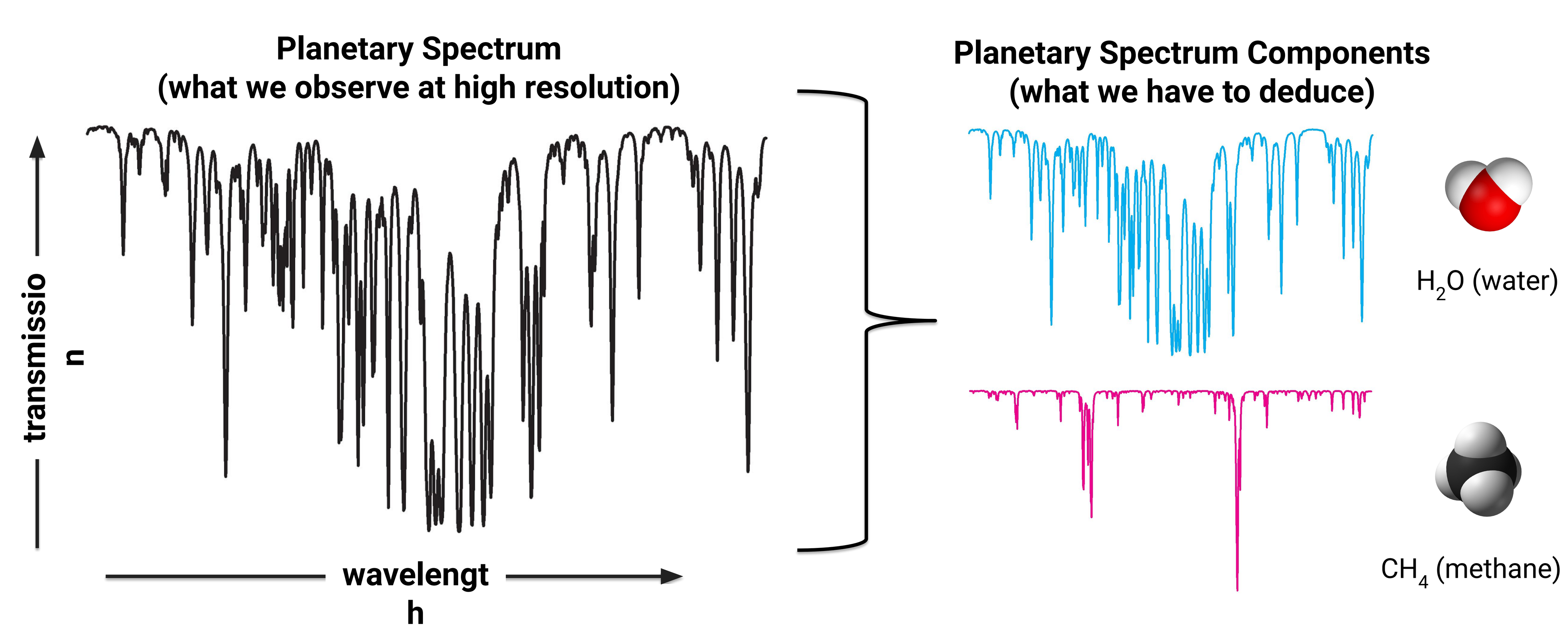
How do we determine if life exists on exoplanets?

We use sophisticated telescopes that record information about a planet's temperature, tilt, rotation, and atmosphere, along with other stellar and planetary parameters. From these parameters we are able to look for *biohints*[1,2].



Biohints may be molecules, patterns or other signals that are known to be indicators of biological activity

We want to know what molecules are in the atmosphere of an exoplanet. Knowing this can help us determine whether or not life may exist on an exoplanet. This is because certain combinations of molecules are indicative of life[1,2].



What we are able to observe is <u>complicated.</u>

Telescopes record emissions from molecules in a planet's atmosphere at different wavelengths. This results in a complicated planetary spectrum, which we then have to deconvolve into potential atmospheric molecular components. This process (called an atmospheric retrieval) is very time-consuming and computationally expensive!

Can we use machine learning to expedite the speed and accuracy of determining the composition of exoplanetary atmospheres?

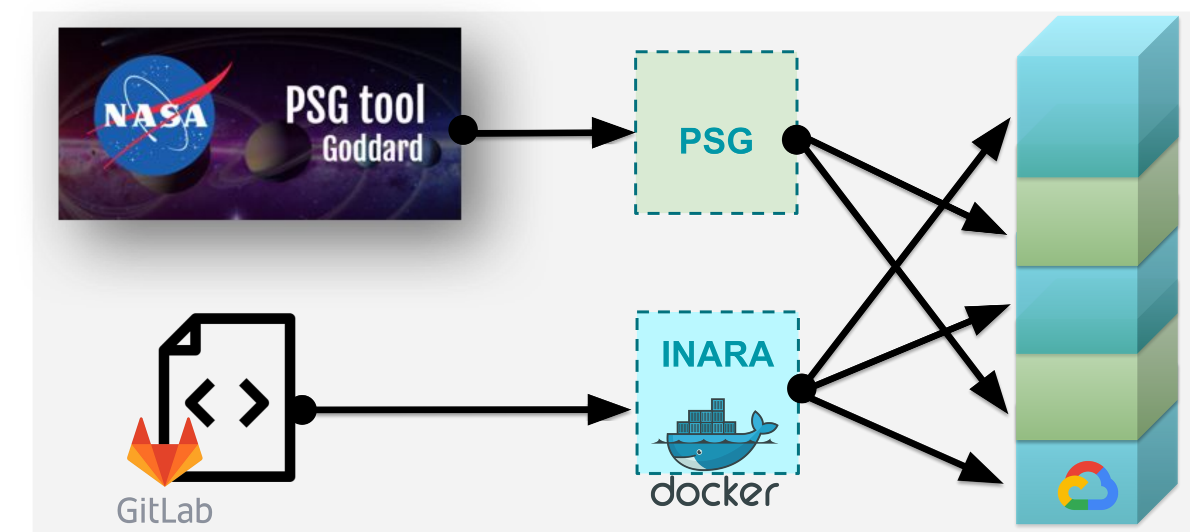
SOLUTION

INARA: Intelligent exoplaNet Atmospheric RetrievAl

Uh, Houston, we need data!

3 million synthetic planetary spectra were generated using PSG (Planetary Spectrum Generator[3], courtesy of Geronimo Villanueva at NASA Goddard) and compute resources supplied by Google Cloud.

High resolution spectra were generated over a range of stellar and planetary parameters (28 total) to maximize the diversity of the produced dataset for machine learning and release to the scientific community.



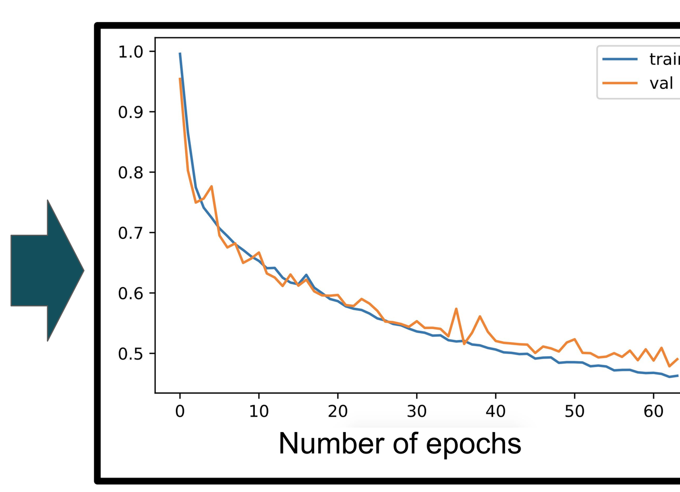
~2000 VMs in Google Cloud running INARA/PSG

Proof of Concept: Synthetic Spectra Input

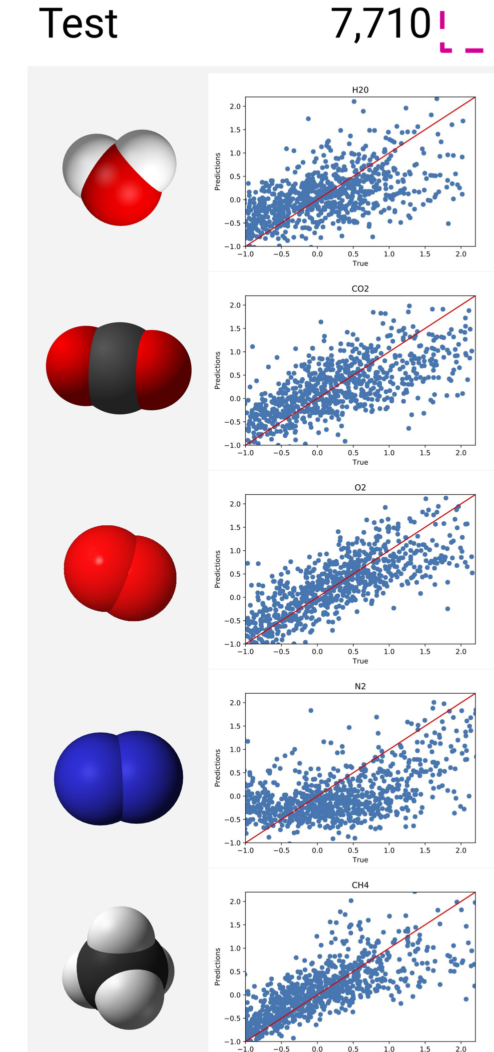
Set	Current	Future
Training	100,000	2.5 million
Validation	10,000	400,000
Test	7,710	200,000

Machine Learning Models

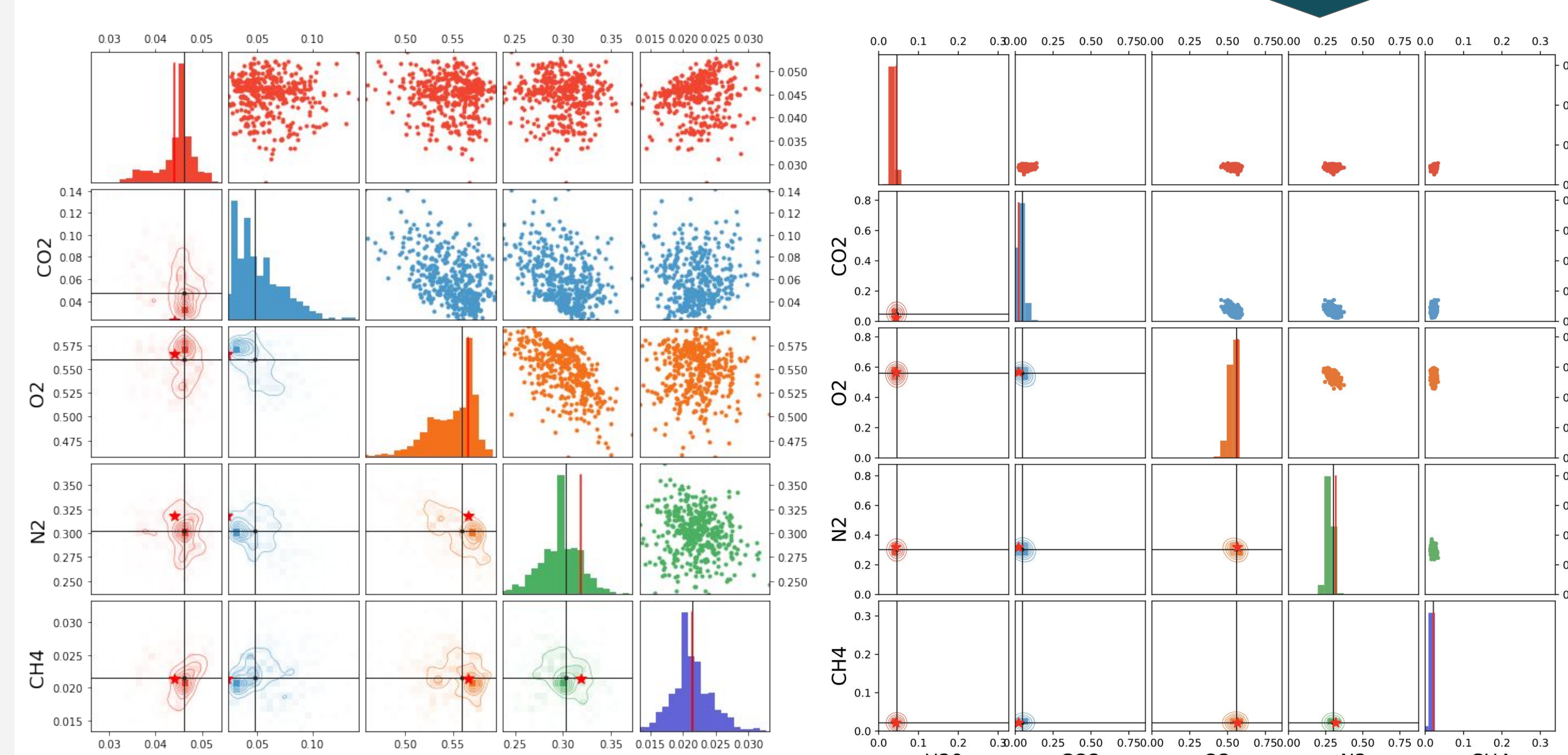
We explored many model architectures ranging in complexity from linear regression and feed-forward neural networks to convolutional neural networks (CNNs). We present results from the best performing model, a 1D CNN with the following configuration: Conv1d(64) - tanh - MaxPool - Conv1d(64) - relu - MaxPool - Conv1d(128) - relu - MaxPool - Conv1d(256) - relu - FC(256) - relu - FC(12) - T. Loss(0.42) - V. Loss (0.49) - 64 epochs.



Loss plot for the chosen CNN



True vs CNN predicted values



*Posterior distributions of the relative molecular abundances for one planet (600 predictions for each molecule). Within each scatter plot, each plot is a single regression in the CNN. The straight lines indicate the median values and the star indicates the true value (**right:** high level overview - **left:** zoomed in scale)*

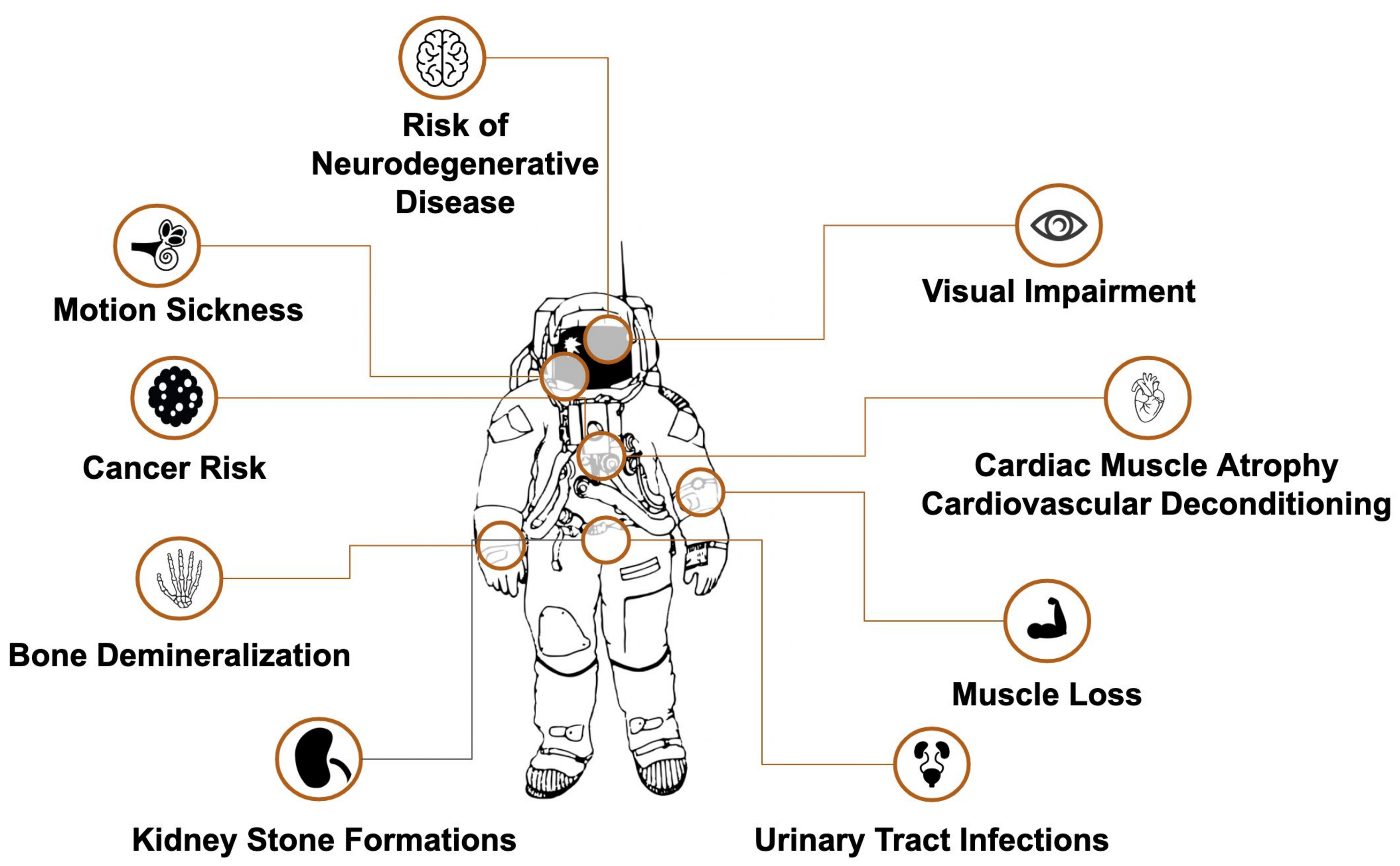
Comparison

Method	Time	Molecules retrieved	Error	H_2O	CO_2	O_2	N_2	CH_4
Traditional	Hours to days	User-specified						
ExoGAN[4]	Minutes	H_2O, CO, CO_2, CH_4	MSE	3.43e-4	1.02e-2	7.00e-3	2.05e-2	1.93e-4
HELA[5]	Seconds	H_2O, HCN, C_2H_2						
INARA	Seconds	H_2O, CO, CO_2, CH_4, C_2H_6, O_2, O_3, N_2, N_2O, NO_2, NH_3, SO_2	± 2σ	2.28e-3	3.53e-2	2.59e-2	5.21e-2	1.07e-3

Generating AI-synthetic biosensor data for future deep space missions

Researchers: Brian Wang, Eleni Antoniadou, David Belo, Krittika D'Silva
Mentors: Annie Martin, Brian Russell, Graham Mackintosh, Tianna Shaw and Frank Soboczenski

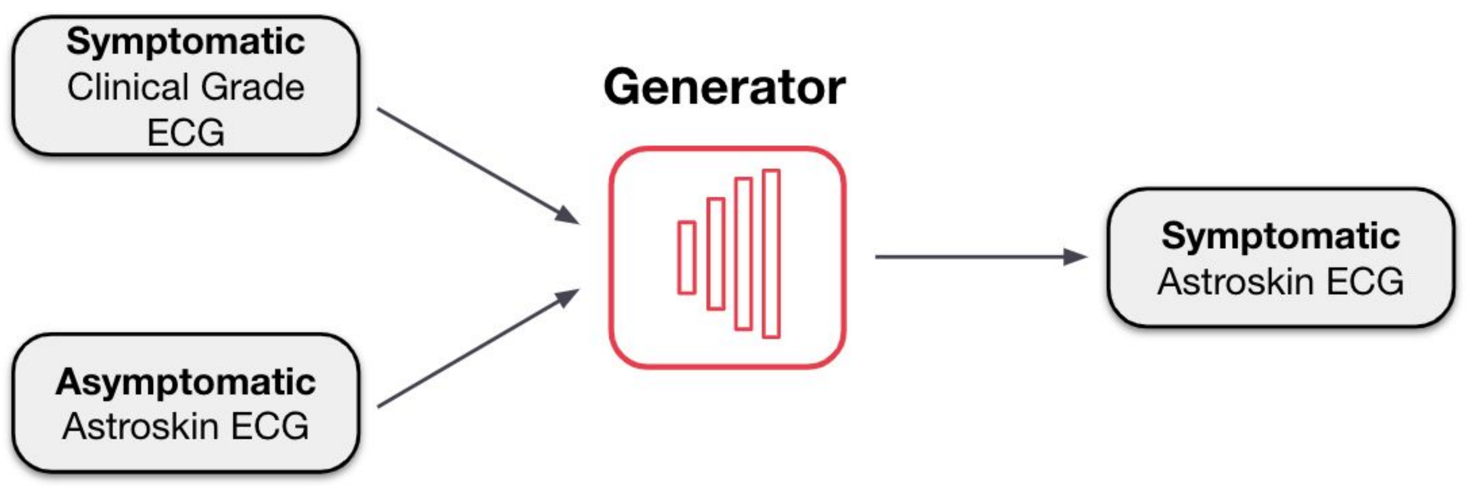
The Effects of Radiation and Microgravity on Astronauts



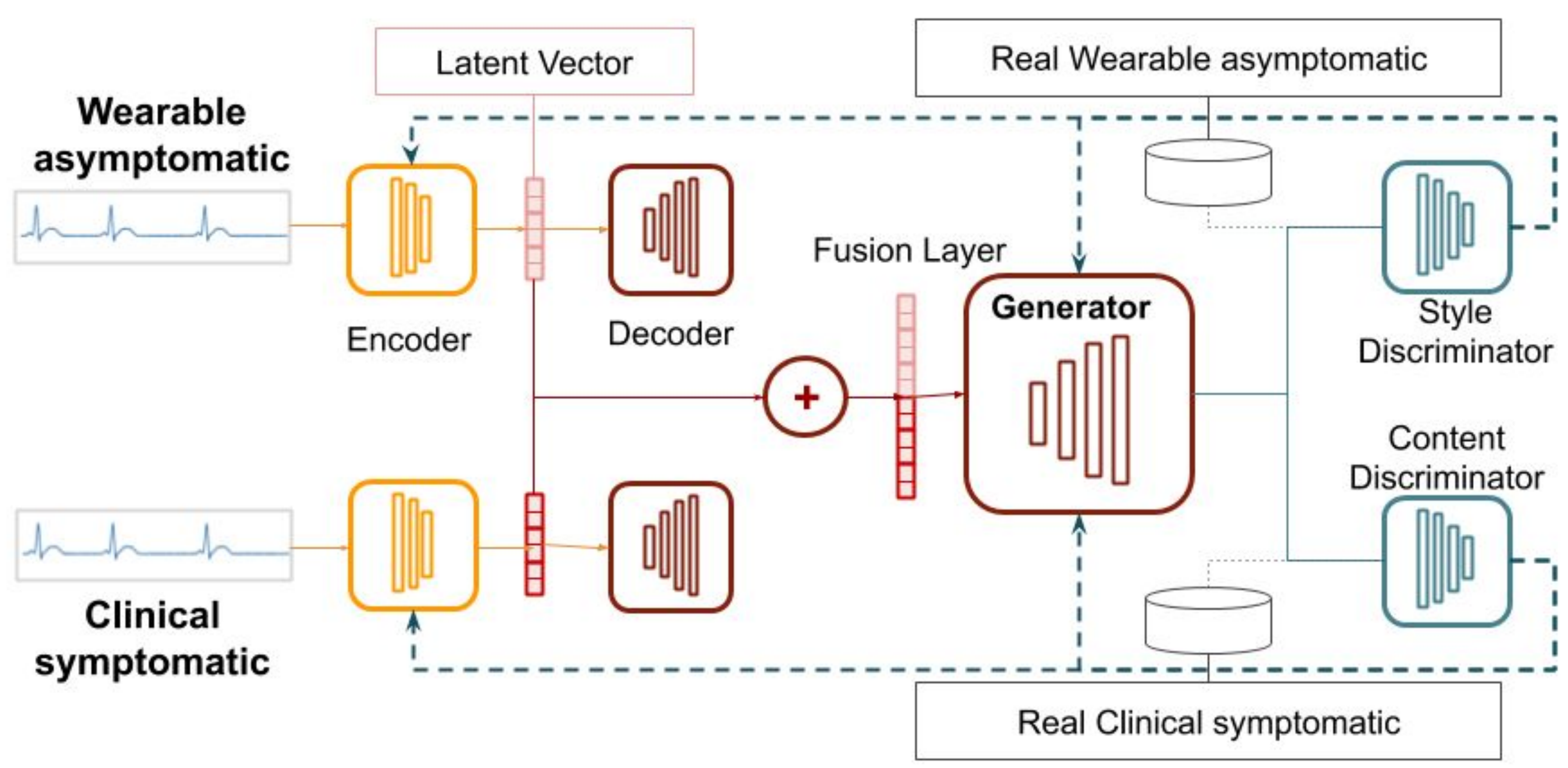
Datasets Utilized

Clinical ECG Data:
- Fantasia (490 hours of Asymptomatic ECG)
- MIT-BIH (95 hours of Atrial Fibrillation)

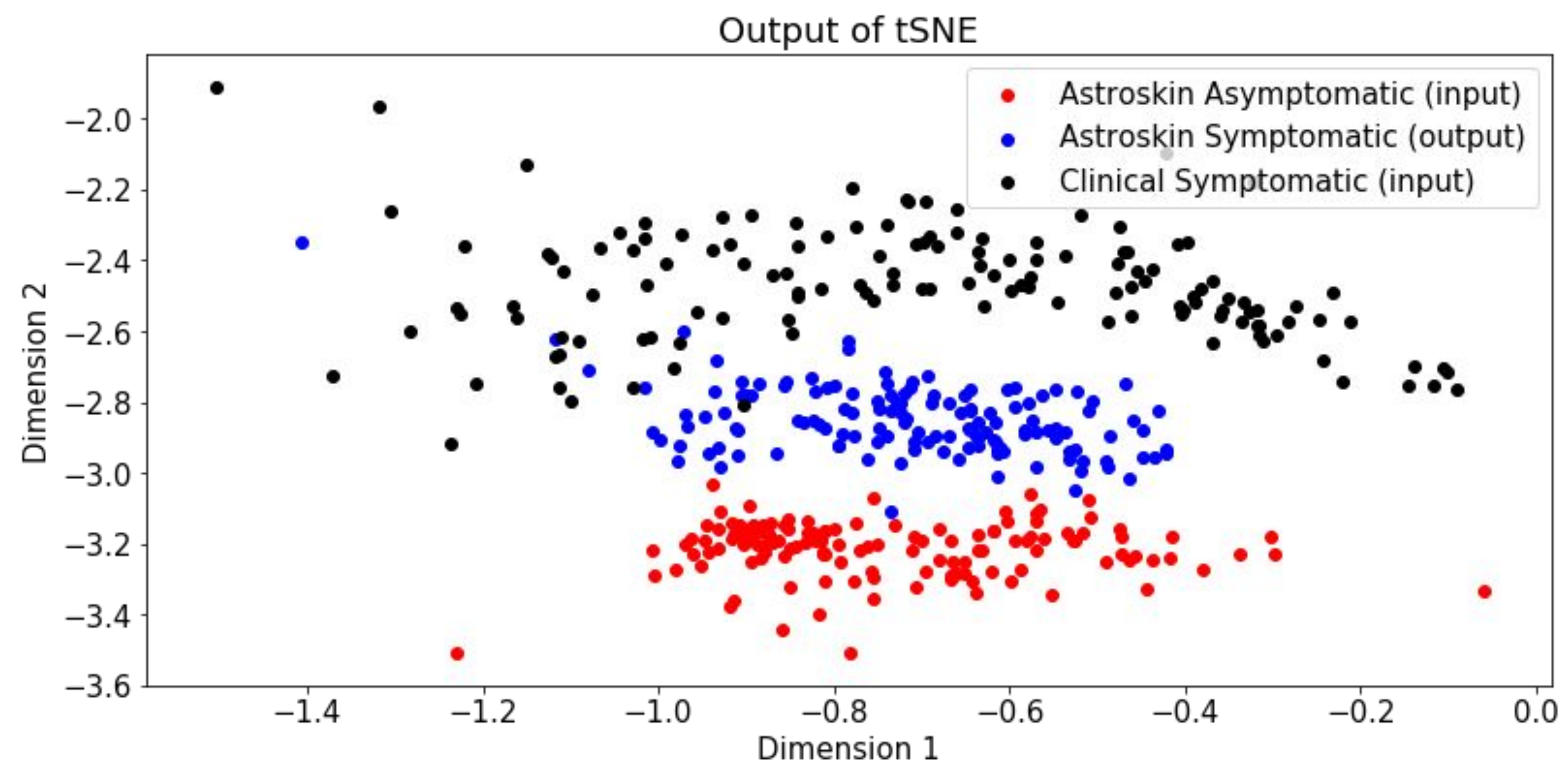
Wearable ECG Data:
- HERA Mission data
- NASA data
- CSA data



Our Model Architecture



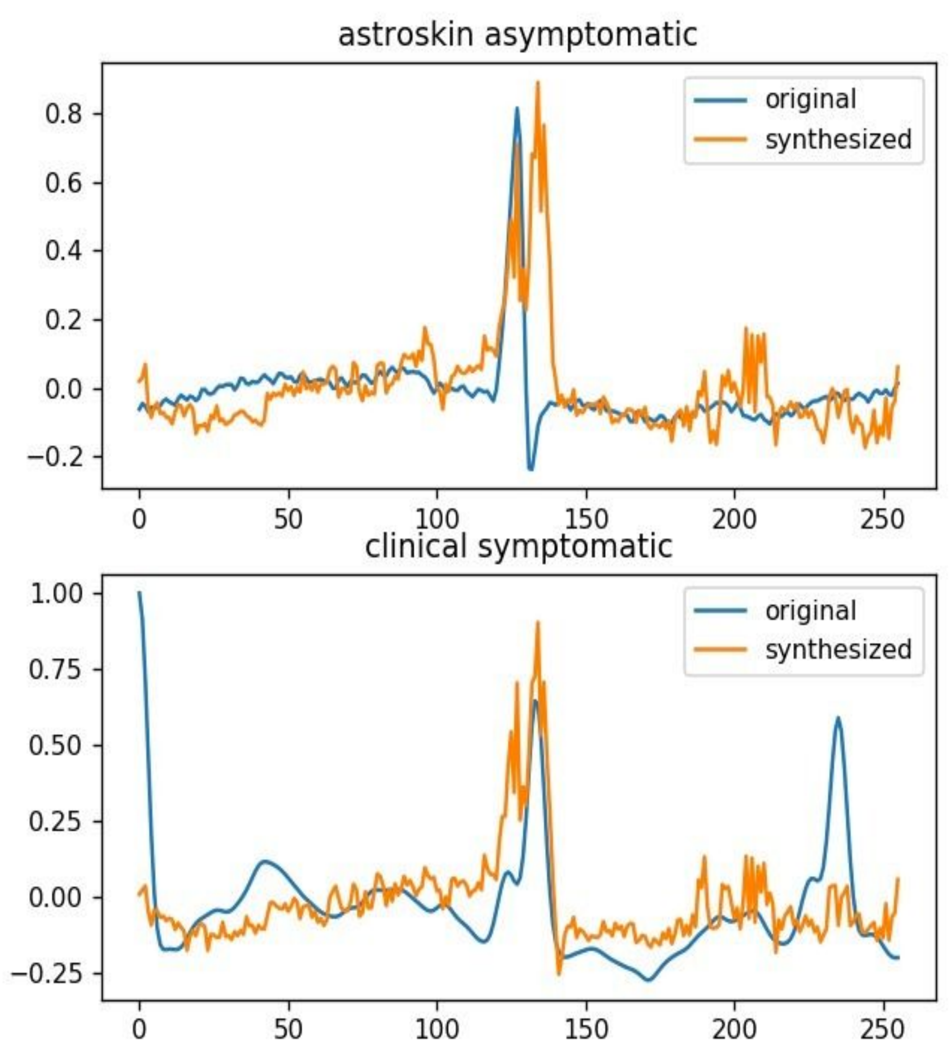
Results



Preliminary Validation

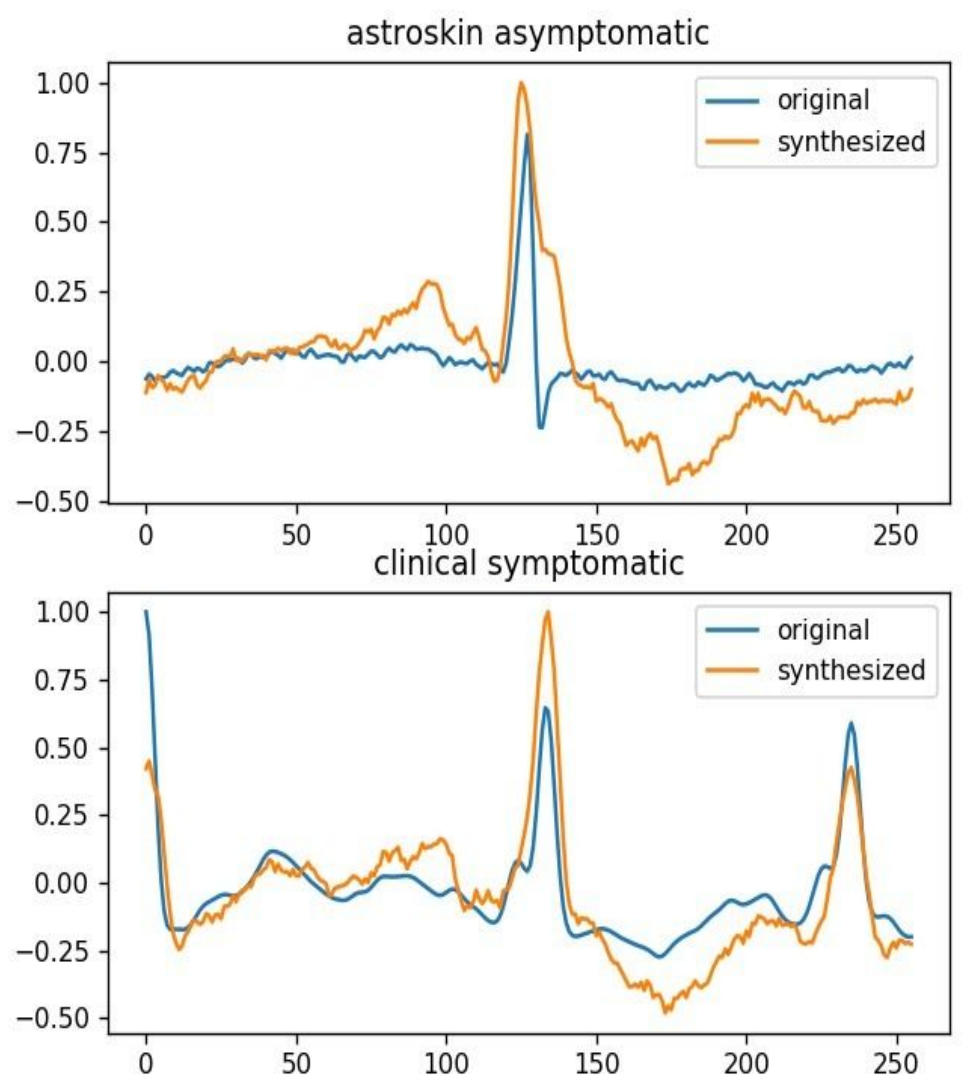
Method A: Generator trained with MSE alone

- R peak and RR interval analysis demonstrated slight variation in synchronicity versus the original for both datasets
- Model yielded a noise pattern approximating >85% Astroskin wearable
- **Mean squared error: 7.79**



Method B (our approach)**: Generator trained with style, content and MSE**

- Higher signal variability
- QRS complex closely approximates original source
- Outcome produces significantly less noise
- **Mean squared error 3.04**



Conclusion: By incorporating the style of a wearable device and the content of a pathology, our model can synthesize symptomatic health care data for astronauts.

Digital Transformation AI & ML Overview
Edward McLarney, Poster 49

Context:

- NASA has formed a Digital Transformation (DT) Strategy and Roadmap, led by the Office of Chief Technologist and Office of Chief Information Officer. This strategy includes AI/ML as one of six key strategic thrusts.
- NASA has a rich history of applying artificial intelligence (AI) to our hardest problems, such as autonomous behaviors in Mars rovers, deep analysis of space suit data, or image analysis to understand material strength. With the advent of powerful, plentiful, and affordable AI in business and industry, NASA is crafting a strategy to use AI as an accelerant for all NASA missions and business functions.

Strategy: As part of NASA's overall Digital Transformation, NASA's AI strategy includes:

- **Apply:** Solve relevant mission and mission support problems via AI / ML.
- **Teamwork:** Lead and synchronize NASA AI/ML via an open Agency AI / ML community.
- **Reskill:** Expand AI training, education, hiring, and retention across the workforce.
- **Tools:** Assess, recommend, and establish AI / ML platforms for NASA-wide adoption.
- **Data:** AI-enabled! Establish secure, authoritative access to the right data.
- **Outreach:** Make selected data and problems available for public / partner AI / ML work.
- **Adapt:** Leverage industry AI / ML work and adapt it to NASA use rather than reinventing.
- **Scale:** Plan to promote selected AI / ML capabilities from pilot to production operations.

The AI/ML team is from **across** the Agency with over 50 active members; additional contributors are always welcome.

Contact:

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