TRILLIUM TECH

NASA
PARTNER

FDL
FRONTIER DEVELOPMENT LAB

LUXEMBOURG SPACE AGENCY

2017-2021

FOR ALL HUMANKIND

FDL FRONTIER DEVELOPMENT LAB

LUXEMBOURG SPACE AGENCY

FDL is demonstrating the potential of Machine Learning for both scientific process and discovery and new paradigms of engineering from predicting GPS scintillation to co- operative robots on the Moon.

Illustrative progress in science includes methods for predicting natural phenomena, but also discovery of new physical insight to enable earlier decisions, better predictions and planning strategies within complex systems.

Artificial Intelligence is enabling an exciting new era of these capabilities and FDL's goal is to explore and apply these to problems critical to space science, exploration and for the benefit of all humankind.

FDL PORTFOLIO

EARTH SCIENCE

- 2022 SMD KNOWLEDGE GRAPH DISCOVERY
- 2022 SAR DATA FOR CHANGE DETECTION
- 2021 AUTO IMAGE ANNOTATION
- 2020 KNOWLEDGE DISCOVERY FRAMEWORK
- 2021 DIGITAL TWIN COASTS
- 2020 DIGITAL TWIN EARTH

MISSION OPERATIONS

- 2021 SOLAR DRAG
- 2020 CONSTELLATION MGMT
- 2019 GROUND STATION PLANNING

CLIMATE

- 2020 CLOUD BEHAVIOUR
- 2019 CLOUD CLASSIFICATION
- 2022 GEOMECHANICS FOR CO2 SEQUESTRATION
- 2022 FORTIFYING THE GRID
- 2018 INFORMAL SETTLEMENTS
- 2021 WORLD FOOD EMBEDDINGS
- 2021 LIGHTNING UPGRADE
- 2020 EARTH INTELLIGENCE ENGINE
- 2020 LIGHTNING & EXTREME WEATHER
- 2020 WATERS OF THE US
- 2019 DISASTER RESPONSE: FLOODS

ON BOARD INTELLIGENCE

- 2019 EDGE INFERENCE: FLOODS
- 2021 HOT SPOT DETECTION
- 2018 DISASTER RESPONSE: DAMAGE ASSESSMENT
- 2023 GENERALIZABLE MODELS FOR SAR

ENERGY FUTURES

- 2022 THE H2 DISCOVERY ENGINE
- 2022 CONCENTRATED SOLAR POWER CONTROLLER

ASTRONAUT HEALTH

- 2021 CAUSAL TRANSFER LEARNING
- 2020 CANCER CAUSAL INFERENCE
- 2019 SYNTHETIC MEDICAL DATA

ASTROBIOLOGY

- 2022 INFORMATION SIGNATURES OF BIOTIC VS ABIOTIC PROCESSES
- 2018 EXOPLANET DETECTION
- 2018 ATMOSPHERIC RETRIEVAL FROM SPECTRA
- 2018 BIOSIGNATURES

LUNAR EXPLORATION

LUNAR MAPPING

- 2017 CRATER IDENTIFICATION
- 2019 LUNAR RESOURCE MAPPING (METALS)
- 2020 LUNAR RESOURCE MAPPING II
- 2021 UP SCALING LUNAR RESOURCES

LUNAR AUTONOMY

- 2018 ROVER LOCALISATION
- 2018 AUTONOMOUS ROUTE PLANNING

LUNAR EXPLORATION

- 2022 CHANGE DETECTION WITH LRO DIVINIER

DISASTER RESPONSE

2020 DATAQUEST

- 2020 EARLY DETECTION
- 2020 FIRE BEHAVIOUR
- 2020 FUEL ASSESSMENT
- 2022 URBAN RAD HUNTER
- 2022 WILDFIRE: MULTISPECTRAL ESTIMATION OF FUEL LOADS
- 2023 FM ADAPTORS FOR DISASTERS

HELIOPHYSICS

- 2022 SEISMIC INSIGHTS WITHIN GEOMAGNETIC AND IONOSPHERIC DATA
- 2021 SOLAR WIND FINGERPRINTING
- 2020 GEOEFFECTIVNESS OF SOLAR STORMS
- 2020 STARSPOTS
- 2022 4Π EUV IRRADIANCE
- 2023 HELIOPHYSICS ONBOARD
- 2019 AUTO CALIBRATION
- 2019 VIRTUAL TELESCOPES
- 2018 SDO UV IRRADIANCE
- 2018 IONOSPHERIC SCINTILLATIONS
- 2019 GNSS DISTURBANCES

SOLAR PREDICTION

- 2017 PREDICT KP INDEX
- 2017 C-CLASS FLARES
- 2019 SUPER RES. MAG. FIELDS

FDL X

- 2023 THERMOSPHERIC DRAG
- 2023 ARD EUV
- 2023 MULTISCALE GEOEFFECTIVENESS

PLANETARY DEFENSE

- 2017 LONG-PERIOD COMET DETECTION
- 2016 ASTEROID DEFLECTION DECISION SUPPORT
- 2016 RADAR SHAPE-MODELING
- 2016 METEORITE HUNTING DRONE

Live on SPACEML | Published Research | Deployed AI | Data Product / Tool | Commercial Partnership

LSA + FDL PORTFOLIO

LSA is determined to increase the research and development capabilities needed by the local space community. Projects of interest range from Earth Observation, robotics to autonomous vehicles. To this end, Luxembourg is determined to further develop the unique skillset needed to create an attractive space ecosystem for academia and industry. At this moment, Luxembourg is amongst the top five per capita contributors to ESA. A heavy drive is on strengthening the Grand Duchy's talent pool of scientists, engineers, and entrepreneurs. Luxembourg strongly supports students of all levels ranging from pre-university to graduates and professionals.

LSA's mission is to promote the Grand Duchy on an international level, inspire young researchers and professionals to the potential the space sector offers, build synergies with businesses, provide financial support for research and development and perhaps most importantly to promote and support the talents and their potential impact on the space community.

FDL is an interdisciplinary and international research program which has formed a perfect synergy to LSA's interests and mission.

With Luxembourg's financial support the Grand Duchy did not only invest in a top-tier research and development program with a high-impact factor but also by sending talented scientists and mentors to take part in the program, enabling them to do the best work of their careers.

Not only does Luxembourg get solutions for some of the most challenging problems the space sector has to offer but also the skills and expertise Luxembourg's researchers and faculty gain from working with top-tier international scientists, supported by major commercial partners and their resources which in turn increase Luxembourg's capabilities for a thriving space community.

Luxembourg had a significant impact on the results of the program over recent years. This was not only limited to the projects the Grand Duchy supported financially such as crater identification, rover localization, autonomous route planning, and lunar resource mapping but also by Luxembourg's talents taking part in other FDL challenges supported directly by NASA such as biosignatures and space weather prediction.

LUXEMBOURG SPACE AGENCY

2017 **CRATER IDENTIFICATION**

CHALLENGE PARTNER + 1 RESEARCHER

2018 **ROVER LOCALIZATION**

CHALLENGE PARTNER

2018 **AUTONOMOUS ROUTE PLANNING**

CHALLENGE PARTNER + 1 RESEARCHER

2018 **BIOSIGNATURES**

1 RESEARCHER

2019 **LUNAR RESOURCE MAPPING METALS**

CHALLENGE PARTNER + 1 RESEARCHER + 2 MENTORS

2019 **DISASTER RESPONSE: FLOODS**

1 MENTOR

2019 **EDGE INFERENCE: FLOODS**

1 MENTOR

2020 **HORUS (PSR Navigation)**

1 MENTOR + 1 RESEARCHER

2021 **UPSCALING LUNAR RESOURCES**

1 MENTOR + 1 RESEARCHER

2021 **WOTUS**

1 MENTOR

LUXEMBOURG TALENT GROWTH

Luxembourg is already home to a significant space industry that generates jobs and supports the broader economy.

Having created legal, research and financial initiatives for the establishment of satellite, telecommunications, and Earth observation businesses in the Grand Duchy, Luxembourg aims to be at the forefront of the next stage of development.

Within the SpaceResources.lu initiative launched in February 2016, the country's overall framework, including but not limited to the legal regime, supports any space companies as well as bolstering global security and stimulating emerging sectors such as robotics and AI.

Since the inception of FDL, Luxembourg has been a significant partner to the program by enabling research projects via financing initiatives as well as sending outstanding researchers and faculty to take part in the program.

Not only have those talents contributed significantly to the success of their respective projects but in turn returned to Luxembourg with new skills and expertise gained from mastering world-class challenges together with leading international experts.

LUXEMBOURG FDL ALUMNI / FACULTY

FRANCISCO RODRIGUEZ-LERA UNIVERSITY OF LUXEMBOURG **RESEARCHER FDL 2018**

SIMONE ZORZAN
LUXEMBOURG INSTITUTE OF SCIENCE & TECHNOLOGY
RESEARCHER FDL 2018

ABIGAIL CALZADA
ISPACE
FDL FACULTY

JÉRÔME BURELBACH TECHNICAL UNIVERSITY OF BERLIN **RESEARCHER FDL 2019**

RAMONA PELICH
LUXEMBOURG INSTITUTE OF TECHNOLOGY
RESEARCHER FDL 2018

GUY SCHUMANN
R&D SCIENTIST AT RSS INC. & RSS-HYDRO
FDL FACULTY

KIBROM ABRAHA HELIOPHYSICS RESEARCHER **RESEARCHER FDL 2018**

DIETMAR BACKES
UNIVERSITY OF LUXEMBOURG
RESEARCHER FDL 2017 / FDL FACULTY

PHILIPPE LUDIVIG
ISPACE
RESEARCHER FDL 2018

MIGUEL OLIVARES-MENDEZ
UNIVERSITY OF LUXEMBOURG
FDL FACULTY 2020 & 2021

LOVENEESH RANA
UNIVERSITY OF LUXEMBOURG
FDL RESEARCHER 2020

JOSE IGNACIO DELGADO CENTENO
UNIVERSITY OF LUXEMBOURG
FDL RESEARCHER 2021

SPACE STRATEGY ALIGNMENT

The Luxembourg Space Agency is the center of gravity for innovation, collaboration, and commercial development focused on building up talent and expertise with financial support to create a lasting space economy.

A significant part of LSA's space policy and strategy focuses on building up a strong as well as a vibrant space sector. This endeavor relies on acquiring key skills and expertise from synergies with organizations within and outside the space sector on an international stage.

LSA's Space Strategy is based on:

EXPERTISE

For more than 30 years Luxembourg has engaged in building infrastructure and high-tech components space travel and satellite communications.

INNOVATION

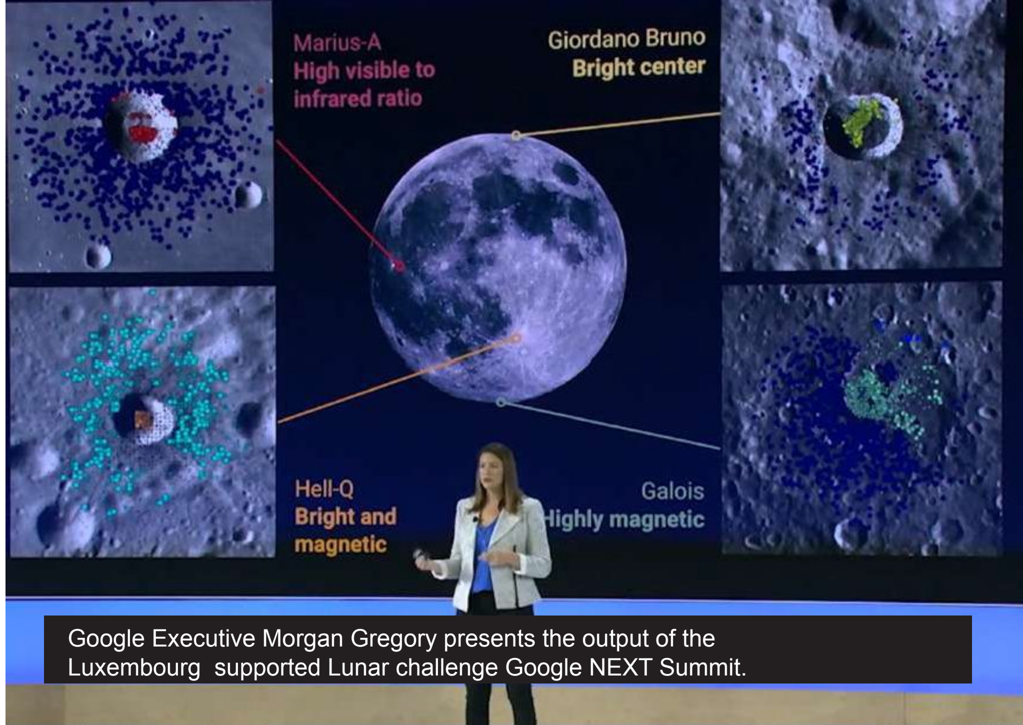
Luxembourg is committed to advance core research and development to foster new technologies that have the potential to change the commercial sector to make space flight accessible to a wider audience. Its digital innovation strategy puts Luxembourg at the forefront of commercializing novel Science and technology.

SKILLS

Being at the forefront of space research and a thriving space economy requires a diverse range of skills and talent. Luxembourg thrives to add the best and brightest to their already international workforce from both academia and commercial communities.

FUNDING

Luxembourg has established itself in the commercial space industry as a major player in creating funding and policy initiatives focused on supporting innovative as well as entrepreneurial ideas within a complex ecosystem. Furthermore, Luxembourg is an active participant in numerous programs of the European Space Agency.



Google Executive Morgan Gregory presents the output of the Luxembourg supported Lunar challenge Google NEXT Summit.

Intel AI VP Amir Khosrowshahi opens proceedings at NASA FDL 'Event Horizon' showcase in Santa Clara.

LIST OF SOLUTIONS SUPPORTED BY LSA

FDL 2017

LUNAR WATER & VOLATILES

FDL 2018

AUTONOMOUS ROUTE PLANNING AND COOPERATIVE PLATFORMS

LOCALIZATION: MERGING ORBITAL MAPS WITH SURFACE-PERSPECTIVE IMAGERY

FROM BIOHINTS TO EVIDENCE OF LIFE

FDL 2019

LUNAR RESOURCE MAPPING: DATA FUSION AND SUPER RESOLUTION

FDL 2020

MOON ENGINE: MOON FOR GOOD, PHASE II

FDL 2021

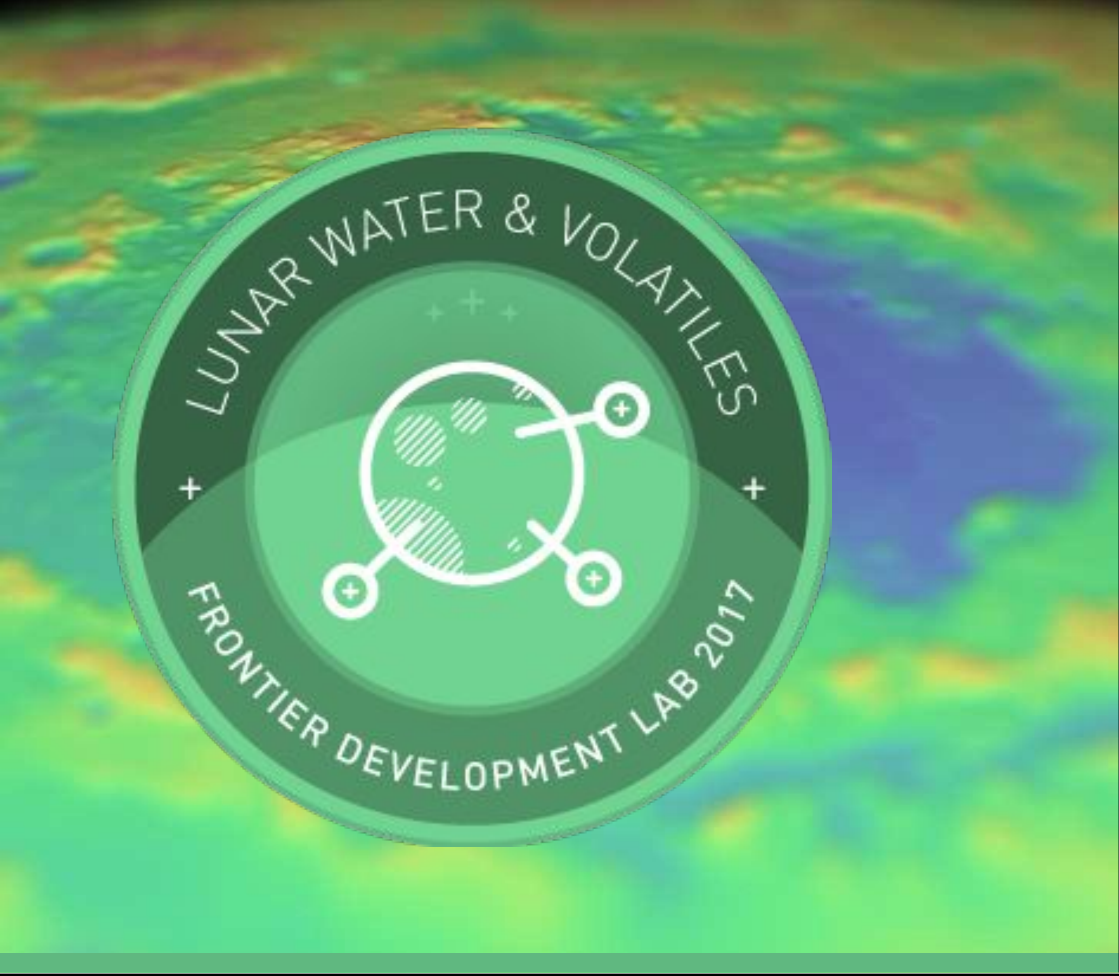
UPSCALING LUNAR RESOURCES

FDL FRONTIER DEVELOPMENT LAB

LUXEMBOURG SPACE AGENCY

FDL 2017

LUNAR WATER & VOLATILES



UTILISE AI TO DEVELOP ENERGY EFFICIENT METHODS OF REMOVING O2 FROM THE LUNAR REGOLITH, OR FIND THE MOST COST EFFECTIVE ACCESS POINTS FOR VITAL H2O.

Space resources is another way of saying, “living off the land”, as we build the new frontier. Our solar system is abundant with mineral resources. Asteroids and lunar regolith promise a new era of exploration where space settlers use what’s there to manufacture habitats, life- support, energy and fuel. However, to unlock this future we need to know where to look, get the economics right and ultimately, determine how to usefully extract and manufacture what’s needed in challenging environments.

Can AI be deployed to improve the economics of space mining or space resources, such as develop energy efficient methods of removing O2 from the lunar regolith, or find the most cost effective access points for vital H2O?

Challenge partners:

LUXEMBOURG SPACE AGENCY

intel

FDL 2017
LUNAR WATER & VOLATILES
RESEARCHERS

Luxembourg Talent

DIETMAR BACKES
COMPUTER SCIENTIST
University of Luxembourg

ELENI BOHACEK
PLANETARY SCIENTIST
UCL-Cambridge

TIMOTHY SEABROOK
COMPUTER SCIENTIST
University of Oxford

NADER MOUSSA
COMPUTER SCIENTIST
Apple

FDL 2017
LUNAR WATER & VOLATILES
FACULTY

PHIL METZGER
LUNAR MENTOR UCF

BRAD BLAIR
LUNAR MENTOR UCF

HAMED VALIZADEGAN
DATA SCIENCE MENTOR NASA

SHASHI JAIN SPECIALIST MENTOR INTEL

YAN LIU PROGRAM MENTOR USC

CHEDY RAISSI
DATA SCIENCE MENTOR INRIA

YARIN GAL
DATA SCIENCE MENTOR
UNIVERSITY OF OXFORD

TONY DOBROVOLSKIS
PLANETOLOGIST SETI INSTITUTE

FDL 2017
LUNAR WATER & VOLATILES
SOLUTION

Supported by the SpaceResources.lu initiative and Intel, the 2017 research team focused on automation of the production of crater maps for the lunar poles - vital for prospecting these water-rich regions.

Lunar reconnaissance has been conducted for decades and remotely sensed data provide clear indications of water deposited at the Polar Regions. With NASA's Artemis mission having its sights on the moon, the location of water and other volatile resources, such as hydrogen, carbon dioxide, nitrogen, and methane on the lunar surface has again gained significant spotlight form the space community.

Most of the lunar water is expected in craters near the moon's poles (**figure 1**). Some floors of these craters never see the sun. They are called Permanently Shadowed Regions (PSRs). In- situ measurements carried out by autonomous rovers are required to provide physical evidence.

A large dataset was compiled for the lunar south polar region and high- level feature extraction focusing on crater detection was performed. The team compiled a new feature dataset, which includes over 40,000-labelled tiles (**figure 3**), for machine learning training purposes. Special attention was given to the data quality of these new training data sets.

The team developed automatic crater detectors based on Deep Convolutional Neural Networks (CNN) for the Digital Elevation Model (LOLA DEM), as well as optical images (NAC). A CNN is a type of neural network that is well suited for object recognition or in this case, crater detection, and feature recognition. CNN's are able to keep and expect spatial relationships by learning from small data inputs.
Input images can be shifted and translated and still be recognized by the CNN.

2017 Lunar Water and Volatiles Solution Continued Over Page >

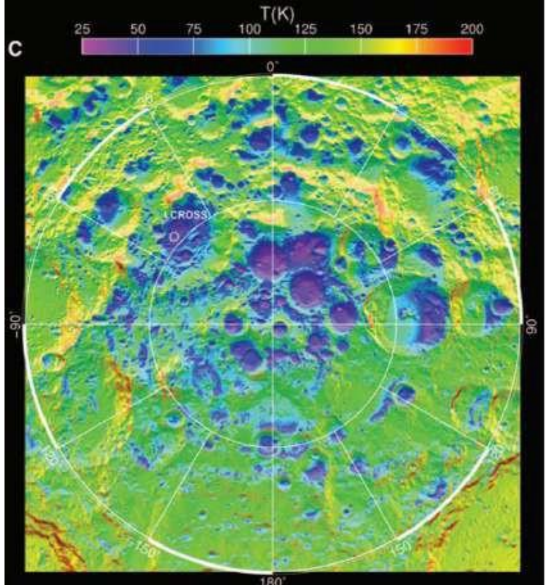


Figure 1: Simulated annual average near-surface temperatures by Paige et al., 2010
Paige et al., 2010, Science 330, sciencemag.org

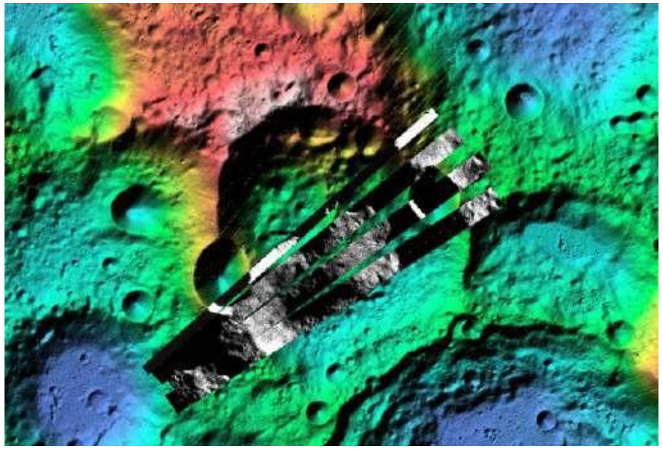
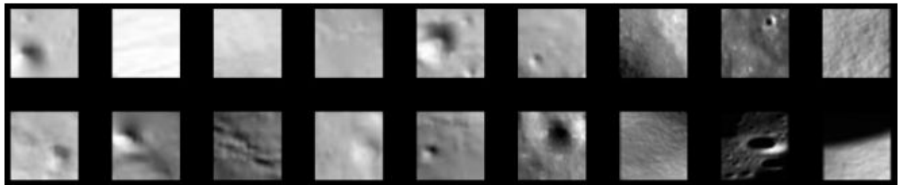


Figure 2: Mapping of mission data



FDL 2017
LUNAR WATER & VOLATILES

SOLUTION

The exact CNN model was based on LeNet-5 architecture (**figure 4**).

Results showed an impressive speedup of 100x of the model compared to human performance (expert labeling) with more than 98.4% success rate. (Table 1)

Additionally, the CNN classifier showed a very low error rate of only 2% and, thus, it outperformed any known crater detection algorithms at that time. (Table 2)

LUNARUSH - GAME

A citizen science game was later developed based on this FDL 2018 research.

lunarush.ai

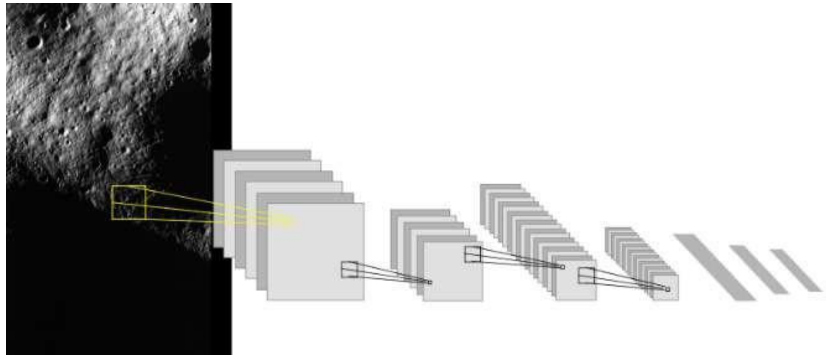


Figure 4: CNN architecture based on LeNet-5, image input passing through several convolution layers

http://yann.lecun.com/exdb/lenet/

GROUP	HUMAN	SINGLE-LAYER	CNN
ACCURACY	-	POOR	98.4%
TIME (1K IMAGES)	1-3 HOURS	10 HOURS	1 MINUTE
PERSON HOURS	1-3 HOURS	-	-

Table 1: Performance comparison (accuracy, timing)

GROUP	Vijayan et al.	Di et al.	Emani et al.	FDL
YEAR	2013	2014	2015	2017
METHOD	PATTERN RECOGNITION	PATTERN RECOGNITION	CNN	CNN
PRECISION	91%	87%	86%	98%
ERROR RATE	9%	13%	14%	2%

Table 2: Error Rate & Accuracy comparisons to alternative methods.

FDL 2017
LUNAR WATER & VOLATILES
COMMUNITY IMPACT

Community Impact

Backes, D., (2017), **NASA-FDL Artificial Intelligence in Planetary Science; Lunar Resource Mission. GRSG 2017 Annual Conference.**
http://hdl.handle.net/10993/39324

Backes, D., Bohacek, E., Dobrovolskis, A., Seabrook, T., (2018), NASA FDL 2017 – Lunar Resource Mission - **Automatic Crater Detection to Improve Topographic Maps on the Moon. Luxembourg Earth Observation and Integrated Applications Day**, poster presentation

Code & Data

github.com/Arcanewinds/FDL-LunarResources

Crater Detection App:

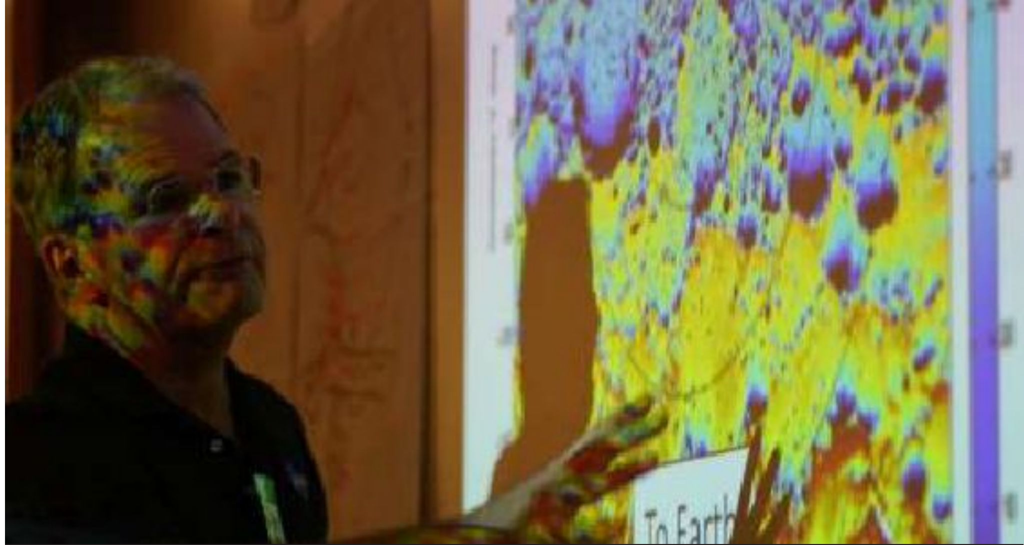
https://frontierdevelopmentlab.org/ai-lunar-mapping/moonshot.html

The Data provided has been primarily collected from NASA JPLs Planetary Data System
PDS-Imaging - https://pds-imaging.jpl.nasa.gov/

LOLA_DEM - Lunar Orbiter Laser Altimeter Digital Elevation Model
http://pds-geosciences.wustl.edu/missions/lro/lola.htm

LROC_NAC - Lunar Reconnaissance Orbiter Narrow Angle Camera
http://lroc.sese.asu.edu/archive

P26_0-18000.txt contains a list of all LROC products that overlap with the 18000 labeled LOLA_DEM tiles.
https://github.com/Arcanewinds/FDL-LunarResources/blob/master/Data/P26_0-18000.txt



Richard Elphic, PhD
Planetary Scientist, NASA Ames Research Center presenting on Lunar polar regions.

FDL 2018

AUTONOMOUS ROUTE PLANNING AND COOPERATIVE PLATFORMS

MISSION PLANNER FOR COOPERATIVE MULTI-AGENT SYSTEMS.

Multi-agent system deployments have the potential to vastly improve upon conventional single-agent operations. Indirect cooperation, such as sharing knowledge and collaborative problem solving, offer to improve the robustness, capabilities and the overall value of lunar missions.

Challenge partners:

LUXEMBOURG SPACE AGENCY

intel

FDL 2018
SPACE RESOURCES 1
RESEARCHERS

Luxembourg Talent

FRANCISCO RODRIGUEZ-LERA
COMPUTER SCIENTIST
University of Luxembourg

DREW BISCHEL
PLANETARY SCIENTIST
University of California Santa Cruz

ZAHI KAKISH COMPUTER SCIENTIST
Arizona State University

ANA MOSQUERA
PLANETARY SCIENTIST
Ohio State University

FDL 2018
SPACE RESOURCES 1
FACULTY

PHIL METZGER
LUNAR MENTOR
UCF

J.L. GALACHE
LUNAR MENTOR
Aten Engineering

TIMOTHY SEABROOK
DATA SCIENCE MENTOR
University of Oxford

MARK SHIRLEY
LUNAR MENTOR
NASA

SHASHI JAIN
SPECIALIST MENTOR
Intel

AMIR BANIFATEMI
DATA SCIENCE MENTOR
XPrize

BRUCE PITTMAN
LUANR MENTOR
NASA

FDL 2018
SPACE RESOURCES 1
SOLUTION

The exploration, identification, and prospecting of space resources are becoming a reality. Mining water, for example, will be essential for life-support systems, and can also be processed and used as rocket propellant. While the 2017 team focused on identifying resources such as water, this team set its sights on developing multi-agent systems to optimally utilize collaborative systems in order to support future missions to harvest identified resources of interest.

Current missions based on human teleoperations of a single robot could be significantly improved and optimized via a multi-agent approach and assistive AI for mission control.
Multiple rovers bring benefits such as increased data retrieval, larger exploration area coverage, and increased return on mission investment. However, this also brings new challenges, including adding cognitive load to the actors involved in mission control and further decision- making and mission-planning workload.

To this end, the team developed a recommender-system based on cooperative multi-robot scenarios using an AI path planning generator for lunar resource prospecting. The system utilized Digital Elevation Maps (DEM) of the lunar target area (**figure 1**).

It aims to reduce the operational cost, enhance the scientific return of the mission, increase mission performance, and improve mission reliability.

The team created the Multi-Agent Resource Mission Operations Tool (MARMOT) which provides an automation tool to plan multi-agent operations in space exploration and prospecting missions. It has the capability to adjust to different operator requirements and to individual mission objective characteristics. The combined use of costmap fusion, multi-agent soft constraints, and waypoint prioritization, offer a transparent set of tools for multi-agent mission planning on the 3D simulated surfaces (**figure 2**).

Along with MARMOT, supporting packages were developed as its base. Graphery and Mapstery are open- source stand-alone packages that perform general network graphing and cost map generation, respectively. The aim of these packages was broad generalizability and extensibility with other open-source packages such as QGIS.

2018 Space Resources 1 Solution Continued Over Page >

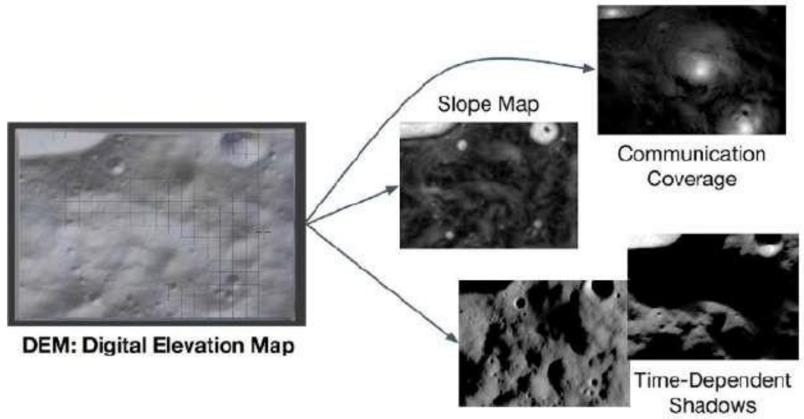


Figure 1: Using a Digital Elevation Model (DEM) (viewed in Blender on the left), multiple cost maps can be generated.

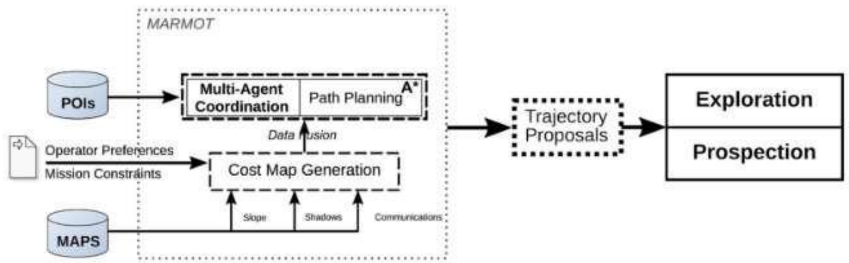


Figure 2: Layout of data pipeline and algorithm structure.

FDL 2018
SPACE RESOURCES 1
SOLUTION

An example output from MARMOT can be seen in **Figure 3**, a relay rover (green path) visits opportunity points (green diamonds) and enters the communication range (yellow clustered regions) of the science rover (blue path). In this mission scenario, the science and relay rover have the same average velocity; the relay rover reaches its final position before the science rover.

In an effort to extend the mission planning capabilities of MARMOT, the team employed more modern search algorithms. These include Distributed Path Consensus (DPC), and it's extension Distributed Path Consensus with Tasks (DPCT) which is an algorithm that optimizes every agent's search path by applying soft constraints iteratively on their respective paths that satisfy some multi-agent constraint. DPCT was applied with a separate aim of minimizing and keeping a consistent distance between two agents. The cost function used was a 50-meter constant communication constraint where each agent must maintain about a 50-meter distance between themselves (**figure 4**).

MARMOT was created as an open- source groundwork to help develop future cooperative, multi-agent systems mission operations. The team's future work will expand upon the current capabilities of MARMOT as well as generalizability with numerous mission scenarios that public and private ventures may seek to investigate.

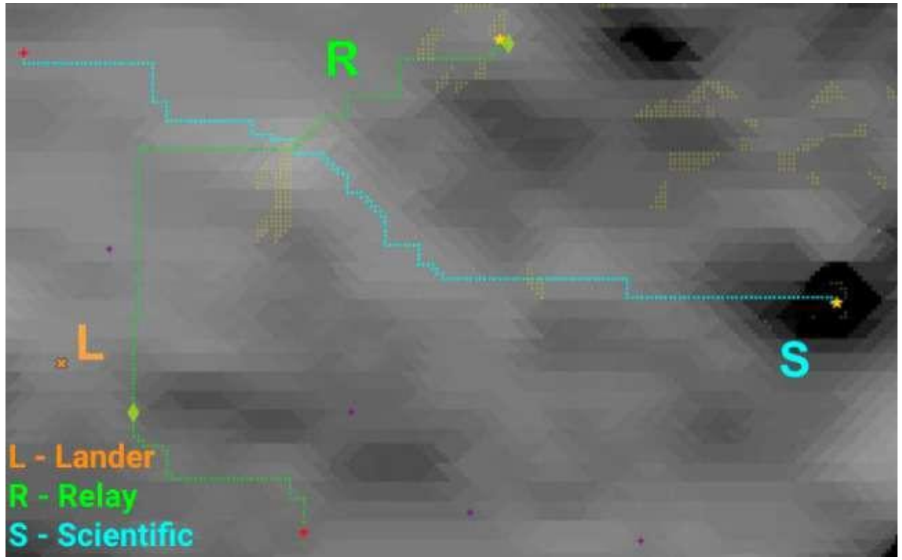


Figure 3: example output from MARMOT

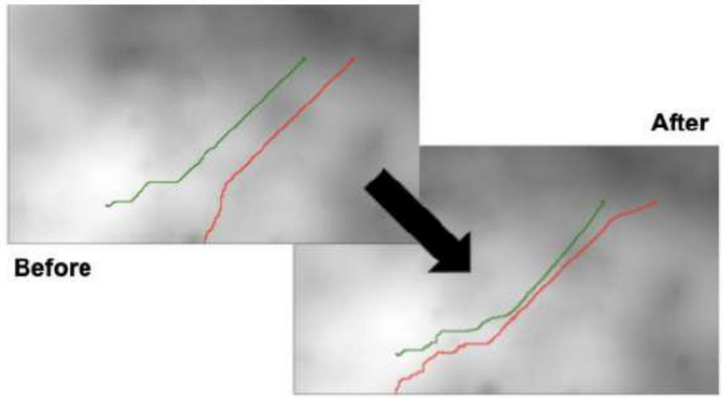


Figure 4: DPCT Applied to Static and Dynamic Agents. Applying soft penalty constraints allow paths generation/modification that maintain constant communication between a science and relay rover as the proceed to different tasks.

FDL 2018
SPACE RESOURCES 1
IMPACT & RESOURCES

Community Impact

Capability:
A tool allowing support robots to determine support strategies in the lunar environment

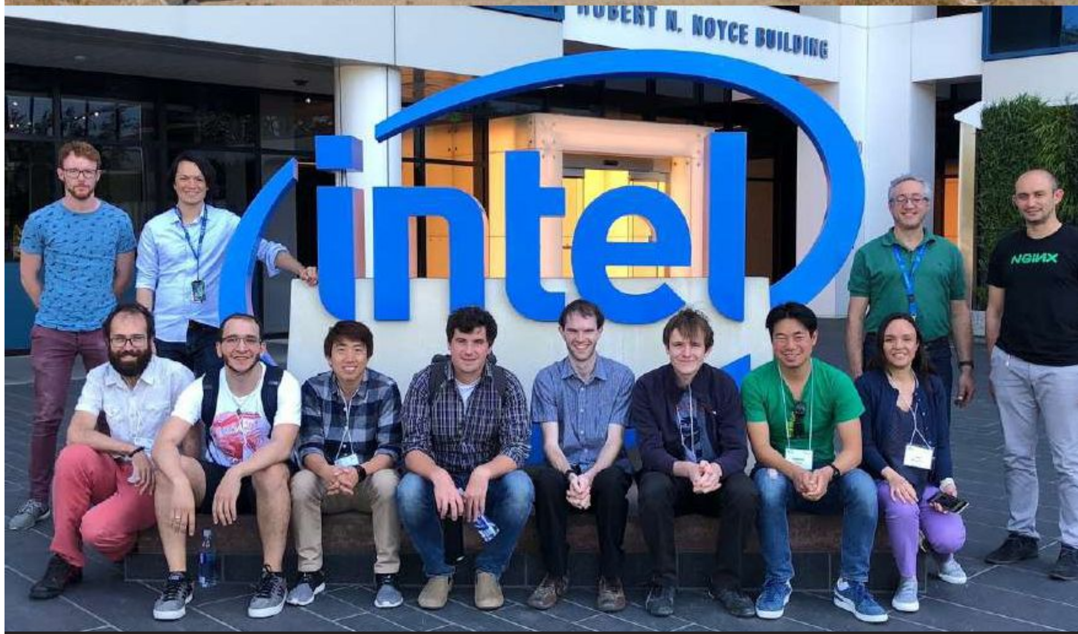
Kakish, Z. M., RodrÃguez-Lera F., Bischel. D., Mosquera, A., Boumghar, R., Kaczmarek, S., Seabrook, T., Metzger, P., Galanche, J.L., (2019). **Open-source AI Assistant for Cooperative Multi-agent Systems for Lunar Prospecting Missions, 8th European Conference for Aeronautics and Aerospace Sciences** (EUCASS), DOI: 10.13009/EUCASS2019-813

Code & Data

Open-Source code:
gitlab.com/frontierdevelopmentlab/space-resources/marmot-project
gitlab.com/frontierdevelopmentlab/space-resources/graphery
gitlab.com/frontierdevelopmentlab/space-resources/mapstery

Data:
Currently, there are no publicly available high-resolution, finely-detailed maps of the lunar surface. A terrain map must thus be made utilizing information that is publicly available.

Moon Trek (**https://trek.nasa.gov/moon/**), a website hosting publicly available Moon data organized by NASA JPL, provides easy and free access to Lunar surface data. The project focused on the crater Hermite A located on the Moon's North Pole since this was the tentative operational area of the Resource Prospector mission.



Both Space Resources teams visiting Intel HQ

FDL 2018

LOCALIZATION: MERGING ORBITAL MAPS WITH SURFACE-PERSPECTIVE IMAGERY

A significant challenge faced during the execution of lunar or planetary surface missions is that of localizing a perspective with respect to satellite imagery - something we on Earth take for granted
in the age of GPS.

Challenge partners:

LUXEMBOURG SPACE AGENCY

intel

XPRIZE

FDL 2018
SPACE RESOURCES 2

RESEARCHERS

Luxembourg Talent

PHILIPPE LUDIVIG
COMPUTER SCIENTIST
iSpace / Luxembourg

ANDREW CHUNG
COMPUTER SCIENTIST
Audi Electronics Venture

BEN WU
PLANETARY SCIENTIST
National Astronomical Observatory of Japan

ROSS POTTER
PLANETARY SCIENTIST
Imperial College London

FDL 2018
SPACE RESOURCES 2
FACULTY

PHIL METZGER
LUNAR MENTOR
UCF

ALLISON ZUNIGA
LUNAR MENTOR NASA

NAGIB HAKIM
DATA SCIENCE MENTOR
Intel

MARK SHIRLEY
LUNAR MENTOR
NASA

BRUCE PITTMAN
LUNAR MENTOR
NASA

FDL 2018
SPACE RESOURCES 2
SOLUTION

The previous teams focused on localizing valuable resources on the Lunar surface and using agent-based systems for optimal path planning for multiple lunar rovers. This team worked on a solution for absolute rover localization on planetary bodies, without access to a satellite navigation system.

Current relative localization techniques (e.g., inertial measurements, wheel odometry, visual odometry) for planetary rovers can be slow and tedious to calculate, with errors accumulating over time. The Mars Exploration Rovers (MER, a.k.a. Spirit and Opportunity) were designed with an acceptable location accuracy error of 10% over 100 meters

The team explored a new approach to localizing planetary rovers: training an artificial neural network to match surface-perspective imagery to corresponding satellite-perspective imagery.

Due to the sparsity of location- referenced planetary surface- perspective images (e.g Apollo mission and martian rover traverses), a synthetic planetary environment was required to generate a dataset of adequate size to train a deep neural network.

This dataset consisted of planetary surface (i.e., rover-perspective) images and corresponding satellite images. The synthetic test environment was built using [Moon Landscape v3.0 and Unreal Engine 4], a free, real-time game engine.

Within the 8 km x 8 km synthetic lunar landscape, three distinct regions were used for dataset generation: a training zone (2.05 km × 2.05 km), a validation zone (1.05 km × 1.05km), and a testing zone (1.05km×1.05km).
Full satellite views of each zone are shown in **Figure 1**. In total, 2.4+ million surface-perspective images corresponding to 600,000+ distinct locations were generated within the synthetic environment.
For each location, 4 specific outputs are produced: (1) a set of 4 surface-perspective images, (2) metadata for the location and camera, (3) a processed top-down reprojection view, and (4) the extracted ground truth satellite image.

These products together comprise our full dataset, the Lunar UNreal Assets (LUNA) Localization Dataset. The dataset is approximately 10 TB and its details are shown in **Table 1**.

2018 Space Resources 2 Solution Continued Over Page >

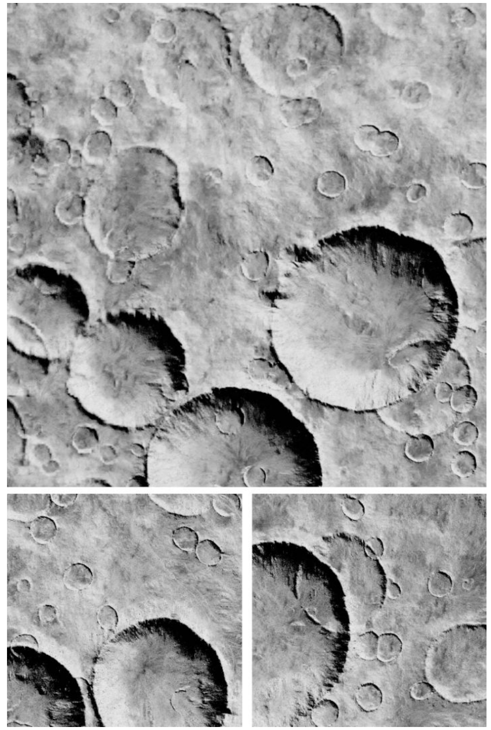


Figure 1: The 2.05km×2.05km training zone (top panel), 1.05km×1.05km validation zone (lower left panel), and 1.05 km × 1.05 km testing zone (lower right panel) within the synthetic lunar landscape.

Item	Physical Scale	Resolution	Quantity
Training Region	2.05 km× 2.05 km	41000× 41000 px	1
Validation Region	1.05 km× 1.05 km	21000× 21000 px	1
Testing Region	1.05 km× 1.05 km	21000× 21000 px	1
Surface Images	$90° \times 50.6°$	1920×1080 px	2.42×10^6
Satellite Images	50 m $\times 50$ m	1000×1000 px	6.06×10^5
Reprojected Images	50 m $\times 50$ m	1000×1000 px	6.06×10^5

Table 1: Summary of the Luna Localisation Dataset

FDL 2018
SPACE RESOURCES 2
SOLUTION

An automated pipeline within Unreal Engine was built to place the rover at random locations within the synthetic lunar environment, capturing four ground perspective images (front, left, rear, right, spaced 90° apart) with minimal overlap (**figure 2**).

Each set of four ground perspective images was processed into a pseudo-aerial image using custom Python scripts utilizing the OpenCV library. The remaining nearby landscape was reprojected using the camera matrix to form one quadrant of an equivalent top-down view. The quadrants were then smoothly stitched and scaled into a representative 50 m x 50 m aerial image with a pixel resolution of

0.05 m.

The training dataset consisted of reprojected images paired with a satellite image from the training zone. The labeled (matching/non-matching) image pairs were used to train a neural network to identify matching pairs of reprojected surface-perspective images and satellite images. The resulting model, Planetary Localization Neural Network (PLaNNet v0), is depicted in **Figure 4**.

PLaNNet is a Siamese neural network. Each head of the network feeds into a pre-trained 50-layer [ResNet v2 feature extractor](). Each head takes a 224 × 224 px RGB image as input, with intensity values in the range [0, 1]. As we use grayscale images, the single channel is replicated across red, green, and blue channels before feeding into the network. Although inefficient, this allowed the team the use of pre- trained weights.

PLaNNet achieves the best localization performance overall in both the 300 m × 300 m sub-region (3600 candidate points) and 1.05 km × 1.05 km testing region (40,401 candidate points). In both cases, the neural network requires, on average, only 5% of the available candidate regions to localize within 10 m and 10% to localize within 5 m. Other methods such as sum of absolute differences (SAD), and the sum of squared distances (SSD) perform approximately a factor of 2 worse.
Random sampling achieves the worst performance for localizing within 5 m.

The current system is able to reduce the search area by 90-95%, providing valuable input for any human-in-the-loop localization. By severely reducing the search space in an automated fashion with high confidence and with calculation times of order seconds, the workload and time required by teams to localize successfully may be sharply reduced.

This method developed by the team is applicable to the Moon and Mars – the main exploration bodies of interest to corporations and space agencies, such as NASA–but could also be applied to other planetary bodies.

In summary the team developed:

1) Production of a synthetic dataset for training and benchmarking localization algorithms.

2) Proof-of-concept implementation of an image-based absolute localization technique, demonstrating (i) the usefulness of the dataset, and (ii) the potential for neural network-based approaches.

3) Code to generate an synthetic areal view of the rover and its surroundings from surface-perspective images, which could provide human navigation support by aiding obstacle avoidance and execution of precise maneuvers.

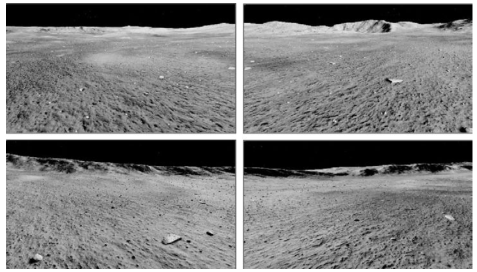


Figure 2: Example ground view images taken at one location within the testing region. The camera, which had horizontal and vertical fields of view of 90° and 50.6°, respectively, was placed 2 m above the surface and tilted downwards by 15° to simulate the rover camera height and orientation. Clockwise from top left panel: front view, right view, rear view, left view.

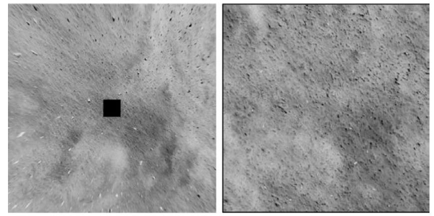


Figure 3: (Left) Example of an aerial reprojection using the ground views in Figure 2. The black square encompasses the camera position and indicates regions near the rover not imaged due to the limited vertical field of view. (Right) The corresponding ground truth satellite view. In both images, the region represented is 50 m × 50 m.

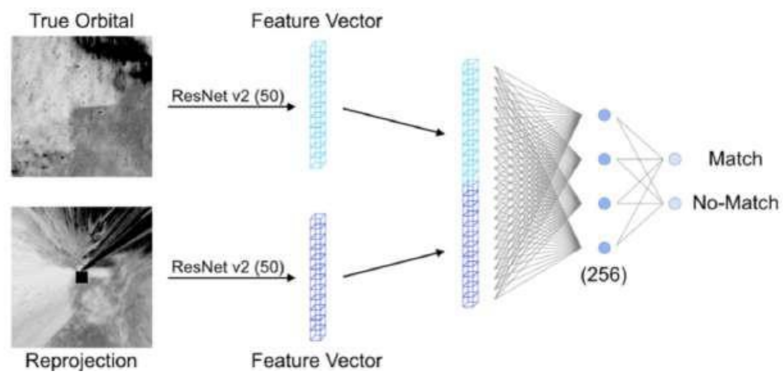


Figure 4: Schematic illustrating the PLaNNet v0 architecture

FDL 2018
SPACE RESOURCES 2
IMPACT & RESOURCES

Community Impact

Capability:

Approach allowing lunar rovers to determine their position without a satellite GPS system.

Publications:

Wu, B., Potter, R.W.K., Ludivig, P., Chung, A.S., and Seabrook, T. (2019). **Absolute Localization Through Orbital Maps and Surface Perspective Imagery: A Synthetic Lunar Dataset and Neural Network Approach.** IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) Macau, China, November 4-8, 2019, pp.3262-3267

Wu, B., Potter, R.W.K., Ludivig, P., Chung, A.S., and Seabrook, T. (2020). **Absolute Localisation for surface robotics in GPS denied locations using a Neural Network.** Accepted and to appear at the 2nd Second AI and Data Science Workshop for Earth and Space Sciences, Jet Propulsion Laboratory, 2020

Code & Data

Open-Source code:

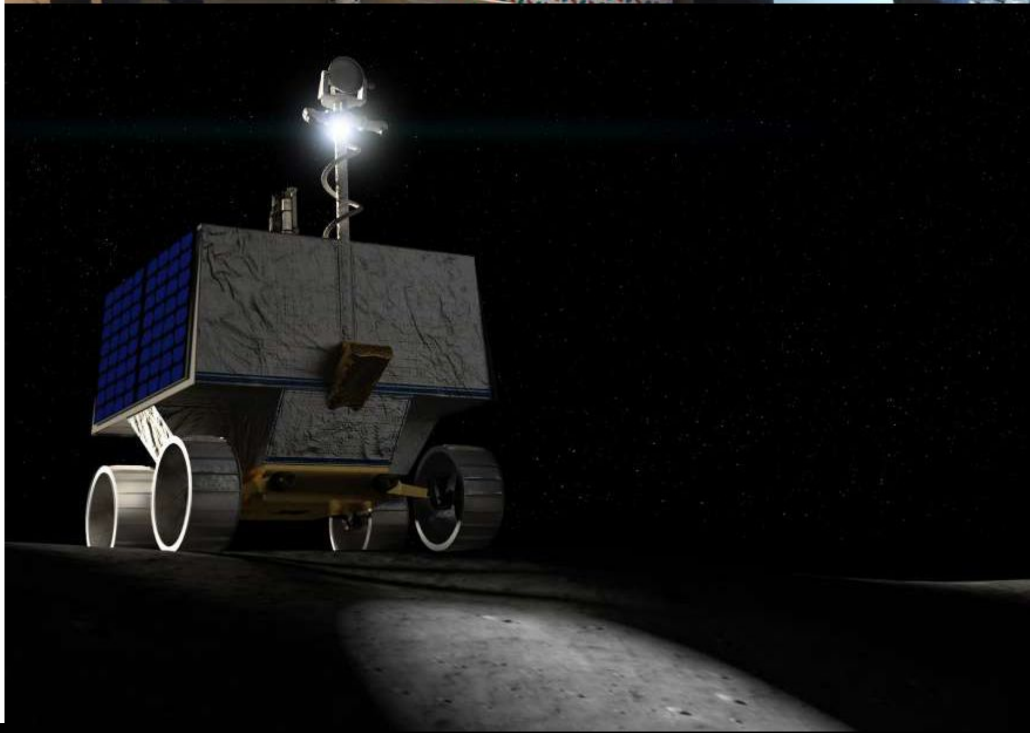
https://gitlab.com/frontierdevelopmentlab/space-resources/sr2018-localization-public

Data:

The team has created data generation executables for Windows OS here.

https://drive.google.com/drive/folders/1E7m0R8WfZ94Xu2EetdFzSc3yWuqQ0wyR

The full **Lunar UNreal Assets (LUNA) Localization Dataset** used for the project (approximately 10TB) is currently hosted on a SETI / INTEL internal system. Alternatively, the data will be available on AWS Open Data mid- late 2020.



FDL 2018

FROM BIOHINTS TO EVIDENCE OF LIFE

FROM BIOHINTS TO EVIDENCE OF LIFE: POSSIBLE METABOLISMS WITHIN EXTRATERRESTRIAL ENVIRONMENTAL SUBSTRATES

Extraterrestrial environments may have coevolved a broad range of alternative life processes markedly different to those we observe on Earth. Can we deploy AI techniques to generate an extended parameter space for possible metabolisms based on given (observed) environmental conditions and substrates?

Challenge partners:

Google Cloud

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ATILIM GUNES BAYDIN
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MASSIMO MASCARO
DATA SCIENCE MENTOR
Google Cloud

FDL 2018 ASTROBIOLOGY **SOLUTION**

The 2018 Astrobiology Team II, benefitted from Luxembourg Talent Simone Zorzan. He and his team supported by NASA's Goddard Space Flight Center and NASA's Astrobiology Institute worked on utilizing existing NASA software to determine atmospheric compositions of exoplanets, generating a massive unseen set of 3,000,000 exoplanetary atmospheres and developing a complete machine learning framework in order to detect possible habitable planets which could support life.

Atmospheric retrieval, the inverse modeling technique used to determine an exoplanetary atmosphere's temperature structure and composition from an observed spectrum, is both time-consuming and compute-intensive, requiring complex algorithms that compare thousands to millions of atmospheric models to the observational data to find the most probable values and associated uncertainties for each model parameter.

For rocky, terrestrial planets, the retrieved atmospheric composition can give insight into the surface fluxes of gaseous species necessary to maintain the stability of that atmosphere, which may, in turn, provide insight into the geological and/or biological processes active on the planet. These atmospheres contain many molecules, some of them biosignatures, spectral fingerprints indicative of biological activity, which will become observable with the next generation of telescopes (**figure 1**).

Observations are simulated using an instrument model of the Large UltraViolet/Optical/InfraRed Surveyor (LUVOIR), a design concept for a multi-wavelength space observatory, but with a much higher resolution.
The prior model comprises planetary parameters (radius, mass, surface pressure, semi-major axis, pressure- temperature profile), and atmospheric compositions. Planetary parameters were randomly selected from ranges and distributions consistent with our solar system and observations of other systems. The ranges for these parameters are chosen such that a planet in an Earth-like orbit can vary in temperature by a few hundred Kelvin.

The team considered 12 molecules based on the composition of atmospheres in our solar system as well as the observability of species: H2O, CO2, O2, N2, CH4, N2O, CO, O3, SO2, NH3, C2H6, and NO2. Concentrations are randomly selected within a range based on the observed composition of atmospheres in our solar system. While cloud mixing ratios were calculated, clouds were currently ignored in simulations due to the computational burden as even poor modeling efforts can increase the computational time by a factor of 50.

The team developed a machine learning-based retrieval framework called Intelligent exoplaNet Atmospheric RetrievAl (INARA) that consists of a Bayesian deep learning model for retrieval and a data set of 3,000,000 synthetic rocky exoplanetary spectra generated using the NASA Planetary Spectrum Generator (PSG). This work represents the first ML retrieval model for rocky, terrestrial exoplanets, and the first synthetic data set of terrestrial spectra generated at this scale.

Thanks to the computational resources the team had access to during FDL, the present data set is the largest collection of rocky planet spectra to date. For the first time in ML atmospheric retrieval, Monte Carlo dropout was applied, providing a predictive distribution comparable to the posterior distributions yielded by traditional, Bayesian approaches (**figure 2**).

2018 Astrobiology Solution Continued Over Page >

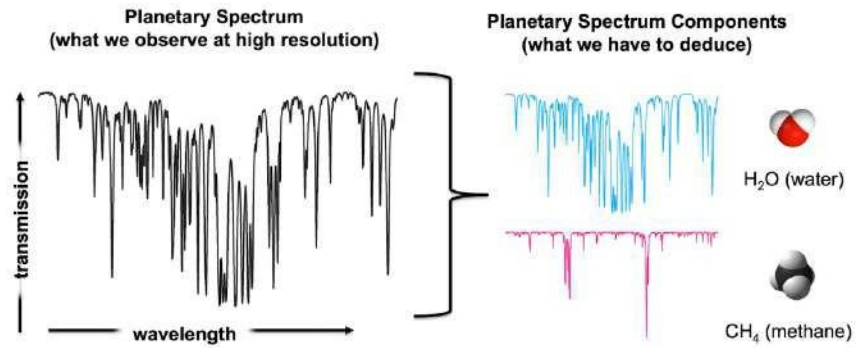

Figure 1: Example Planetary Spectrum with components

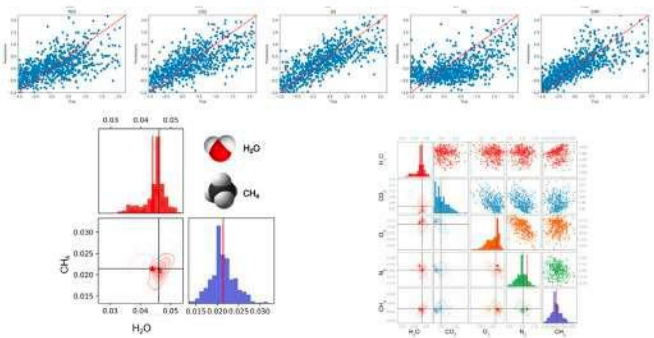

Figure 2: Predictions of H2O, CO2, O2, N2, CH4 based on the best performing model; training limited to 64 epochs on 110,000 parameter–spectra pairs hence some uncertainties reflect calibration issues.

FDL 2018 ASTROBIOLOGY
SOLUTION

Traditionally, the study of exoplanetary atmospheres has been done by fitting forward models to observational data, which is based on the relative decrease in flux when the exoplanet is in front of or behind its host star. This is usually performed using a Monte Carlo sampling method in a Bayesian framework to propose atmospheric models, simulate the spectrum, and compare it to the observed data. Degeneracies among atmospheric parameters complicate this process, necessitating the evacuation of hundreds of thousands to millions of atmospheric models to fully explore the parameter space. This results in a posterior distribution that characterizes these degeneracies and informs the relative probability of the ranges of values considered for each model parameter. While these sampling methods are executed in parallel, this task still requires a significant amount of computational time.

INARA outperforms traditional Monte Carlo-based approaches by several orders of magnitude while computing a larger set of parameters and atmospheric molecules. **Table 1** shows how INARA compared to other methods used in the field in terms of performance.

Docker image are publicly available. To interact with NASA Goddard PSG, the simulator at the core of our spectrum generation setup, the team also implemented a Python package called pypsg that handles data generation in PSG format and http- based two-way communication with NASA PSG servers.

The INARA codebase covers the running of server instances for data generation, ML model training, and inference in a distributed fashion currently utilizing the Google Cloud infrastructure but the framework can be tied to any computational backend. For the generation of the data set of 3M parameter and spectrum pairs, the team employed approximately 2,000 high-end VMs (groups of 16 INARA instances connected to one PSG node).

The team explored over 70 combinations of different architectures (linear regression, feed-forward neural networks, and CNNs). Due to time constraints, model training used a training set of 110,000, a validation set of size 10,000 and a test set of 7,000 parameter–spectra pairs. 1-Dimensional CNNs produced the best results in the INARA framework, which has approximately 18M trainable parameters.

O2, N2 and CH4 are shown in the five plots in **Figure 2** top row, where each dot represents the average of 600 runs of our model with dropout for each planet. The details for predictive joint distributions for a random planet among those simulated is shown in the two bottom plots of **Figure 2**. The true value, indicated by the red star and the red line, falls within the predictive distribution for both parameters. **Figure 3** presents predictions for the full set of 12 molecules.

The team has since focused their attention on improving used machine learning models and is currently in process of publishing results of the 3,000,000 data point trained machine learning model. The team also currently prepares to share the complete datasets, trained models on the NASA Exoplanet Archive.

Method	CPU inference time	Molecules retrieved
traditional	Hundreds of hours	user-specified
ExoGAN	Minutes	4
HELA	Seconds	3
INARA	Seconds	12

Table 1: Comparison of atmospheric retrieval methods.

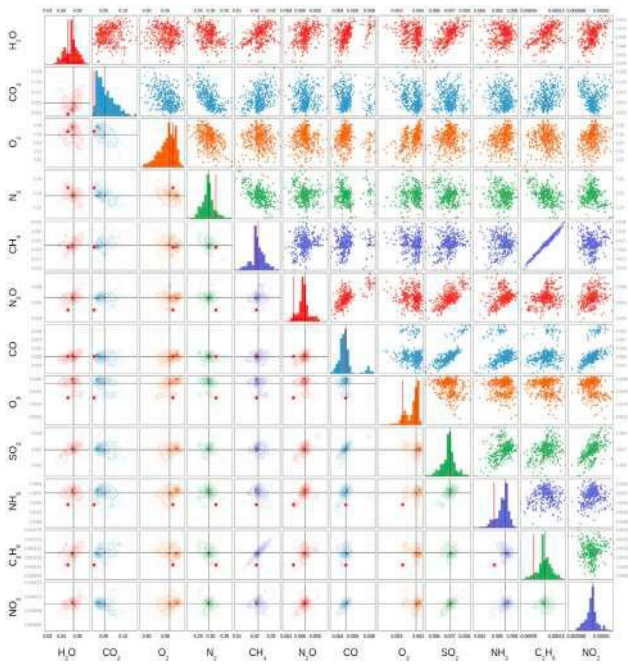

Figure 3: Posterior results with all 12 molecules in the model.

FDL 2018 ASTROBIOLOGY
IMPACT & RESOURCES

Community Impact

Capability:

Modular Bayesian machine learning framework capable of creating synthetic exoplanet data and predicting 12 atmospheric molecules in exoplanetary atmospheres. The model is able to provide uncertainty measurements of the predictions.

Publications:

Michael D. Himes, Joseph Harrington, Adam D. Cobb, Atilim Gunes Baydin, Frank Soboczenski, Molly D. O›Beirne, Simone Zorzan, David C. Wright, Zacchaeus Scheffer, Shawn D. Domagal-Goldman, Giada N. Arney. (2020). **Accurate Machine Learning Atmospheric Retrieval via a Neural Network Surrogate Model for Radiative Transfer**, https://arxiv.org/abs/2003.02430

Cobb, Adam D., Michael D. Himes, Frank Soboczenski, Simone Zorzan, Molly D. O'Beirne, Atılım Güneş Baydin, Yarin Gal, Shawn D. Domagal- Goldman, Giada N. Arney, and Daniel Angerhausen. 2019. "**An Ensemble of Bayesian Neural Networks for Exoplanetary Atmospheric Retrieval.**" The Astronomical Journal, Volume 158, Number 1

O'Beirne, Molly D., Michael D. Himes, Frank Soboczenski, Simone Zorzan, Adam Cobb, Atılım Güneş Baydin, Yarin Gal, Daniel Angerhausen, Massimo Mascaro, Giada N. Arney, and Shawn D. Domagal-Goldman.
2019. "**INARA: A Machine Learning Retrieval Framework with a Data Set of 3 Million Simulated Exoplanet Atmospheric Spectra.**" In Astrobiology Science Conference (AbSciCon 2019), Bellevue, Washington, June 24–28, 2019.

Soboczenski, Frank, Michael D. Himes, Molly D. O'Beirne, Simone Zorzan, Atılım Güneş Baydin, Adam D. Cobb, Yarin Gal, Daniel Angerhausen, Massimo Mascaro, Giada N. Arney, and Shawn D. Domagal-Goldman.
2018. "**Bayesian Deep Learning for Exoplanet Atmospheric Retrieval.**" In Third Workshop on Bayesian Deep Learning (NeurIPS 2018), Montreal, Canada.

Publications continued:

Soboczenski, Frank, Michael D. Himes, Molly D. O'Beirne, Simone Zorzan, Atılım Güneş Baydin, Adam D. Cobb, Yarin Gal, Daniel Angerhausen, Massimo Mascaro, Geronimo Villanueva, Shawn D. Domagal-Goldman and Giada N. Arney. (2020). **INARA: A Bayesian Deep Learning Framework for Exoplanet Atmospheric Retrieval**. Accepted and to appear at the 2nd AI and Data Science Workshop for Earth and Space Sciences, NASA Jet Propulsion Laboratory, 2020

Code & Data

Open-Source code:

https://gitlab.com/frontierdevelopmentlab/astrobiology/inara

Data:

The full dataset curated (~100TB) is currently hosted by Google Cloud. The data will be available for the wider community in mid-end 2020 as it is currently being prepared for release on the NASA Exoplanet Archive
https://exoplanetarchive.ipac.caltech.edu/

FDL 2019

LUNAR RESOURCE MAPPING: DATA FUSION AND SUPER RESOLUTION

THE MOON FOR GOOD

It is estimated that billions of tons of metallic deposits could exist on the Moon from M-class impactors. How might we use data fusion and emerging super-resolution techniques to develop high-resolution lunar resource maps of these metallic deposits to aid mission planners looking to locate resources for future robotic and human lunar missions?

Challenge partners:

LSA Luxembourg Space Agency · Google Cloud · intel AI · Hewlett Packard Enterprise · ELEMENT AI · USGS science for a changing world

FDL 2019
THE MOON FOR GOOD

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FDL 2019
THE MOON FOR GOOD

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LUNAR MENTOR
Skycorp Inc

FDL 2019
THE MOON FOR GOOD
SOLUTION

The 2019 Lunar research team produced a global, multi-sensor, multi-spacecraft AI-ready data stack of several lunar orbiter measurements and uncovered clusters and anomalies across this dataset by applying machine learning methods. As a result the team generated new types of thermal anomaly maps which could correlate with the location of metals on the lunar surface. The data stack and developed models could inform future lunar resource missions and have a potentially high scientific and commercial value.

In order for humanity to establish a long-term presence on the Moon, it is critical to understand what resources are available on the lunar surface.
Impactor influx can deposit large pieces of metal and nickel in the form of metal meteorites, which could serve as highly desired raw materials for future Moon bases and orbital facilities. Metallic meteorites are also of interest to the lunar research community, as it will provide insights into the evolution of the Moon as well as the solar system. The presence of metal meteorites is known to influence the electromagnetic, thermal, and magnetic properties of the lunar surface, providing a potential method for detection. it is estimated that 3-4% of impacts are from nickel-iron bodies. Nickel-iron meteor fragments have also been found embedded in samples from the Apollo missions.

Data from seven different spacecraft and 12 individual active and passive instruments has been curated into a ML-ready datastack consisting of 42 global layers (**figure 1**): Clementine, Lunar Prospector, Kaguya (Selene), Chang'e 1 & 2, the Gravity Recovery and Interior Laboratory (GRAIL), and the Lunar Reconnaissance Orbiter (LRO). These instruments cover a wide range of the electromagnetic spectrum as well as physical data such as gravity and topography. Due to unfavorable warping effects in map projections, all data products have been projected to two different systems, cylindrical equirectangular (equatorial regions, 70N to 70S) and polar stereographic (90N to ~75N and 90S to ~75S). The combined data cube (360° by 180° by 42 layers) that includes all used layers has an uncompressed size of about 35 TB.

The team focused their analysis around 43 Areas of Interest (AOIs), chosen based on their physical properties. 38 have anomalies which could indicate the presence of metals. The identified AOIs are usually Infrared hot/cold spots, microwave hot/cold spots, or both. Additional properties include rock abundance, feature age, magnetic properties, and thermal behavior of the surroundings.

2019 Moon for good Solution
Continued Over Page >

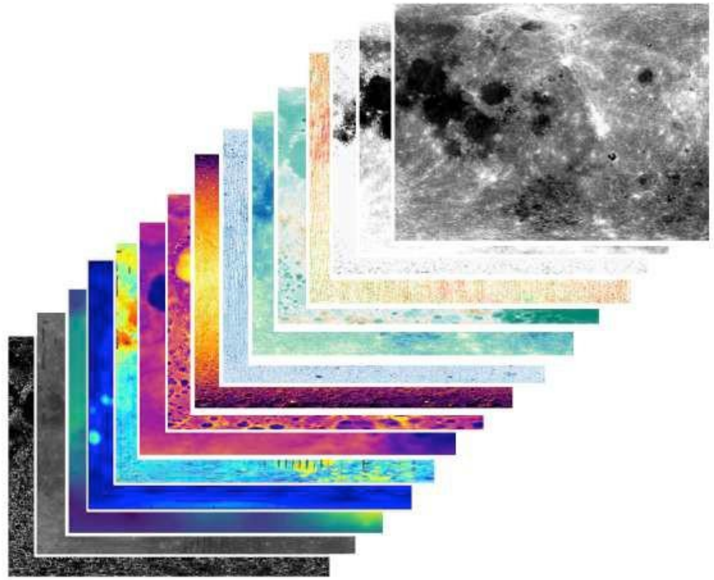


Figure 1: Generated data stack consisting of 42 layers of lunar mission data

FDL 2019
THE MOON FOR GOOD
SOLUTION

The team then used dimensionality reduction and clustering methods (DBScan) to search for anomalies across this data stack as well as use the DIVINER dataset to examine temperature profiles. **Figure 2,**
presents a selection of these plots for six different craters where thermal or magnetic anomalies are detected. Notably, there is a clear spatial correlation between points of the same cluster, supporting the idea that anomalies are related to different topographical features. As evidenced by the craters Aristarchus, Marius-A, Hell-Q and Giordano Bruno, thermal anomalies mainly occur in the crater center, whereas magnetic anomalies can stretch from the crater center (Hell-Q, Galois) to the surrounding ejecta blankets (Dollond).

Using the thermal data, the team could extract the temperature variation with local lunar time at each point on the lunar surface and apply unsupervised machine learning on these profiles. This produced new types of data-driven thermal anomaly maps, which they compared to numerical thermal simulations of metals on the lunar surface.

Of particular interest was channel 7 of the DIVINER data, which records radiance in the 25-41 μm band and is the most sensitive channel for recording temperature values between 69-178K. For each AOI we bin the temperature measurements from this channel onto a 200m x 200m grid. The team sorted all of the points in each bin by the local lunar time they were recorded, producing a temperature- local lunar time profile for each bin.
Each profile is then interpolated into regularly spaced temperature measurements in time before using them for machine learning. Observing that the temperature measurements are noisy, hence Gaussian Process (GP) were used to interpolate each profile. Samples are taken every 0.2 hours, resulting in 120 temperature values for each profile. Four examples of these profiles extracted from the Tycho crater AOI are shown in
Figure 3.

The team developed the Lunar Orbiter-derived Variational AutoEncoder (Lord VAEder) consisting of eight convolutional layers in the encoder and seven transposed convolutional layers in the decoder using temperature profiles sampled from all of the AOIs. The team used the VAE to compress each profile into a small set of latent variables and then map these latent variables over the lunar surface (**figure 3**).

2019 Moon for good Solution Continued Over Page >

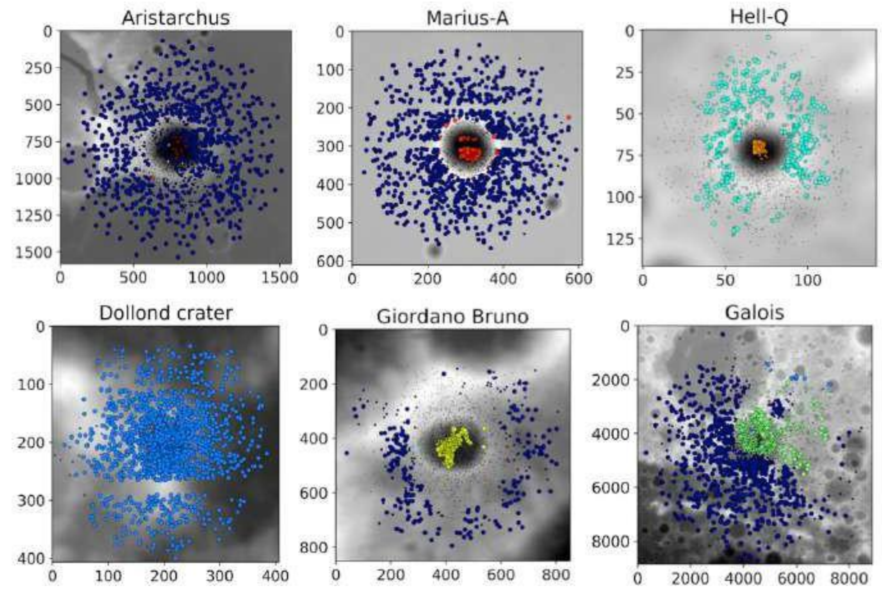


Figure 2: Labeled AOI maps showing the different thermal and magnetic anomalies derived from cluster analysis. Scale in hectometers.

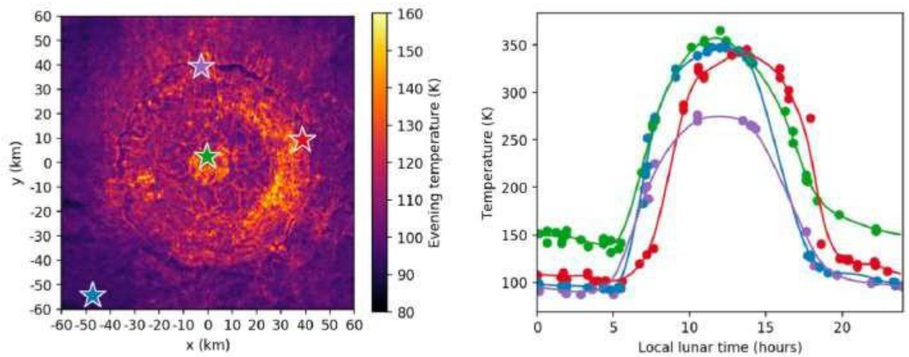


Figure 3: Left: evening temperature map over the Tycho crater, plotting the average temperature over 12 am-4 am in local lunar time. Right: four example temperature profiles extracted over Tycho. Points show temperature measurements, solid lines show the Gaussian process fits of the profiles used for interpolation. Colour coded stars in the left plot indicate the locations of the profiles.

FDL 2019
THE MOON FOR GOOD
SOLUTION

200+ CPU cores in five virtual machines over two weeks to carry out the processing of the DIVINER dataset, 500+ GB of RAM to visualise and explore our data stack, 4 Nvidia V100 GPUs to train the machine learning models and nearly 100 TB of working cloud storage were used. All the computing resources were provided by Google Cloud Platform.

Additionally, physically-interpretable correlations between the VAE's latent representation and estimated thermal parameters from physics- based inversion could be found.
Using this representation the team was able to efficiently generate new types of thermal anomaly maps which potentially indicate the presence of metals on the surface of the Moon (**figure 4**).

We note that generating these maps is two orders of magnitude faster than running the inversion, which allows this approach to be scaled over large areas. The L2 loss map can also be
used to identify locations with extreme thermal behaviour outside of the
VAE training distribution which could relate to high contrasts in chemical or mineralogical composition.

The team is currently working on producing **global anomaly maps** with this workflow, building more complex physics models to aid our
physical interpretation of the VAE and incorporating physics models directly in the training of our VAE to constrain our latent representation further.

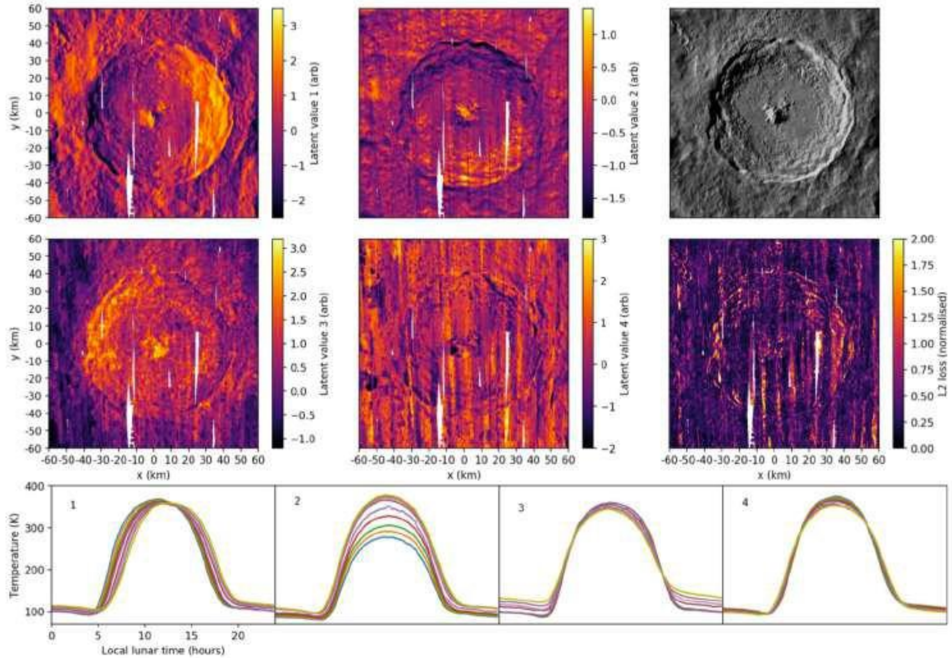
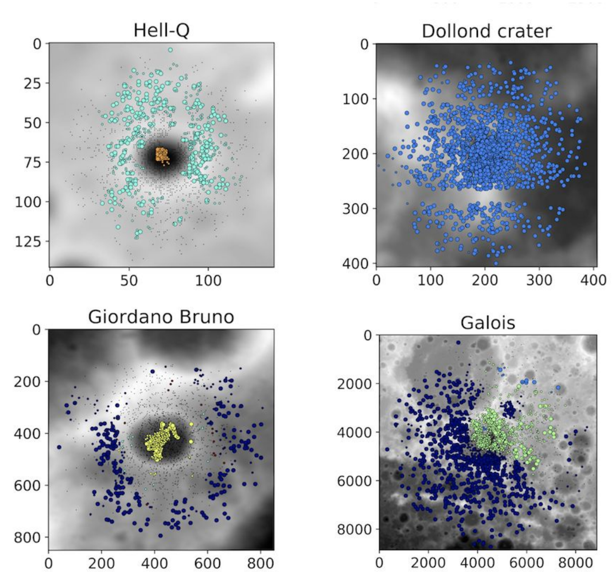


Figure 4: Top left two columns show maps of the four VAE latent variables over the Tycho crater. Top right shows an optical image of Tycho. Middle right shows a map of the VAE L2 reconstruction loss. Bottom plots show the reconstructed profiles generated from the VAE when sampling each latent variable independently and fixing the other latent variables to their mean value.

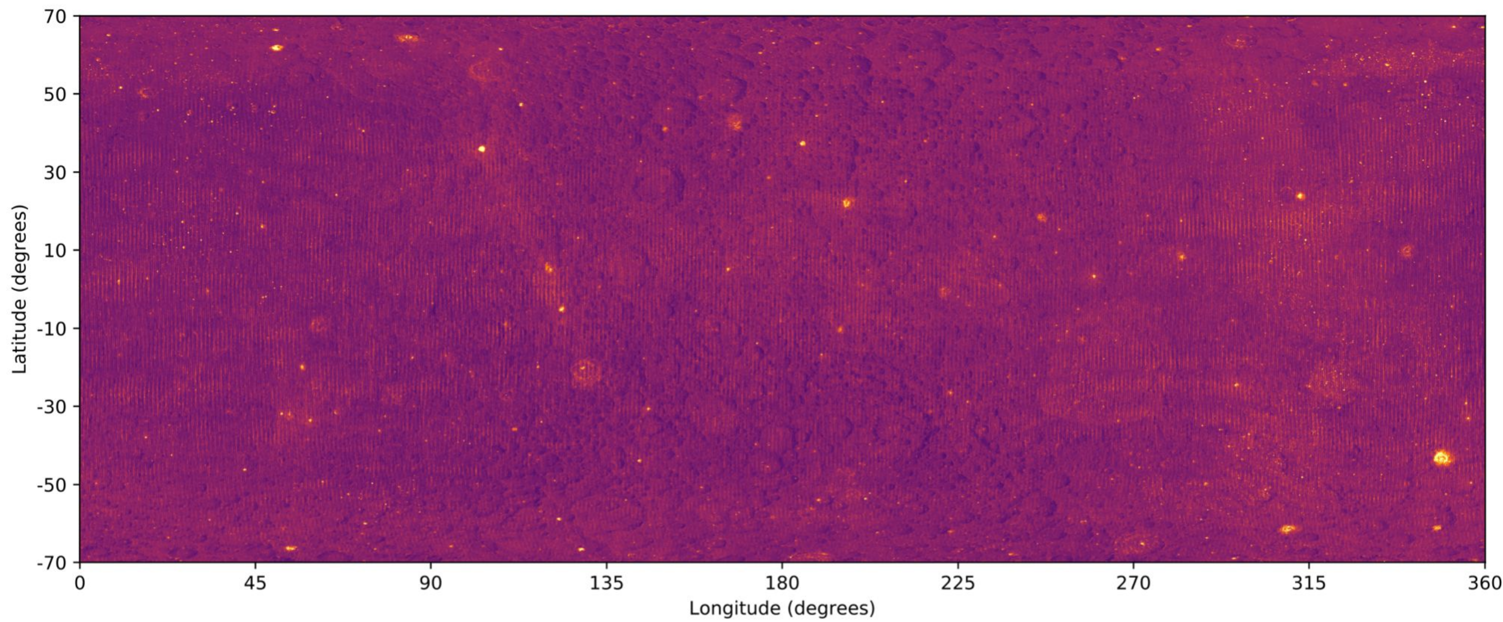
Lunar Metallic Anomalies

Data fusion of 42 layers or multisensor orbiter data and unsupervised ML techniques to locate thermal and magnetic anomalies - indicating Lunar metallic deposits in high resolution for the first time.



1 pixel = 100 m

- magnetic
- bright
- highly magnetic
- noise
- background



Unsupervised Learning for Thermophysical Analysis on the Lunar Surface

https://iopscience.iop.org/article/10.3847/PSJ/ab9a52

FDL 2019
THE MOON FOR GOOD
IMPACT & RESOURCES

Community Impact

Capability:

Data stack and machine learning model capable of creating temperature profile maps with the potential of identifying metals on the moon; currently expanding to generate a global lunar resource map.

Publications:

Moseley, B., Bickel, V., Burelbach J., Relatores, N., Angerhausen, D., Soboczenski, F., Wingo, D. (2019). **Unsupervised learning for thermal anomaly detection on the lunar surface**. Machine Learning and the Physical Sciences Workshop at the 33rd Conference on Neural Information Processing Systems (NeurIPS)

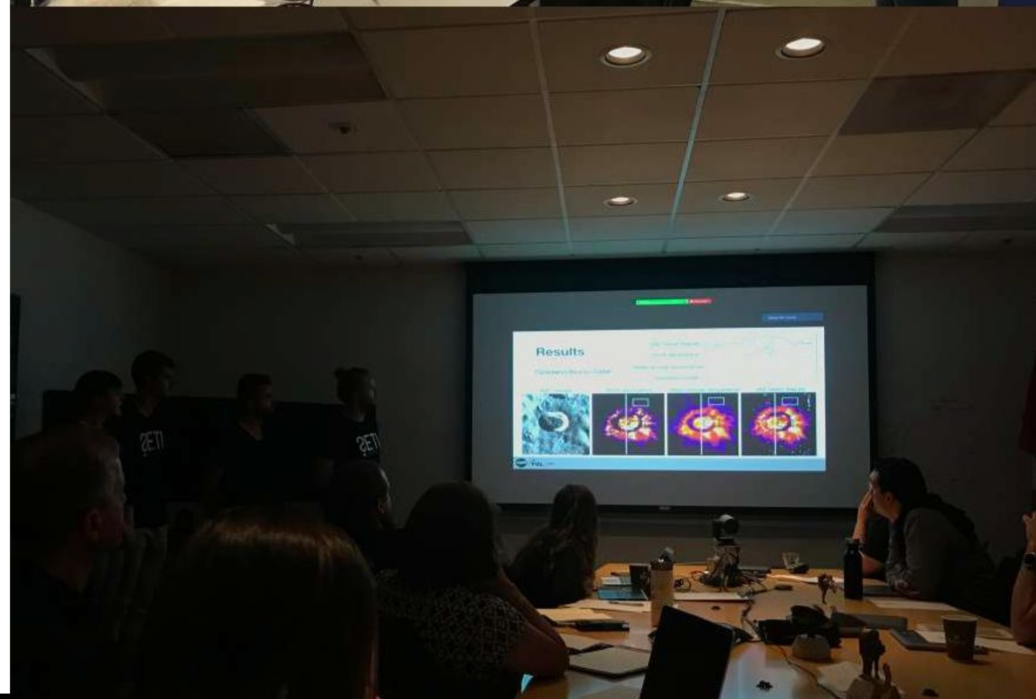
Code & Data

Open-Source code:

https://gitlab.com/frontierdevelopmentlab/the-moon-for-good

Data:

The full dataset curated (~35TB) is currently hosted by Google Cloud and the SETI Institute.



FDL 2020

MOON ENGINE: MOON FOR GOOD, PHASE II

FDL 2020

Where is the ice?

Water ice is an invaluable resource on the Moon - it is the backbone of any future sustainable, permanent presence. Understanding where it is located and how much exists is key.

NASA will soon be going back to the Moon to study this resource further. The primary targets are shadowed polar regions (PSRs), which are thought to bear large amounts of water ice. However, no satellite data exist which provide the spatial resolution required to plan a safe PSR rover traverse with high confidence.

PSR regions are a completely unknown terrain and pose a significant engineering challenge (complete darkness, temperatures close to 30K, etc.). The location and distribution of ice in PSRs is unknown. The distribution of hazardous obstacles like small craters and boulders is unknown as well. A successful resource prospection and extraction mission will need to be able to plan and execute a safe rover traverse into and out of a PSR.

High-resolution NAC PSR imagery would have a massive impact, as it would not only enable the community to improve mission planning and target selection, but would also allow for the analysis of other key science questions, like the lunar volatile cycle, the relation between ice and geomorphology, and many more.

Challenge partners:

LUXEMBOURG SPACE AGENCY

MOON FOR GOOD

MOON ENGINE: MOON FOR GOOD, PHASE II

TEAM

ALLISON ZUNIGA

VALENTIN BICKEL

BEN MOSELEY

IGNACIO LÓPEZ-FRANCOS

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LOVENEESH RANA

DENNIS WINGO

SUPPORTED BY

intel
LUXEMBOURG SPACE AGENCY
SPACE RESOURCES.LU
Google Cloud

NEED > CHALLENGE

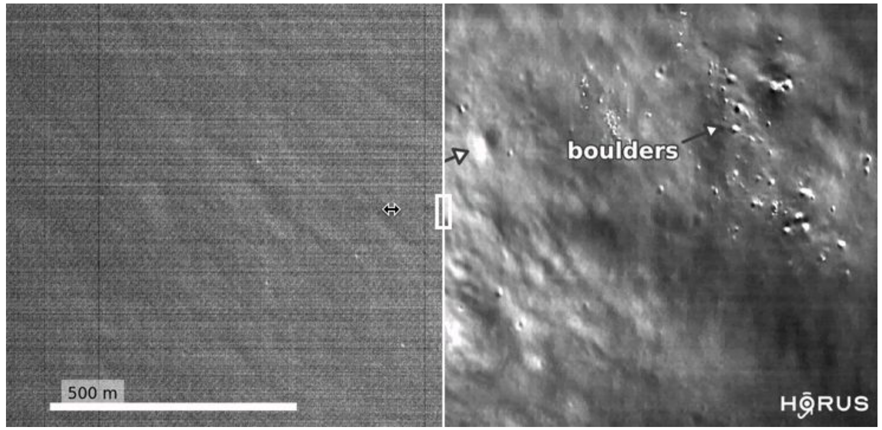
1. Finding water-ice in-situ is key to enable a sustainable human presence on the Moon and beyond as it provides life support and serves as a potential source of propellant. There is evidence that water-ice is abundant in and around topographic depressions at the lunar poles, in the so-called Permanently Shadowed Regions (PSRs) which have not received sunlight for millions of years and are among the coldest regions in our solar system.

2. One of the main limitations for identifying exposures of water-ice (or related geomorphic features) in PSRs as well as for planning safe and effective rover traverses is the quality of the available high-resolution optical imagery and topographic information. Currently, the best imagery of lunar polar regions is produced by Lunar Reconnaissance Orbiter Narrow Angle Camera (LRO NAC) instrument with a nominal (sunlit) spatial resolution of about 0.5 to 2 m/px. Over PSRs, NAC images are either taken with very long exposure times, resulting in low-noise but low-resolution images (10 to 40m/px), or with default exposure times, resulting in high- resolution but high-noise images (1 to 2 m/px) due to the extremely low light conditions in these regions. This means that our current ability to make meaningful observations of water-ice and related features in PSRs is strongly limited by either spatial resolution or noise.

RESULTS

- We developed a method to produce high-resolution, low-noise optical imagery over lunar PSRs. We achieved this by developing a two-stage, physics-based, deep neural network to model and remove CCD-related and photon noise in existing low-light optical imagery. We called this network HORUS (Hyper-effective nOise Removal U-net Software). HORUS operates on noisy LROC NAC PSR images and outputs denoised, analysis-ready images. On one hand, the resulting enhanced image products will enable the scientific and exploration community to perform a wide range of analyses, such as in-PSR crater counting for PSR age estimation, optimization of soil mixing models (ice depth analyses), and boulder track analyses for PSR trafficability estimation. On the other hand, HORUS-enhanced imagery will enable future ground missions to plan and execute safe and effective traverses into, around, and out of lunar PSRs —a critical step in our endeavor to explore the Moon and beyond.

Imagery inside lunar PSRs for the upcoming VIPER traverse.



FDL 2020 MOON FOR GOOD

MOON FOR GOOD II

POSTER TITLE AND RESEARCHERS

HIGH RESOLUTION IMAGERY OF LUNAR PERMANENTLY SHADOWED REGIONS

Ben Moseley, University of Oxford, Oxford, UK
Valentin Tertius Bickel, ETH Zurich/MPS, Zurich/Goettingen, CH/GER
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Loveneesh Rana, University of Luxembourg, Luxembourg, LUX

Advisory Board:
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Allison Zuñiga, NASA Ames Research Center, CA, USA
Dennis Wingo, Skycorp Inc., CA, USA

CHALLENGE

Humanity is going back to the Moon for good!

Water is a key resource for establishing and sustaining a human presence on the Moon.

Large quantities of water may be abundant at the lunar poles, specifically inside the **permanently shadowed regions (PSRs)** – topographic depressions which see no direct sunlight.

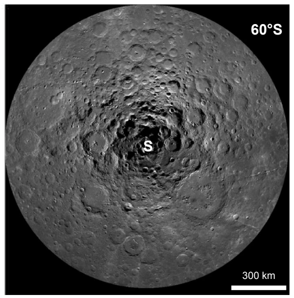
The **problem**: mission planners and scientists **struggle to understand** PSRs because existing optical imagery either contains **high levels of noise** or has low spatial resolution.

Image credit: NASA

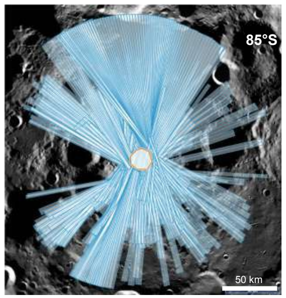
OPPORTUNITY

The Lunar Reconnaissance Orbiter Narrow Angle Camera (LRO NAC) has captured over **1.9 million high-resolution optical images** of the lunar surface over the last 10 years.

Moon's South Pole



NAC images over Shackleton crater



Example NAC image

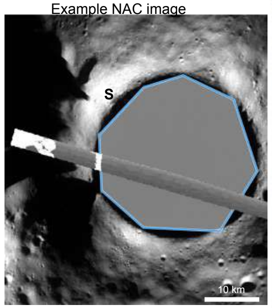


Image credits: LROC/ASU/QuickMap

Our vision: produce denoised, high-resolution NAC images of lunar PSRs by applying **state of the art machine learning** techniques

Google Cloud Platform

We utilized:

- 100 CPU cores
- 8 GPUs
- 10 TB storage

Noise formation model for CCD sensor

We assume that an image captured by the LRO NAC can be formulated as:

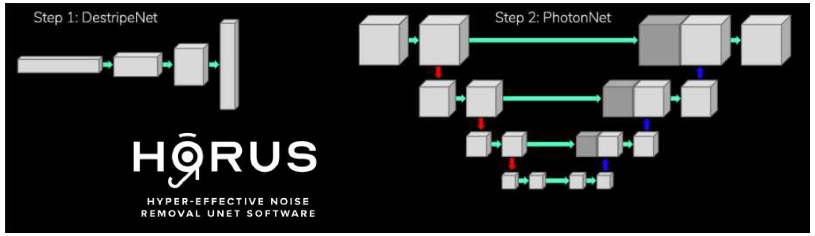
$$I = S + N_p + N_d + N_r + N_b$$

where I is the EDR raw image, S is the surface mean signal, N_p the photon noise (Poisson-distributed), N_d is the dark noise (Poisson-distributed), N_r the readout noise and N_b is the dark bias.

OUTCOME

SOLUTION

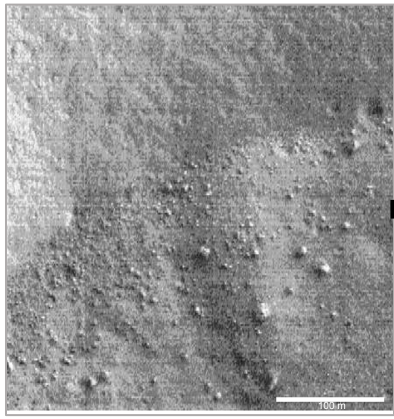
HORUS (Hyper-effective nOise Removal U-net Software) is a two-stage machine learning routine that first removes the **dark bias** using a **convolutional decoder network** (DestripeNet) and then removes **photon noise** with a state-of-the-art **U-Net** architecture (PhotonNet)**.**



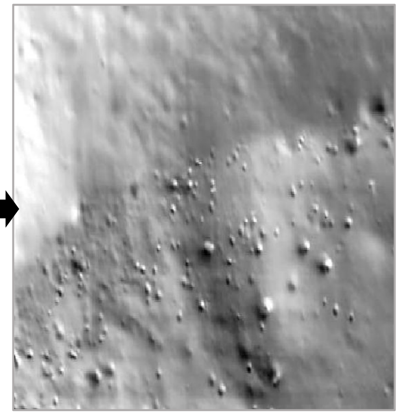
RESULTS

We **successfully removed** noise from high-resolution low-light raw PSR NAC imagery.

Raw NAC EDR image | Wapowski crater (82.9°S 53.5°E)



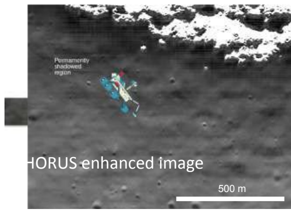
Our result (HORUS)



OUTLOOK & NEXT STEPS

A key application of our approach is **traverse planning**: enabling future rovers to navigate reliably into, through, and out of PSRs.

Our method can also benefit other science and exploration applications such as: **crater counting**, **boulder track analyses**, and **geomorphological mapping**. We are currently running additional analyses to further validate our results.



PLANETARY SCIENCE CHALLENGE 1

UPSCALING LUNAR RESOURCES

Boosting ground-based exploration & empowering lunar science

Before they can return to the Moon for Good, future missions have to answer a number of fundamental and strategic questions: Where can we land? Where are potential science targets? How do we get there safely? Their best source of information are high resolution images that reveal small boulders, craters, and other features on the surface. Unfortunately, only a fraction of the lunar surface is covered by high resolution images. However, there are plenty of intermediate resolution images available. We propose to use machine learning-driven techniques to super-resolve intermediate to high resolution images. The improved images could have substantial value for lunar science and the imminent exploration of the Moon.

Google Cloud SPACE RESOURCES.LU LUXEMBOURG SPACE AGENCY TRILLIUM TECH

FDL 2021
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Luxembourg Talent

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FDL 2021
FACULTY

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University of Oxford

SIDDHA GANJU
Nvidia

‘Worldfloods’ on Wild Ride - “Dauntless David”

Sample Release for Social

#ESA #ESA_EO #AI4EO #FDLeurope #phi-lab #D-Orbit #Unibap #spacecloud

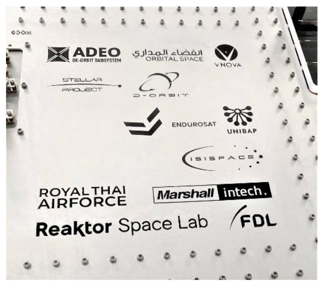
FDLeurope (fdleurope.org) supported by the ESA’s Φ-lab in ESRIN announces the deployment of a proof-of-concept “Machine Learning (ML) payload” on D-Orbit’s upcoming ‘Wild Ride’ mission being launched by SpaceX’s Falcon 9 on June 25th 2021 from Cape Canaveral.

The ML payload, called ‘Worldfloods’, will leverage ML techniques to rapidly send to the ground a **segmentation map** of Earth Observation (EO) images acquired in Low Earth Orbit (LEO) indicating classes such as water, land and cloud. Guy Schumann (founder of RSS-Hydro, an accredited private R&D institute in Luxembourg) and Dietmar Backes (University of Luxembourg) both mentored the Worldfloods team during FDL Europe 2019, the team devised a generalised model for prediciting the liklihood of a flood even (and moment of peak (flood height) after a known rainfull.

Worldfloods is testing the potential of how ML derived **flood maps anywhere on Earth** can be sent to emergency responders rapidly after image acquisition via technologies such as Nebula, an on-demand, on-orbit cloud computing and data storage service being developed by D-Orbit UK, which features Unibap’s SpaceCloud iX5-100 radiation tolerant computing module.

Worldfloods powered by Nebula offers a glimpse of a future where **rapid insight** is delivered in real-time to users from space. Demonstrating this functionality on the D-Orbit Wild Ride mission in LEO is the first step to automating satellite cooperation, ML payloads and hybrid solutions that amplify the utility of existing Copernicus resources.

Worldfloods, was developed by FDLeurope, a partnership with the University of Oxford, Trillium Technologies, ESA Φ-lab and leaders in commercial AI, such as Google Cloud and Intel.



FDL IN NUMBERS

5 YEARS

8 RESEARCH SPRINTS

5 NASA
3 ESA

7 BIG THINKS

1,204 applicants

257 in 2021

<5% ACCEPTANCE RATE ('18/19)

SIMILAR ACCEPTANCE RATE TO MIT

3 SPACE AGENCY PARTNERS

NASA
esa
LSA LUXEMBOURG SPACE AGENCY

18 PARTNERS

Google Cloud
intel
Lockheed Martin
IBM
USGS
nVIDIA
planet
AIRBUS
Berkeley Lab
University of Oxford
Microsoft
Catapult
Mayo Clinic
SR
MIT Portugal
Institute for Simulation Intelligence

1500
FDL COMMUNITY & ALUMS
100+ active

37 MACHINE LEARNING WORKFLOWS

10 ENHANCED DATA PRODUCTS
(To be made public)

29% Women (Industry average: 22%)

33% Ethnic Minorities

50/50
US / International split
FDL USA

152
RESEARCHER ALUMNI
(Phd and Post-Doc)

633 IN PARTNER REVIEWER COMMUNITY
25 UNIVERSITIES

37 RESEARCH PROJECTS

#1 PAPER ON ARXIV IN SPACE PHYSICS
09.08.2019

BEST PAPER AT NEURIPS CLIMATE CHANGE & AI WORKSHOP
2019

$2.8m USD COMPUTE
(partner-in-kind)

41 CORE MENTORS **97** GUEST EXPERTS

30+ SCIENTIFIC & AI CONFERENCES

PAPERS PRESENTED AT

12 NEURIPS WORKSHOPS 2019
6 AGU 2019

60+ BLOGS & ARTICLES

NewScientist
Scientific American
TechCrunch
Fast Company
NASA

2 DOCUMENTARIES
(JapanTV / "Age of AI")

1 TOP 30 AI PRESENATIONS 2019
RE-WORK FEATURE

THE FDL EXPERIENCE

FDL is an interdisciplinary Ph.D. / Post doc level research program. The central value is that subject experts - with deep knowledge of the problem domain, can develop AI enhanced work-flows and solutions with peers from the data sciences. The format's emphasis on rapid iteration and prototyping ensures a high success rate.

The FDL format blends the expertise and capacity of academia and commercial partners to support rapid experimentation in building AI inference models in data intensive areas. The special sauce is its interdisciplinary research teams, which are composed of subject specialists from the space sciences and specialists from the data sciences at the Ph.D. or post doc level.

Each team comprises of four researchers working closely with two world class faculty - experts in the fields of space science and AI. FDL faculty help teams to drive to excellence and problem solve; they act as critical friends and enable teams to vault some of the challenges the sprint method generates.

FDL is about enabling researchers and faculty to do some of the best work of their careers and draws heavily on a broader network. It is supported by dozens of people and organisations providing reviews, unlocking data sources, giving practical insights on problem definition and deployment. They are drawn from academic, commercial and not for profit settings that delivers a network for participants that lasts far beyond the eight weeks of the sprint.

"NASA gathers approximately 2 gigabytes of data every 15 seconds from over 100 currently active missions! We do this every hour, every day, every year – and the collection rate is growing exponentially with its volume and complexity. Data is one of our most valuable assets and its strategic importance in our research and science is huge. We human are wired to make sense of a three dimensional world, four if you include time series. So if the exploration and discovery involved finding anomalies and patterns that criss-cross 25 dimensions of multivariant data, AI systems are showing great value.

Take the problem of predicting solar events and their geoeffectiveness: the system is so complex, and yet the intuition is that buried within the churning data features that make up the Sun's dynamics are a multitude of hints that, when stitched together, may give us the predictive foothold we are seeking. And that is what FDL is making possible!"

Madhulika (Lika) Guhathakurta, PhD
On Detail at NASA Ames Research Center Program
Scientist/Heliophysics

FROM OUR PARTNERS

"The Luxembourg Space Agency is really looking forward to the results of this year's FDL Challenge focused on lunar resource mapping. Using data fusion and super-resolution techniques will better prepare future lunar prospectors to locate valuable space resources."

DR. MARC SERRES,
CEO OF THE LUXEMBOURG SPACE AGENCY

"Google Cloud is thrilled to support NASA FDL's deployment of AI to help solve humanity's biggest challenges. We believe it is essential to deploy AI responsibly, to push the frontiers of human knowledge, realize its broad benefits, and empower current and future generations. We are honored that our technology and innovation will be used to support these efforts for the common good. "

ANDREW MOORE, HEAD OF GOOGLE CLOUD AI

"FDL is a tremendous opportunity to contribute to a universe-class scientific mission and help launch NASA into the AI race. Intel with FDL will help strengthen an amazing space program using our technologies and expertise. We're doing this because these are very hard problems that require industries to cooperate on solutions."

SHASHI JAIN, INNOVATION MANAGER INTEL

"At FDL we apply AI to supercharge our ability to monitor and predict the Sun and space weather."

MARK CHEUNG,STAFF PHYSICIST AT LOCKHEED MARTIN
AND PRINCIPAL INVESTIGATOR FOR NASA SOLAR DYNAMICS OBSERVATORY / ATMOSPHERIC IMAGING ASSEMBLY

"The Canadian Space Agency (CSA) is excited to join this year's NASA FDL program and contribute to the Astronaut health challenge. Artificial intelligence will play an important role in enabling future deep space exploration missions;as we are witnessing the promises it has to offer, we, along with the global space community, are eager to discover new solutions and approaches that the FDL participants will develop. The CSA looks forward to the outcomes of this year's FDL challenges."

MARIE-CLAUDE GUÉRARD,DIRECTOR GENERAL,
SPACE SCIENCE AND TECHNOLOGY, CANADIAN SPACE AGENCY

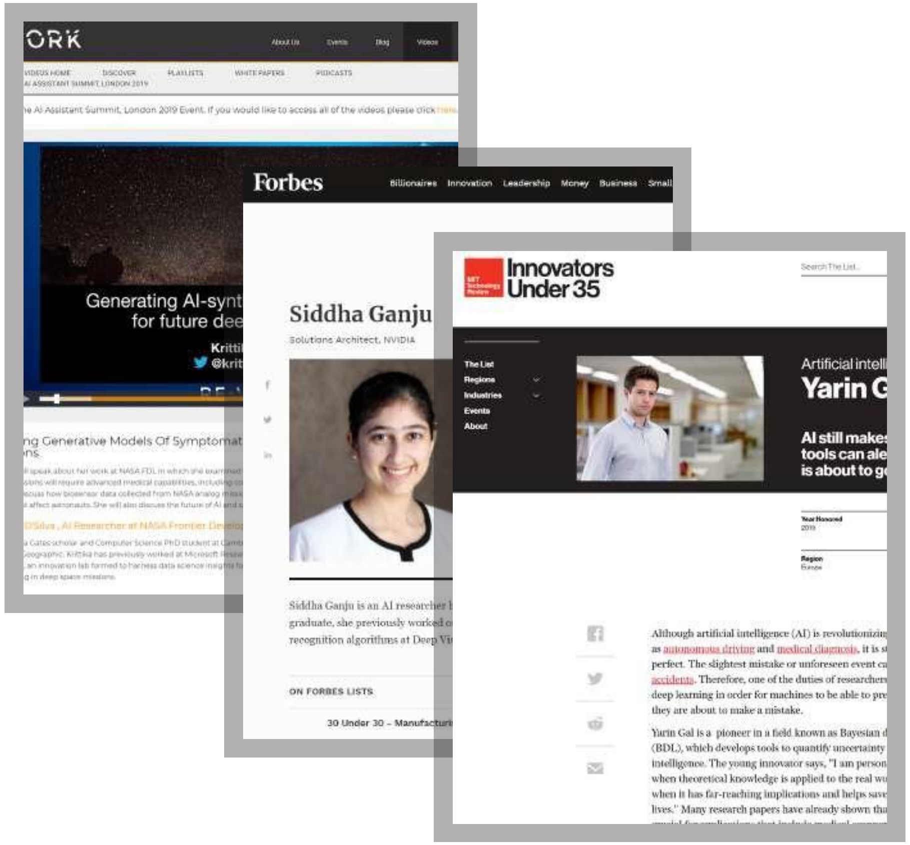
"NVIDIA is proud to have been one of 'the Mavericks', at the inception of the Frontier Development Laboratory. Our headquarter is named Endeavor and its companion will be Voyager - mighty ships for our journey to the stars.

We are delighted to support the FDL as we push the frontiers for the human race."

JEN-HSUN HUANG, PRESIDENT & CEO,
NVIDIA CORPORATION

"IBM is excited to be a sponsor of the Frontier Development Lab and to participate in the innovative progress being made in the application of artificial intelligence technology to space science problems. Maintaining leadership in emerging technologies, such as Deep Learning and quantum computing, is central to IBM's strategy, so working with the FDL researchers to tackle problems with demanding computing requirements is a natural fit; it helps IBM to push the boundaries of our tools and validate our commercial solutions for the broader market. Moreover, the scientific objectives of the FDL program are intuitively inspiring, such as improving our understanding of environmental trends and solving problems which are critical to the success of humanity's exploration of space. These goals are well aligned with IBM's long and principled history of playing a central role in innovation that matters to society. We look forward to seeing the FDL program continue to expand in both scope and impact."

MAC DEVINE, VICE PRESIDENT & CTO,
IBM WATSON CLOUD DIVISION, IBM CORPORATION

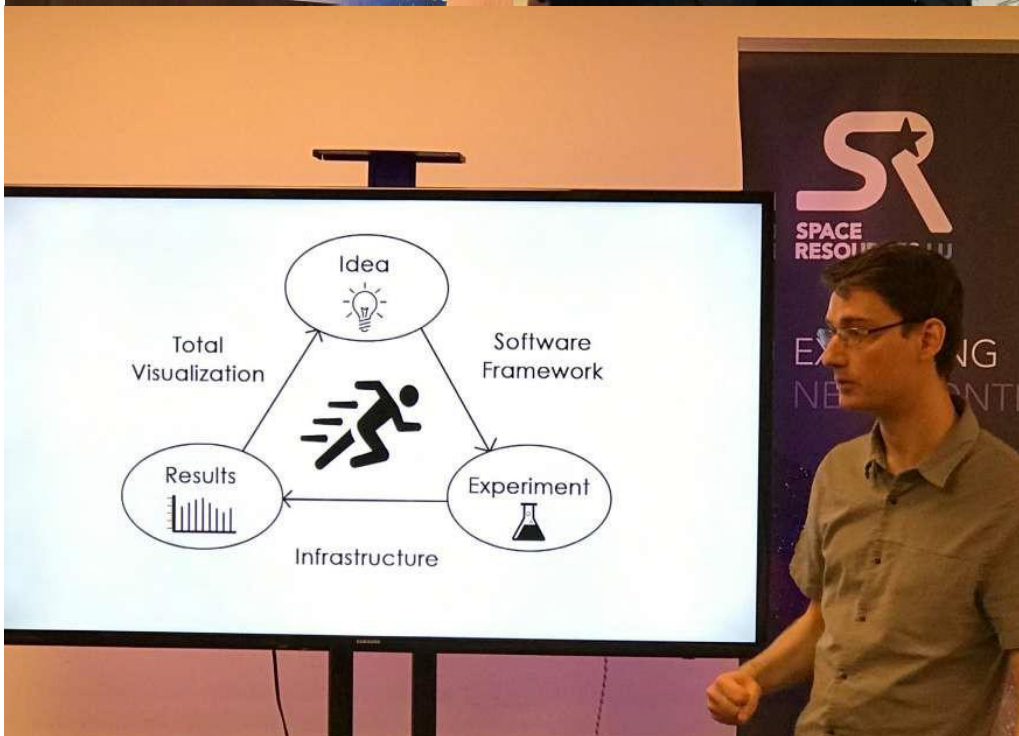


FDL RESEARCHERS & MENTORS FEATURED

RE-WORK 30 Influencial AI Presentations from 2019
Astronaut Health by FDL Researcher Krittika D'Silva

Forbes 30 under 30 Manufacturing & Industry 2019
FDL mentor Siddah Ganju

MIT Technology Review Innovators Under 35
FDL mentor Yarin Gal



Google's François Chollet (inventor of the Keras.io framework) explains the relationship between ideas, experimentation and results
- and the value of rapid iteration.

PARTNER

FRONTIER DEVELOPMENT LAB

LUXEMBOURG SPACE AGENCY

2017-2021

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TRILLIUM TECH