Machine Learning in Space

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University of Oxford Space Tech Conference
7 Nov 2023

UNIVERSITY OF OXFORD

Outline

- About
- Frontier Development Lab (NASA, ESA, Oxford)
- Machine learning and space
    - Case I: constellations and collision avoidance
    - Case II: thermospheric density estimation
- Machine learning onboard spacecraft
    - Case III: flood detection from space, ML in Low Earth Orbit
    - Case IV: measuring molecular complexity, ML onboard robotic missions
- Community

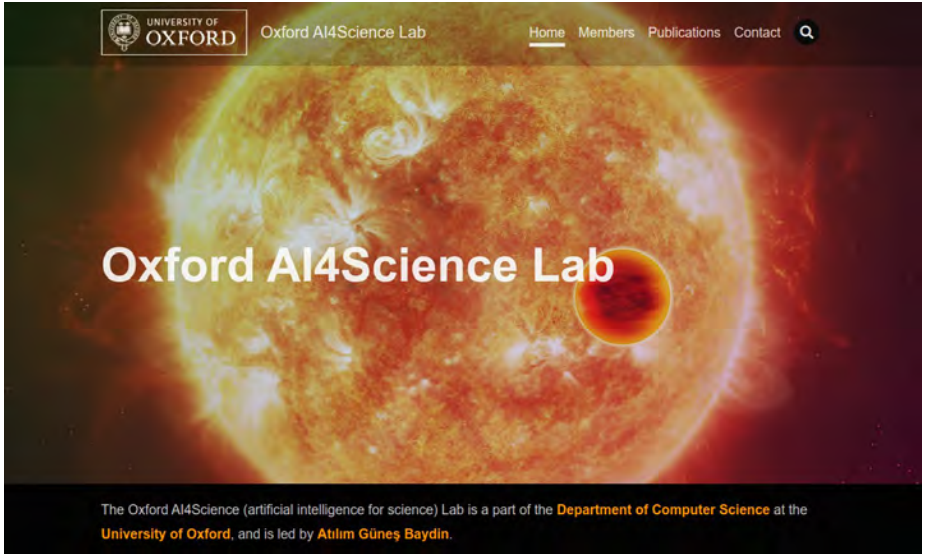
Atılım Güneş Baydin

Departmental Lecturer in Machine Learning, Department of Computer Science

UNIVERSITY OF OXFORD

Oxford AI4Science (Artificial Intelligence for Science) Lab

https://oxai4science.github.io



- Specializing in **probabilistic machine learning and scientific discovery**
- Working with experts in high-energy physics, heliophysics, astrobiology, Earth science, space safety and other disciplines
- Solve challenging problems through application and development of AI methods

Collaborators at:

CERN NASA esa BERKELEY LAB SLAC NATIONAL ACCELERATOR LABORATORY Microsoft

Frontier Development Lab
NASA, ESA, Oxford

Frontier Development Lab

https://fdl.ai

- A research accelerator for state-of-the-art ML and space sciences
- Two main versions
  - NASA Ames & SETI Institute (FDL US)
  - ESA & University of Oxford (FDL Europe)
- Access to compute provided by industry (Google, Intel, Nvidia and others)
- Teams of
  - PhD students / postdocs (two machine learning, two domain science)
  - supervising faculty


NASA
AMES RESEARCH CENTER
NASA RESEARCH PARK

esa
Buildings 1 - 2 - 3 - 4 - 5 - 12 - 14
Buildings 6 - 7 (Magazzino - Store)
Building 8
Buildings 9 - 10 - 11
Reception
Parking
Building 15 Child Care - Sport Facilities

Heliophysics System Observatory

FDL
FDL

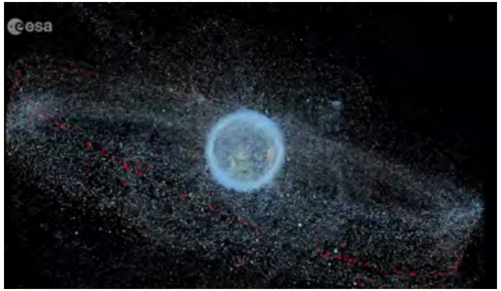
Machine learning and space

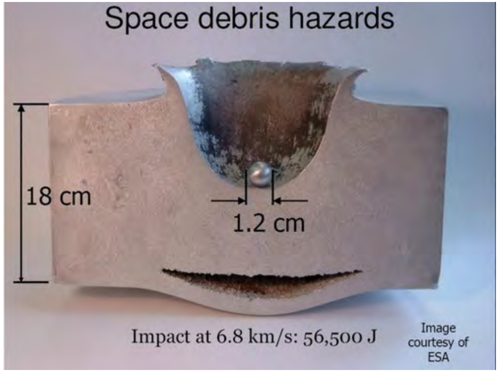
CASE I

ML for spacecraft collision avoidance

Low Earth orbit (LEO) has millions of uncontrolled objects (~1cm) at ~28,000 km/h orbital speeds

- **Kessler Syndrome:** chain reaction of collisions can pollute the orbit and render it inaccessible
- Danger to satellites, scientific missions, future human access
- Large constellations, e.g., SpaceX StarLink (40k), OneWeb and rapidly increasing commercial space activities contribute to the problem





Acciarini, Pinto, Metz, Boufelja, Kaczmarek, Merz, Martinez-Heras, Letizia, Bridges, **Baydin** *"Kessler: a Machine Learning Library for Space Collision Avoidance"* **8th European Conference on Space Debris 2021**

Pinto, Acciarini, Metz, Boufelja, Kaczmarek, Merz, Martinez-Heras, Letizia, Bridges, **Baydin** *"Towards Automated Satellite Conjunction Management with Bayesian Deep Learning"* **AI Earth Sci Workshop, NeurIPS 2020**

Acciarini, Pinto, Metz, Boufelja, Kaczmarek, Merz, Martinez-Heras, Letizia, Bridges, **Baydin** "Spacecraft Collision Risk Assessment with Probabilistic Programming" **ML4PS workshop, NeurIPS 2020**

ML for spacecraft collision avoidance

Worked with ESA Space Debris Office to
automate risk assessment and maneuver decisions

- Working with conjunction data messages (CDMs)
- Probabilistic programming with physical orbit simulators that generate scenarios and synthetic CDMs
- Bayesian deep learning to predict event evolution as a sequence of CDMs

KESSLER

https://github.com/kesslerlib

Named after Donald J. Kessler

PyProb PyTorch

Funding: ESA ESRIN / PhiLab, Google Cloud
Funding: UK Space Agency (£250k, with Surrey Space Centre and Cranfield)

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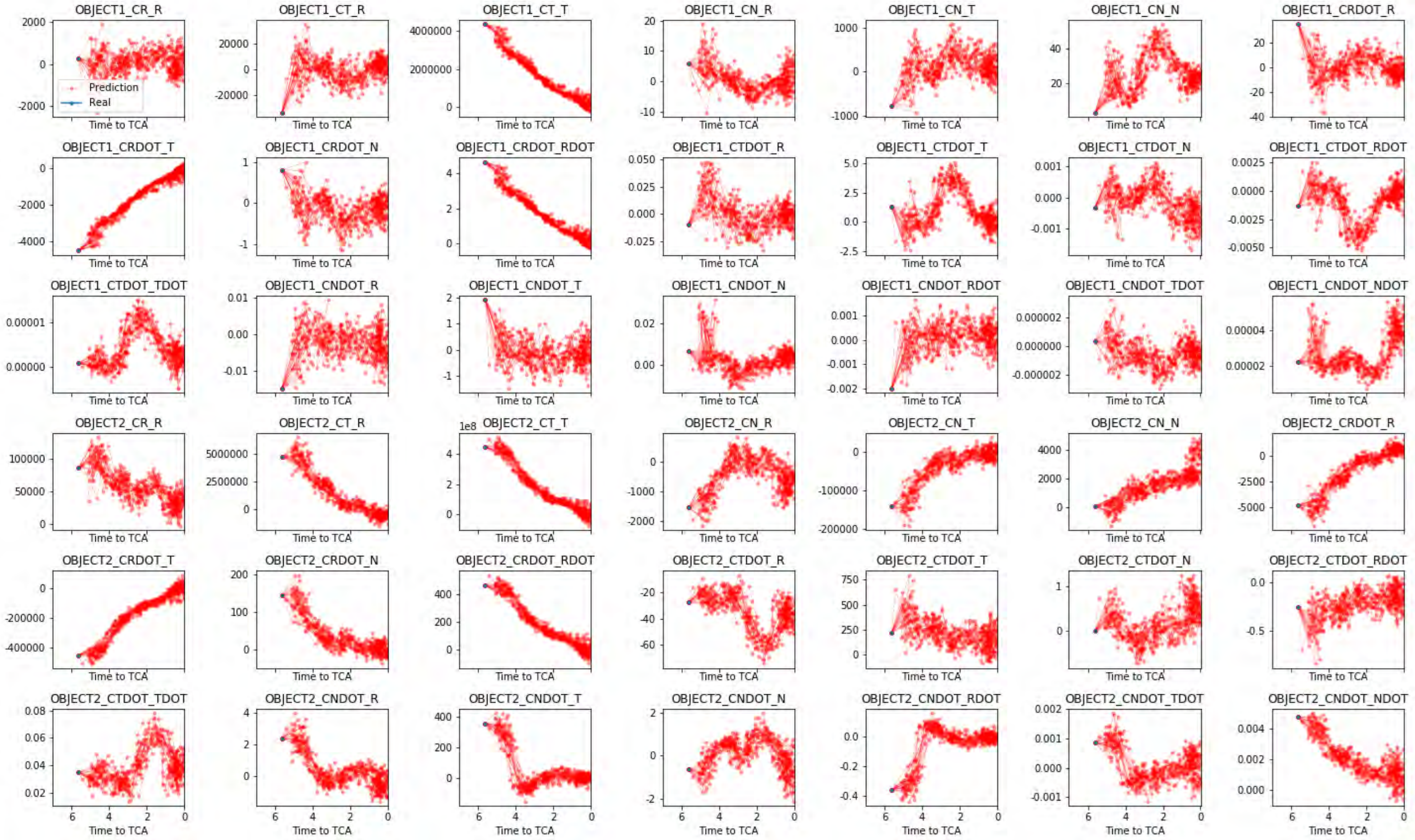
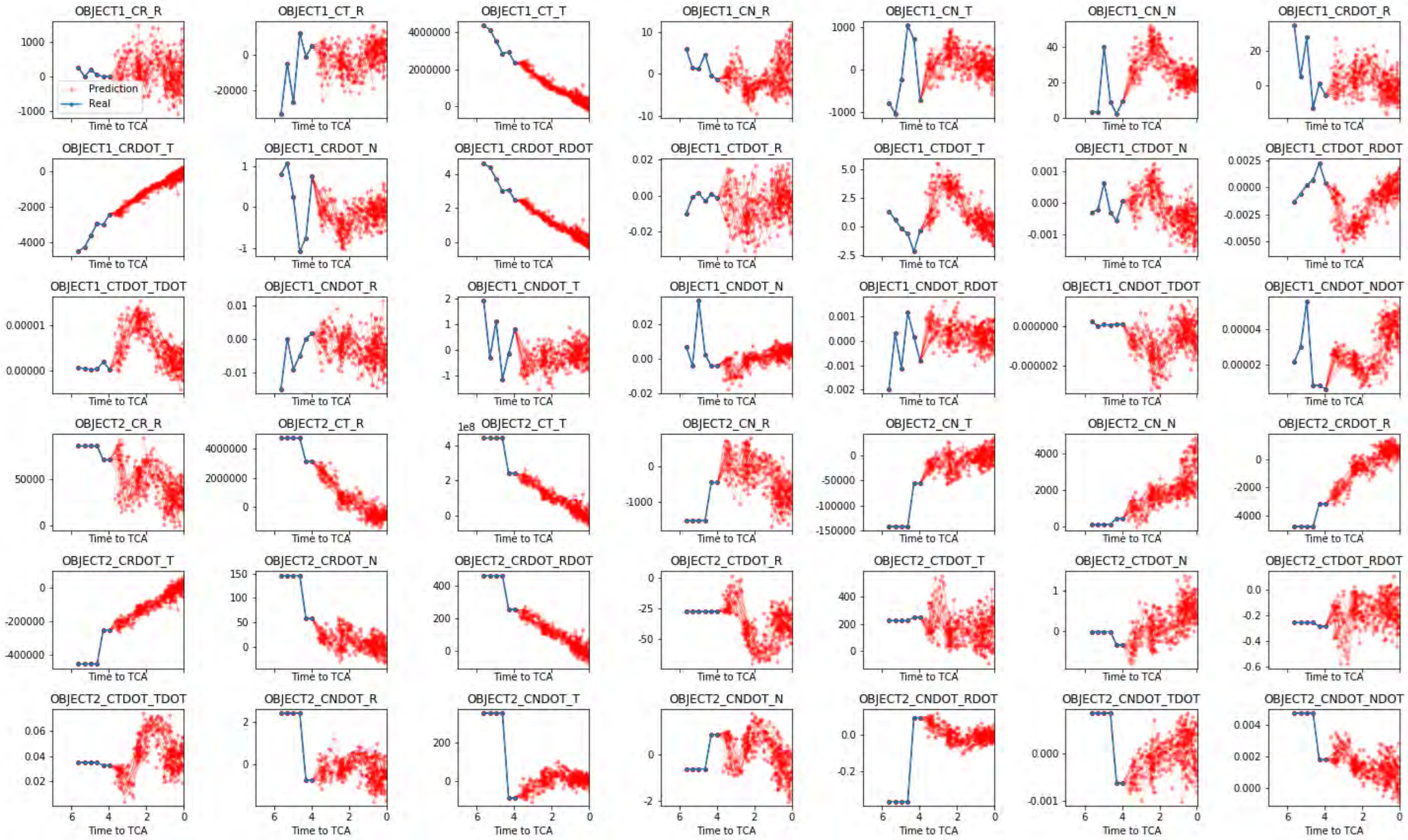


FDL FRONTIER DEVELOPMENT LAB · esa · Google Cloud · NVIDIA · SCAN · IBM · AIRBUS · planet. · IWMI · CATAPULT · UNIVERSITY OF OXFORD · TRILLIUM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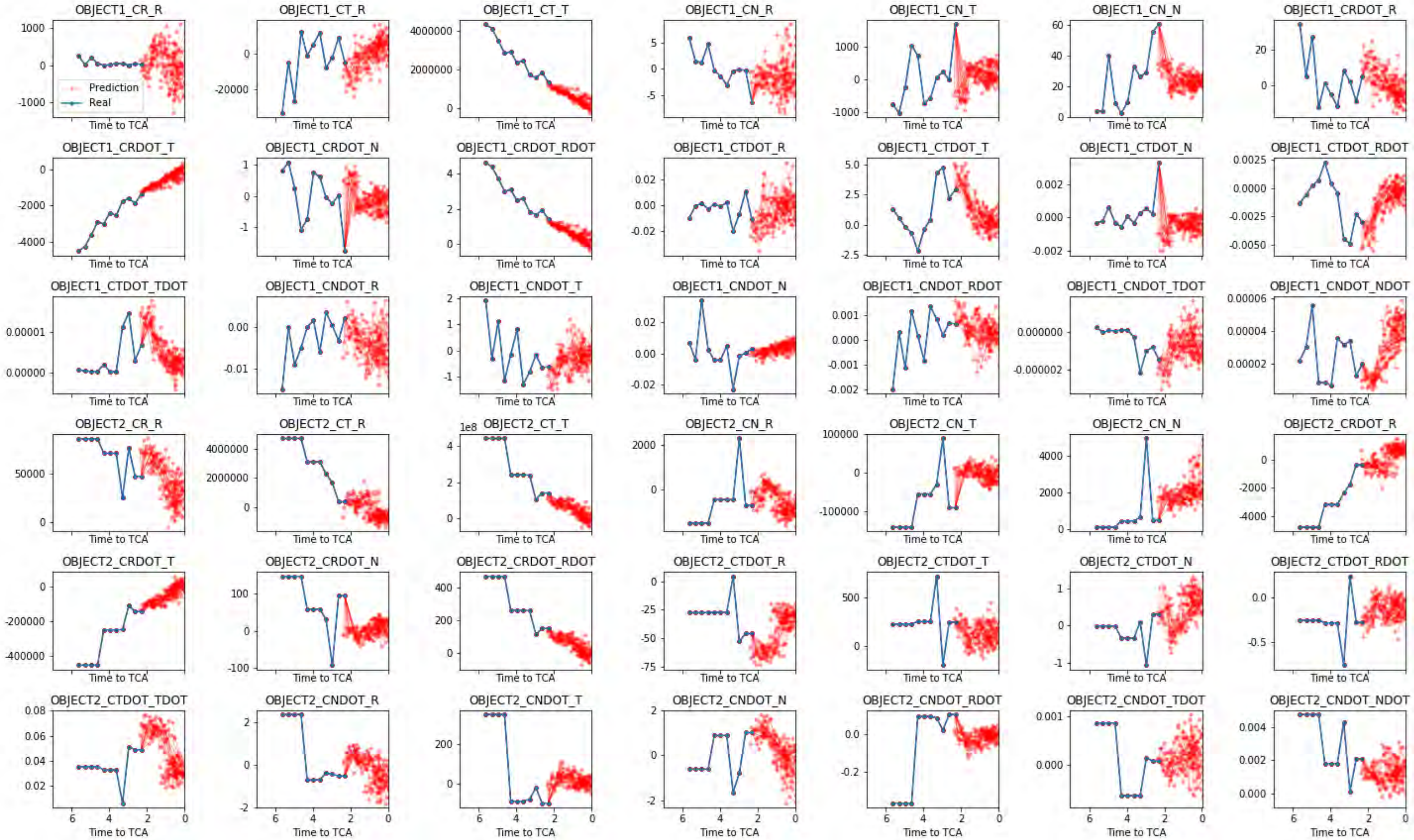
Prediction
Real
Time to TCA
1e8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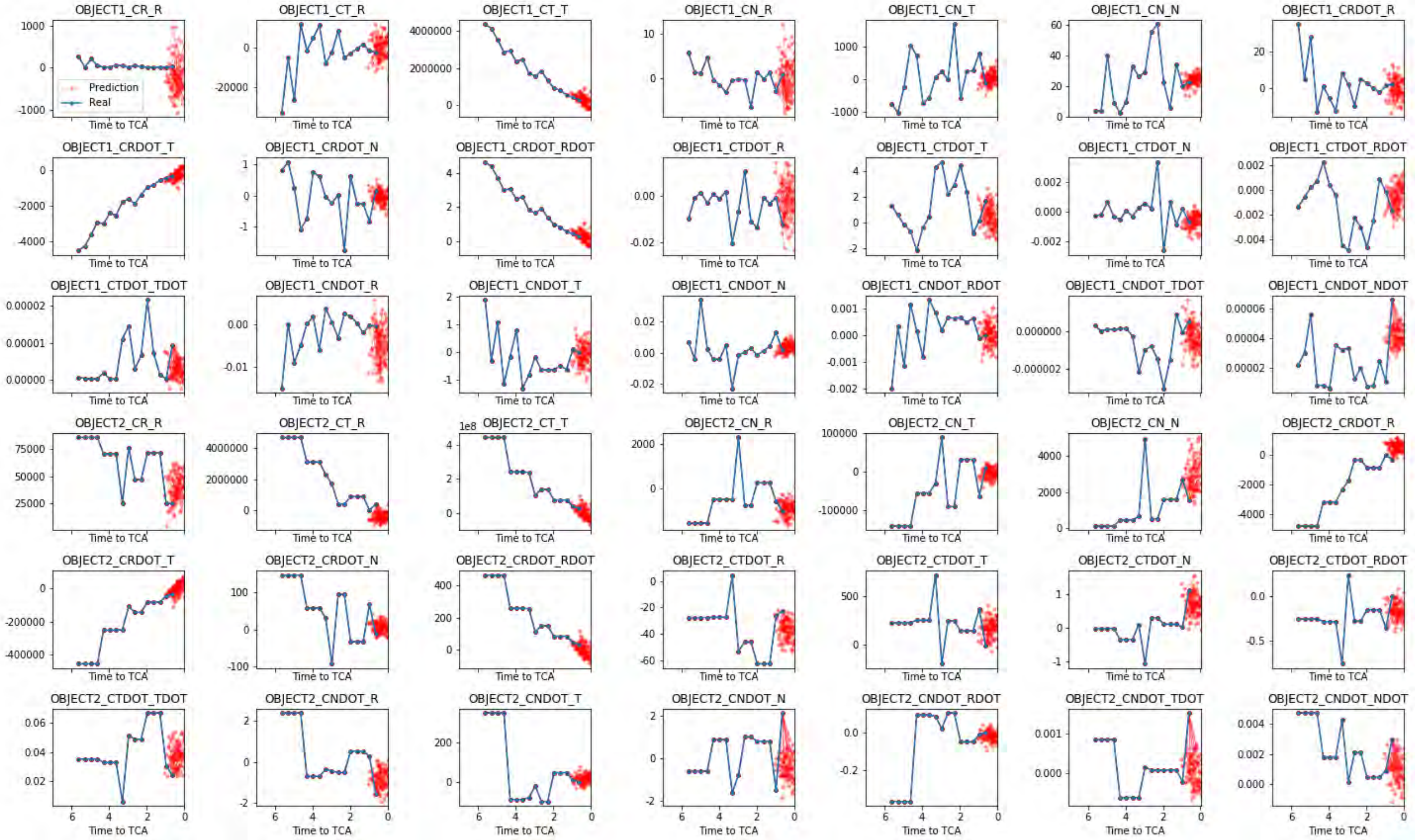
Prediction
Real
Time to TCA



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Prediction
Real
Time to TCA


CASE II

Thermospheric density estimation using machine learning

Thermospheric density models are **a key ingredient in mission planning and operations** in Earth orbit

- Orbital motion is affected by gravity and non-gravitational perturbations (drag)
- **Thermospheric density** is a major component of drag, affected by solar activity
- Current models are not accurate, computationally expensive**,** based on **proxies** for of solar activity (solar irradiance *F10.7*, geomagnetic indices *ap*, *Kp*)

Work requested by NASA SMD to develop **benchmarks of thermospheric density estimation** using ML with direct solar data from in-orbit instruments (NASA SDO)

Funding: NASA SMD Heliophysics Division

NEWS

Home | Cost of Living | War in Ukraine | Coronavirus | Climate | UK | World | Business | Politics | Tech | Science

World | Africa | Asia | Australia | Europe | Latin America | Middle East | US & Canada

SpaceX loses 40 satellites to geomagnetic storm a day after launch

9 February

GETTY IMAGES

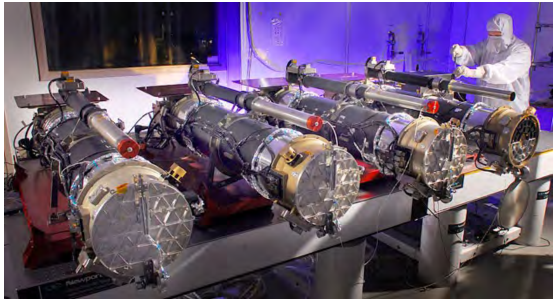
This Falcon 9 rocket launch on 3 February carried 49 Starlink satellites, most of which were caught by the storm

SpaceX has lost dozens of satellites after they were hit by a geomagnetic storm a day after launch, causing them to fall from orbit and burn up.

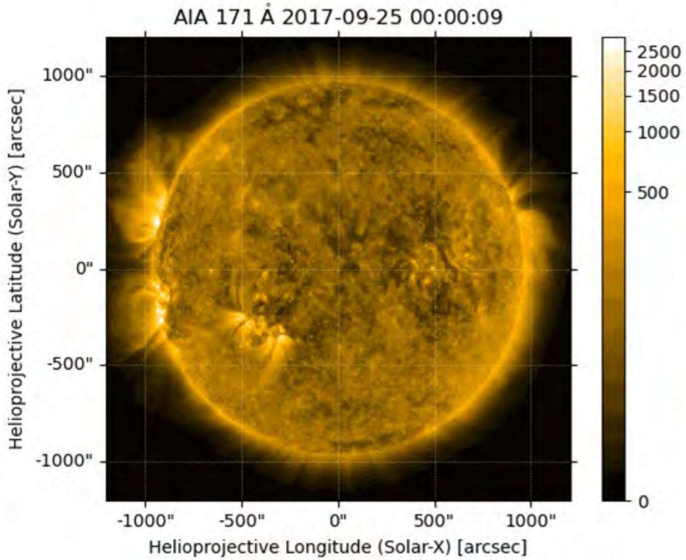
Such solar "storms" are caused by powerful explosions on the sun's surface.

Thermospheric Density Estimation

- State-of-the-art thermospheric models governed by **on-ground irradiance proxies/geomagnetic indices**
    - *F10.7* → Solar irradiance
    - *ap, Kp* → Geomagnetic field
- Solar data available from **in-orbit instruments such as the Solar Dynamics Observatory (SDO)**
- Curated solar data available (SDOML dataset)
- Machine learning techniques can leverage data to
    - Improve and forecast solar proxies
    - Generate surrogate atmospheric models
    - Drive knowledge discovery for other planets/moons

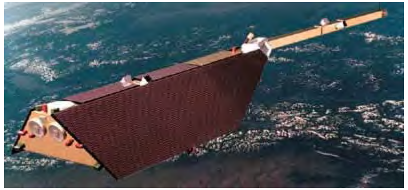


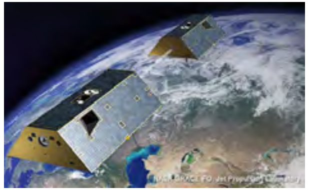
SDO AIA instrument

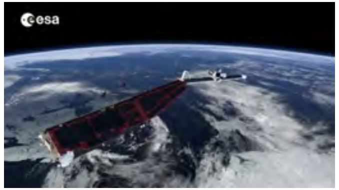


Thermospheric Density Estimation: Combining Data from Multiple Missions

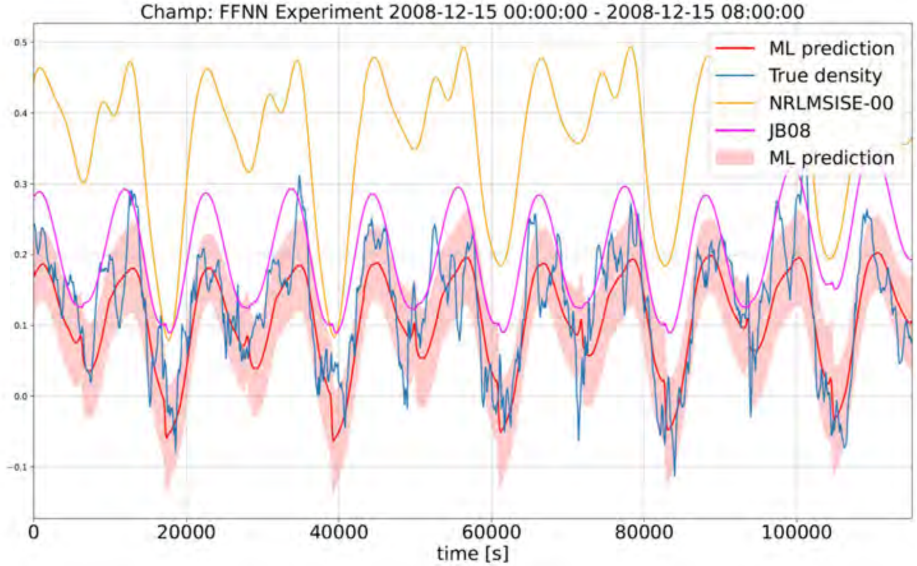
Trained with ground truth data from
- CHAMP
- GRACE
- Swarm A - B
- GOCE

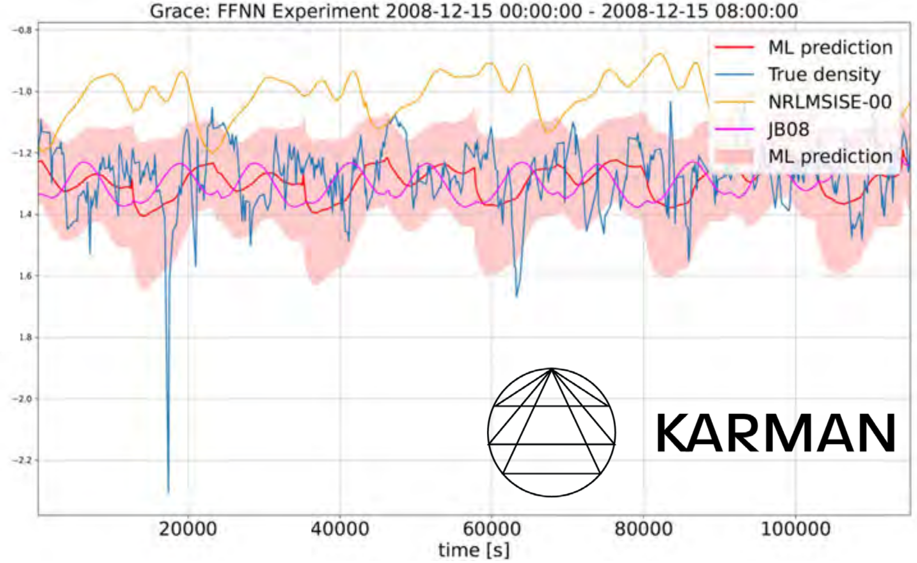

CHAMP (GFZ), 2001 - 2010


GRACE (NASA), 2002 - 2009


Swarm (ESA), 2013 - 2021

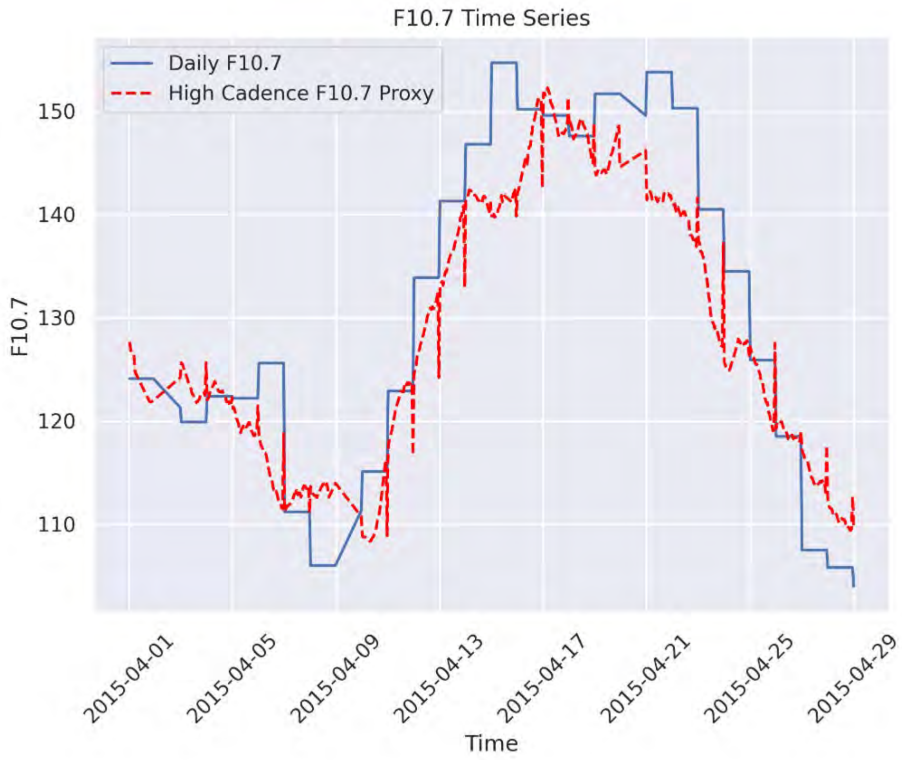

GOCE (ESA), 2010 - 2013





KARMAN

Key Result:
ML-informed replication of F10.7 at **higher cadence.**



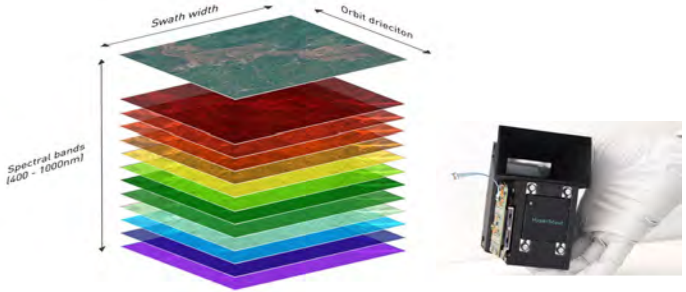
Machine learning on board

SpaceX Transporter 2 launch,
30 June 2021

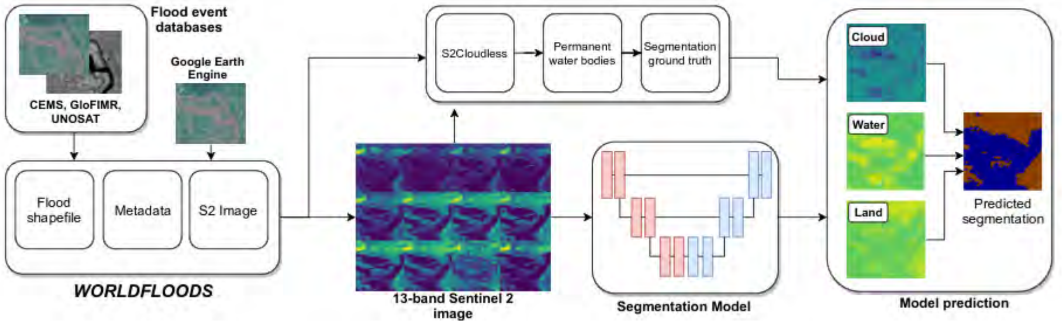
CASE III

Deploying ML in space

- CubeSats can provide affordable **disaster response at a fraction of cost of larger missions**, making it accessible to developing countries
- Perform **flood segmentation onboard satellite** to reduce downlinked data, using weight-quantized U-nets and convolutional neural networks



50-band hyperspectral camera



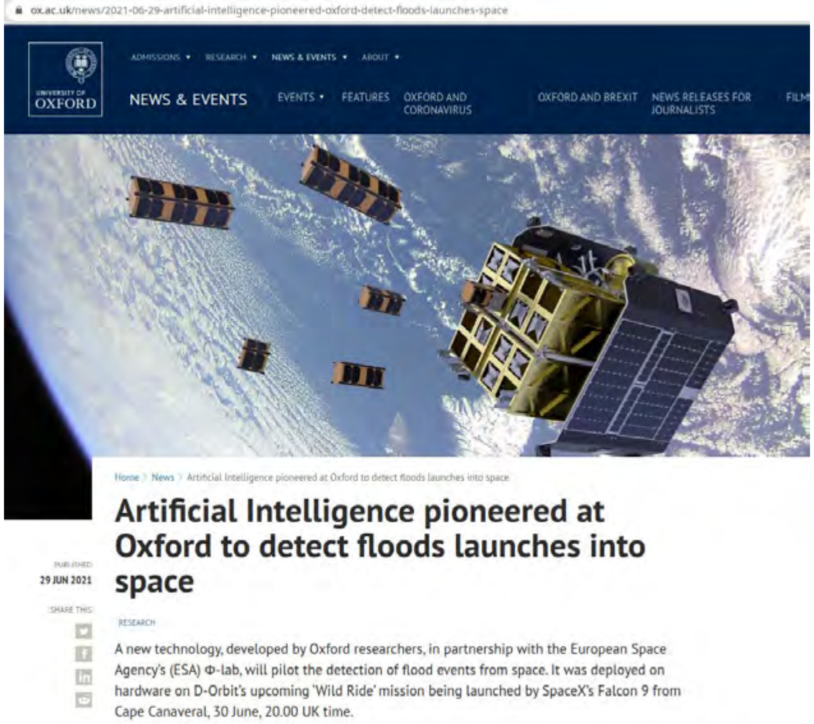
Mateo-Garcia, Veitch-Michaelis, Smith, Oprea, Schumann, Gal, **Baydin**, Backes *"Towards Global Flood Mapping Onboard Low Cost Satellites with Machine Learning"* **Scientific Reports 2021** (in press)

Mateo-Garcia, Oprea, Smith, Veitch-Michaelis, **Baydin**, Backes "Flood Detection On Low Cost Orbital Hardware." **AI for Humanitarian Assistance and Disaster Response Workshop, NeurIPS 2019**

Deploying ML in space

Worked with ESA Centre for Earth Observation (ESRIN)

- Originally targeted the PhiSat-1 (Sep 2020)
- **First step:** demonstrated feasibility on Intel hardware (Movidius ML accelerator) identical with the one on board satellite
- **Second step:** Pilot the detection of flood events from space on **D-Orbit**'s Wild Ride mission
- Successfully **launched on SpaceX Transporter-2 Mission**, 30 June 2021



https://www.ox.ac.uk/news/2021-06-29-artificial-intelligence-pioneered-oxford-detect-floods-launches-space

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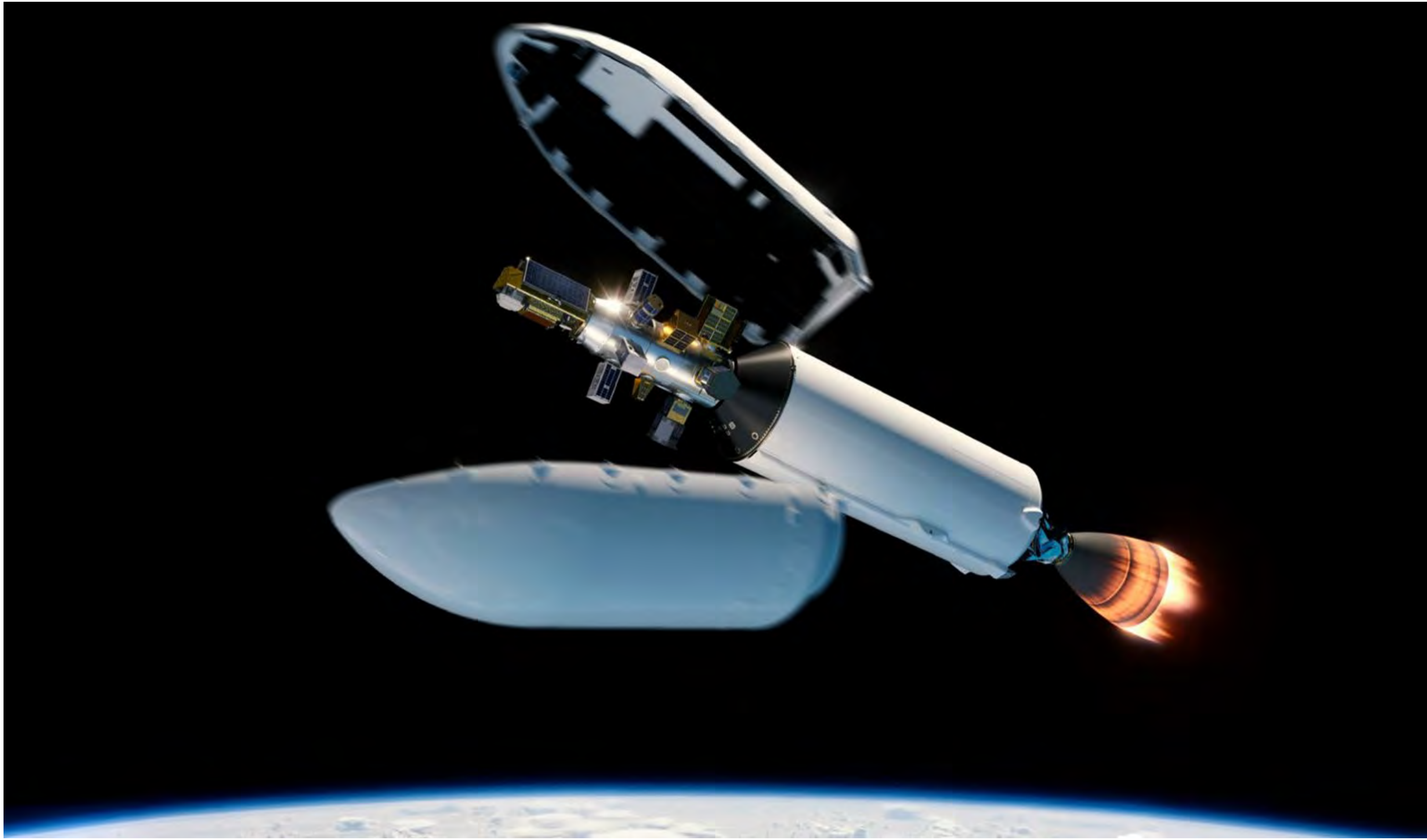
“Transporter 2”



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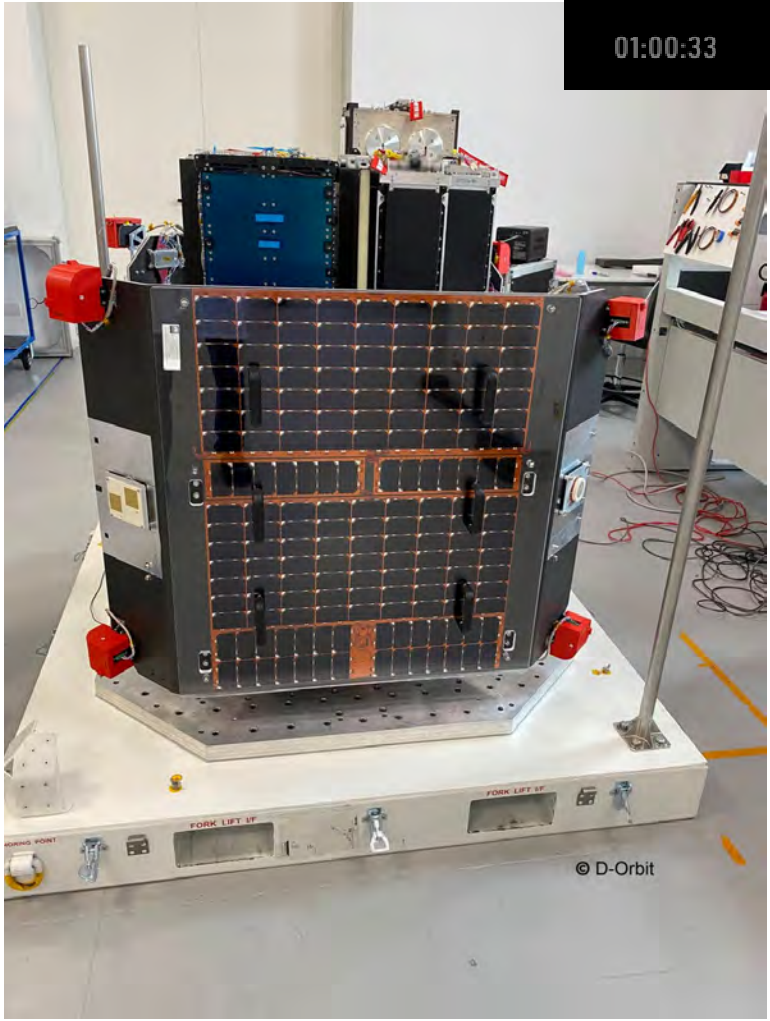
ION Satellite Carrier



01:00:33 D-Orbit's ION satellite carrier deploys

FDL FRONTIER DEVELOPMENT LAB

D-ORBIT

“Transporter 2”

“Transporter 2”

SpaceX Falcon 9 rocket.

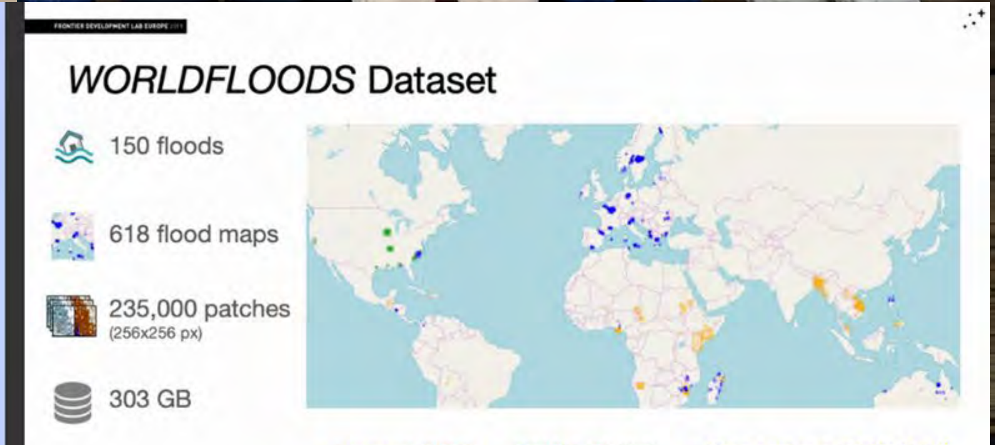
Space Launch Complex 40 (SLC-40)


U.S. SPACE FORCE
Cape Canaveral Space Force Station
WARNING
HELIUM GAS
PIPELINE


LC-39B
LC-39C
LC-39A
LC-48
SLC-41
SLC-40
LC-47
SLC-37
LC-34
LC-20
LC-19
LC-16
LC-15
LC-14
LZ-1 & LZ-2
LC-12
LC-11
LC-36
LC-1,2,3,4
LC-21,22
LC-46
Lighthouse
LC-31,32,10
LC-18
SLC-17
LC-26 (Museum)
LC-5,6
LC-30
LC-25
LC-29
Skid Strip
Port
Canaveral


Flood Detection On Low Cost Orbital Hardware
esa
FDL


FDL
EUROPE


FRONTIER DEVELOPMENT LAB EUROPE 2019
WORLDFLOODS Dataset
150 floods
618 flood maps
235,000 patches
(256x256 px)
303 GB

'Worldfloods' on Wild Ride - "Dauntless David"

Sample Release for Social

#ESA #ESA_EO #AI4EO #FDLeurope #phlab #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.

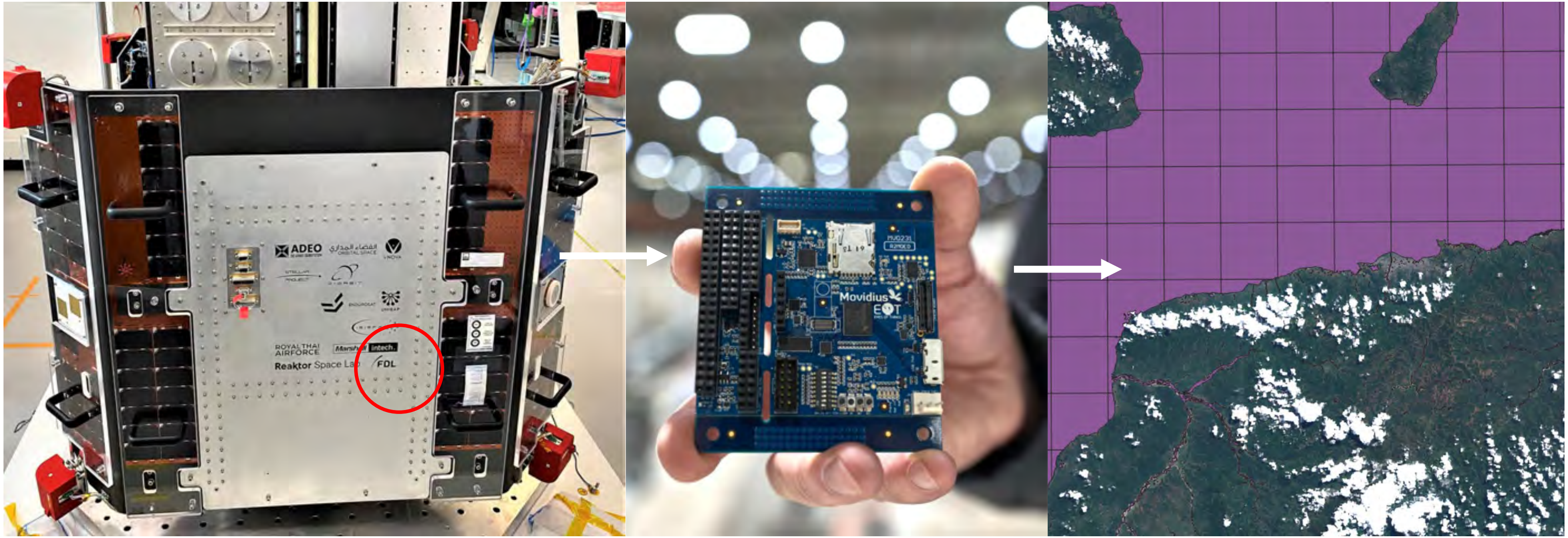
Worldfloods is testing the potential of how ML derived **flood maps anywhere on Earth** can be sent to emergency responders rapidly after image acquisition via technologies such as Nebula, an on-demand, on-orbit cloud computing and data storage service being developed by D-Orbit UK, which features Unibap's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

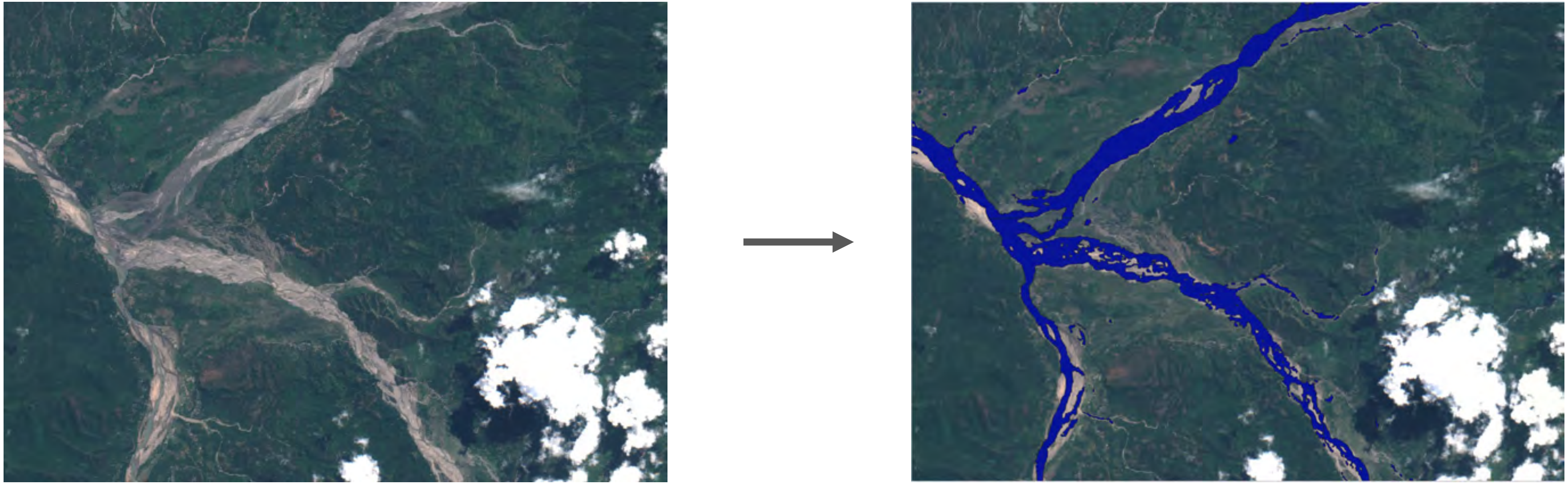
Worldfloods, was developed by FDLeurope, a partnership with the University of Oxford, Trillium Technologies, ESA Φ-lab and leaders in commercial AI, such as Google Cloud and Intel.

Worldfloods + Space Cloud

Processing S2 imagery in orbit to obtain a flood segmentation.

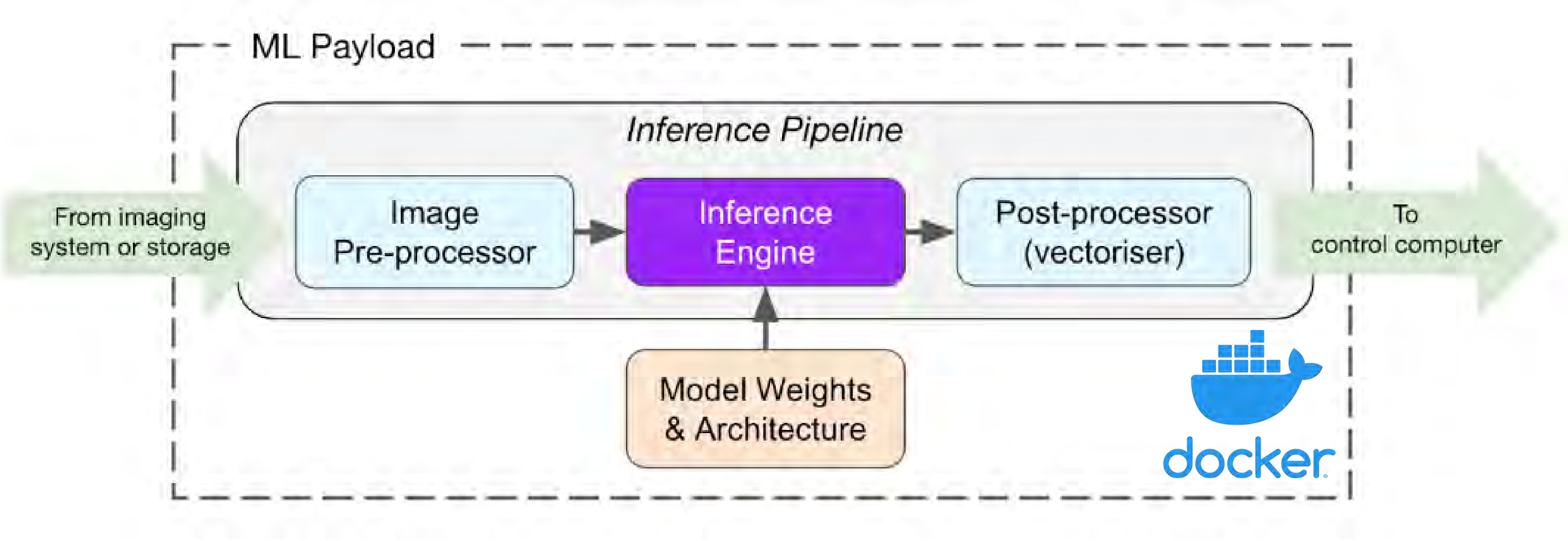


Worldfloods



Worldfloods + Space Cloud

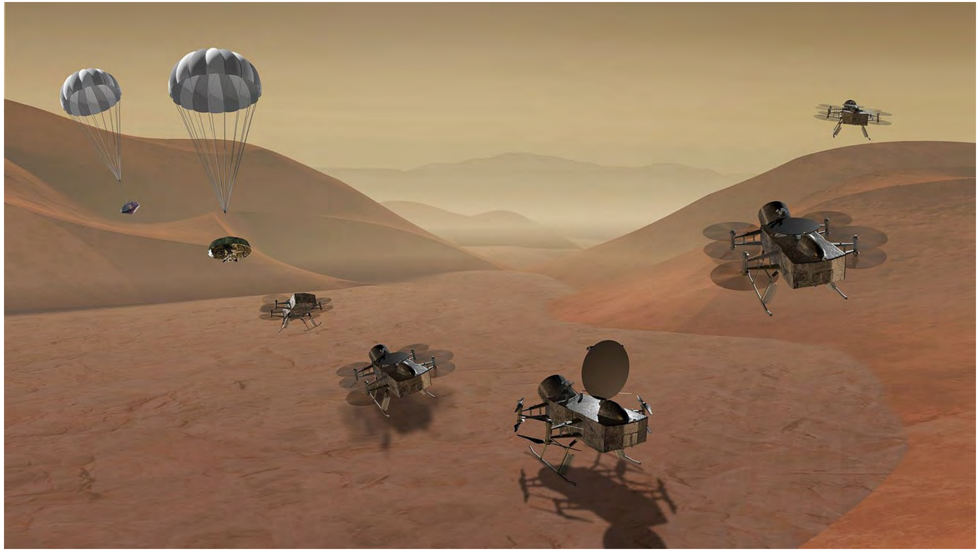
Dockerized Inference pipeline deployed in D-Orbit hardware




NASA DragonFly Mission to Saturn/Titan
CASE IV

ONBOARD DETECTION OF MOLECULAR BIOSIGNATURES

- Dragonfly is a NASA mission to Saturn/Titan (launch planned June 2027)
- Robotic rotorcraft (VTOL)
- Instruments
  - Dragonfly Mass Spectrometer (DraMS)
  - Dragonfly Gamma-Ray and Neutron Spectrometer (DraGNS)
  - Dragonfly Geophysics and Meteorology Package (DraGMet)



https://www.nasa.gov/dragonfly

We are working on ML methods to show feasibility of running an onboard biosignature detection with data from DraMS

Defining “life” is hard!

What if alien life looks nothing like anything we’ve ever seen on Earth?

Illustrations: flaticon.com

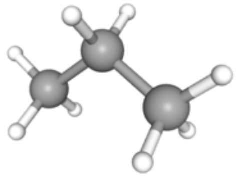
WHAT IS MOLECULAR COMPLEXITY | **WAYS TO MEASURE IT**

How big is it?
Da: Mass of atoms in the molecule

How diverse are its atomic ingredients?
C_m : Number and nature of bonds in a molecule and asymmetry

What holds it together?
BHI : Number of bonds + diversity of atoms in that make up the molecule

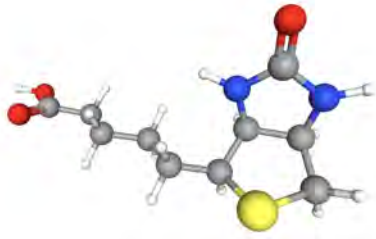
How is it made?
MA : Pathway to synthesize a given molecule



Propane

C_3H_8

44.11 g/mol (Daltons)



Biotin

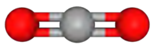
$C_{10}H_{16}N_2O_3S$

244.31 g/mol (Daltons)

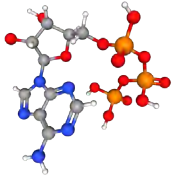
HYPOTHESIS[1] | "LIFE" IS LIKELY TO PRODUCE COMPLEXITY-IN-ABUNDANCE

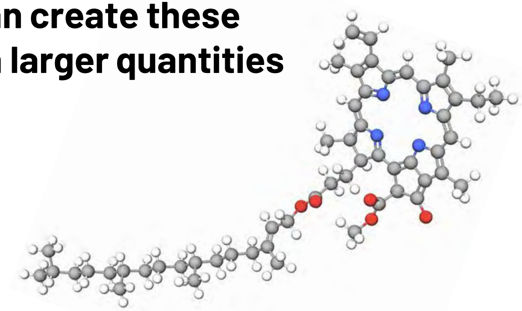
Threshold?!

These molecules can be formed through abiotic processes



Only "life" can create these molecules in larger quantities





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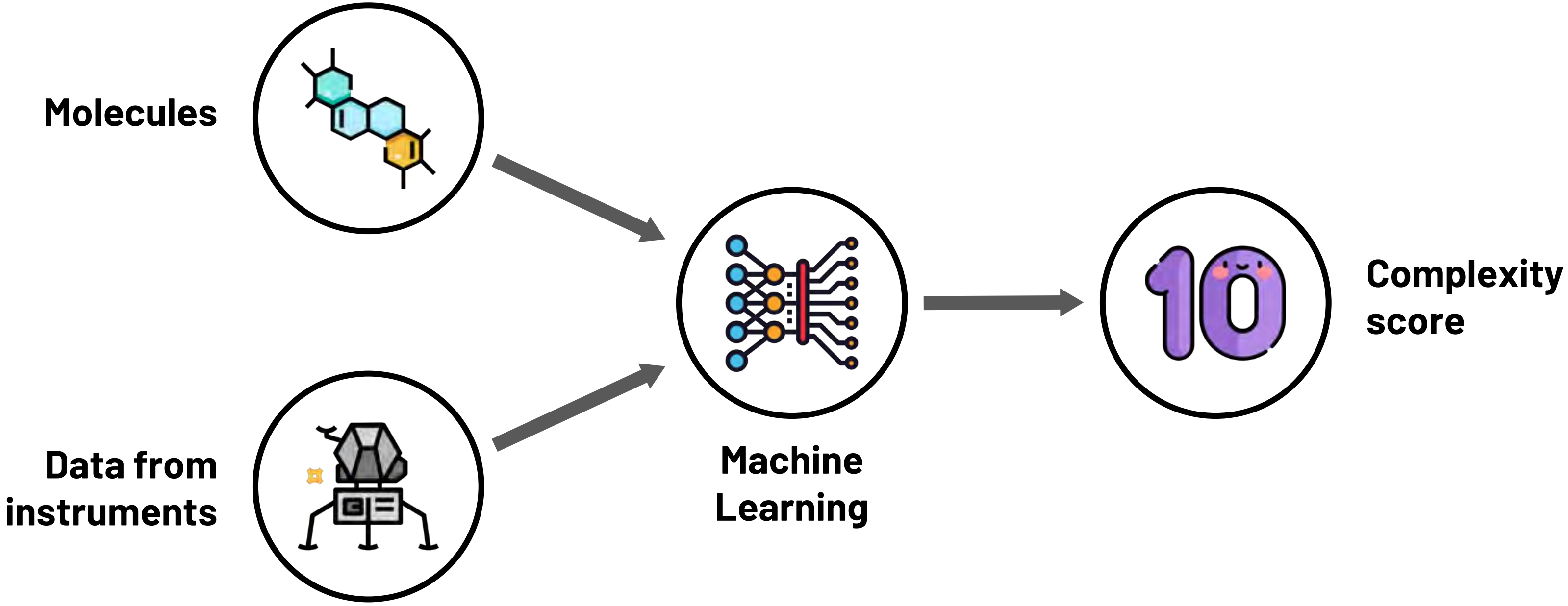
Increasing *complexity scores* →

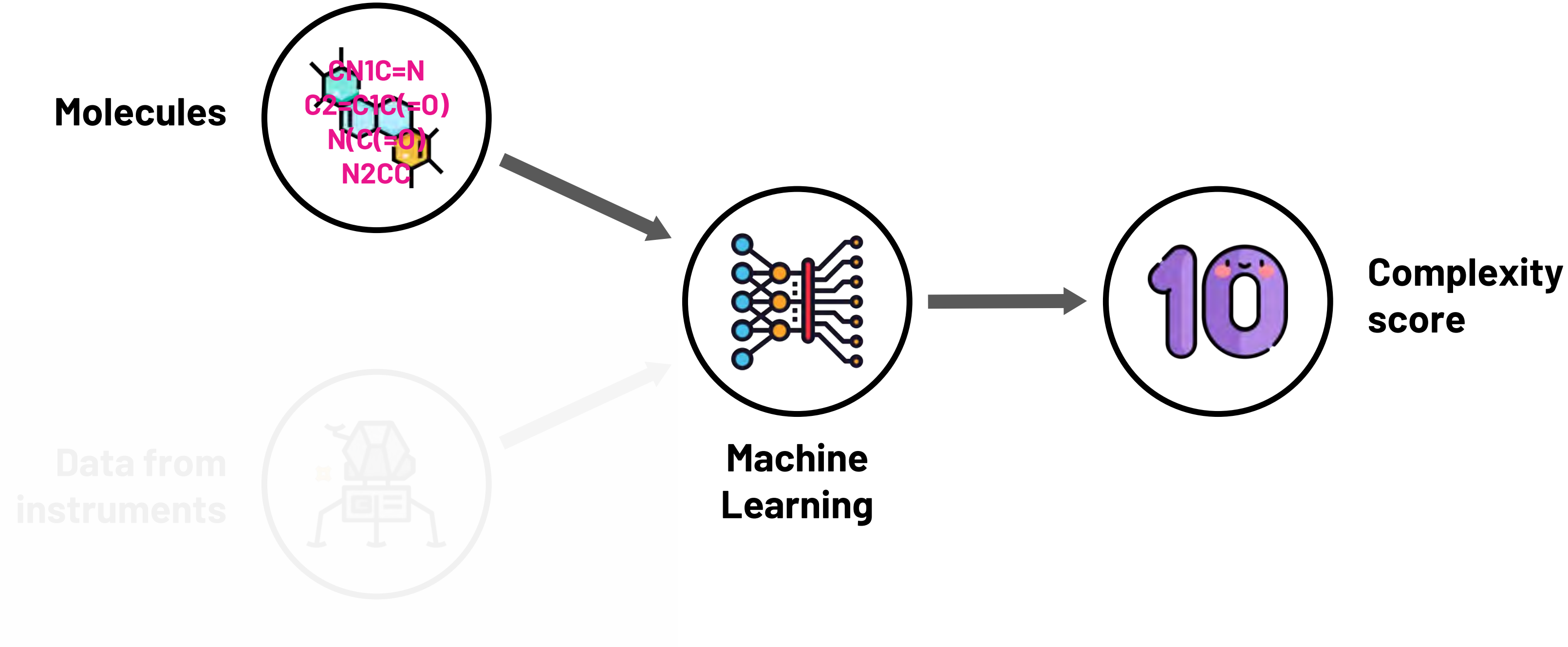
[1]See, e.g., Marshall et al. (2017, 2021)

MACHINE LEARNING | OUR WORKFLOW



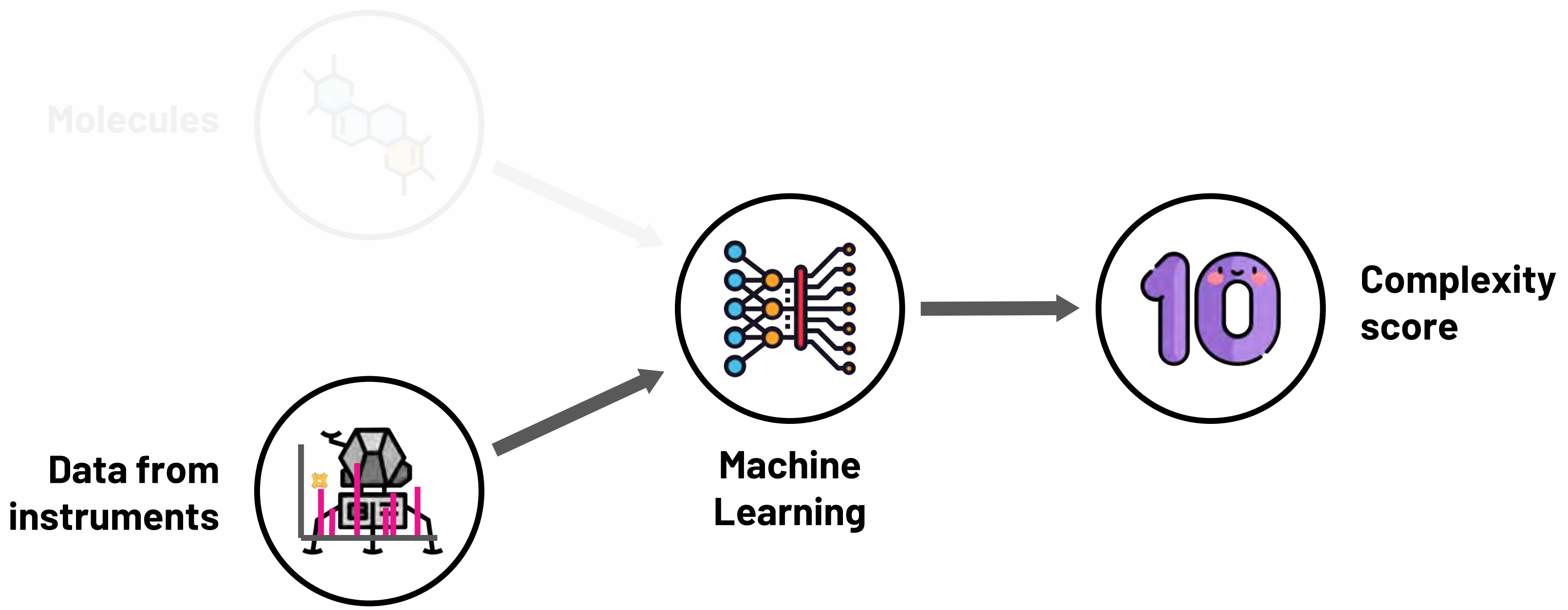
Illustrations: flaticon.com

MACHINE LEARNING | **OUR WORKFLOW**



Illustrations: flaticon.com

MACHINE LEARNING | OUR WORKFLOW



Illustrations: flaticon.com

DATASET | MOLECULAR DATA AGGREGATED FROM MANY SOURCES

NIST National Institute of Standards and Technology, U.S. Department of Commerce

PubChem

ChEMBL

NIH National Cancer Institute

Reaxys®

Google Scholar

...

query → collect

complexipy

Our code

(and brains!)

combine → compute

150,000+

unique molecules

14,000+

mass spectra

100,000+

CPU node hours

DATASET | CURATING DATA MEANS LOTS OF "INVISIBLE" WORK!

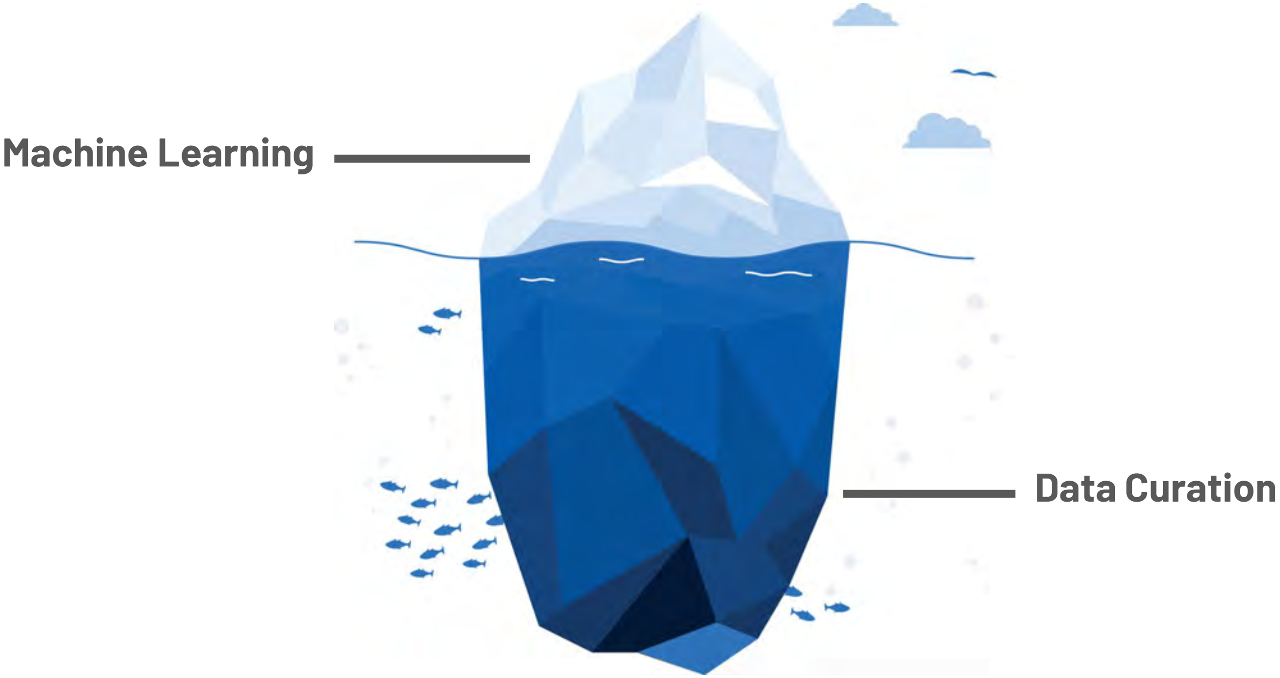
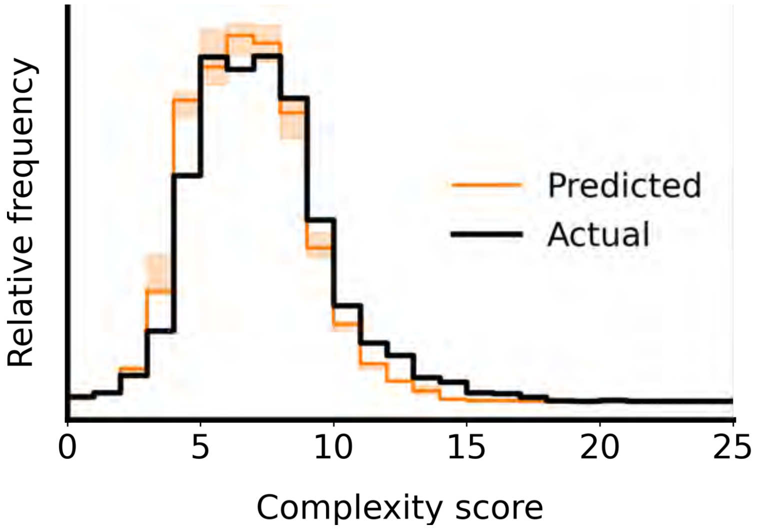
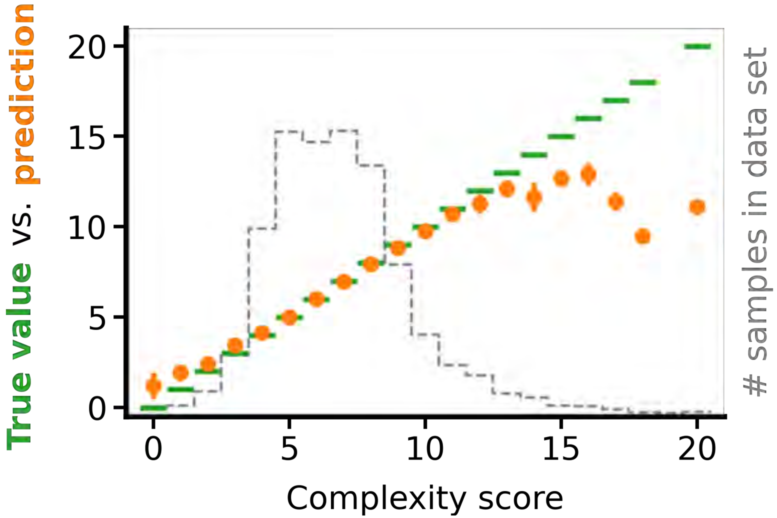


Illustration: freepik.com

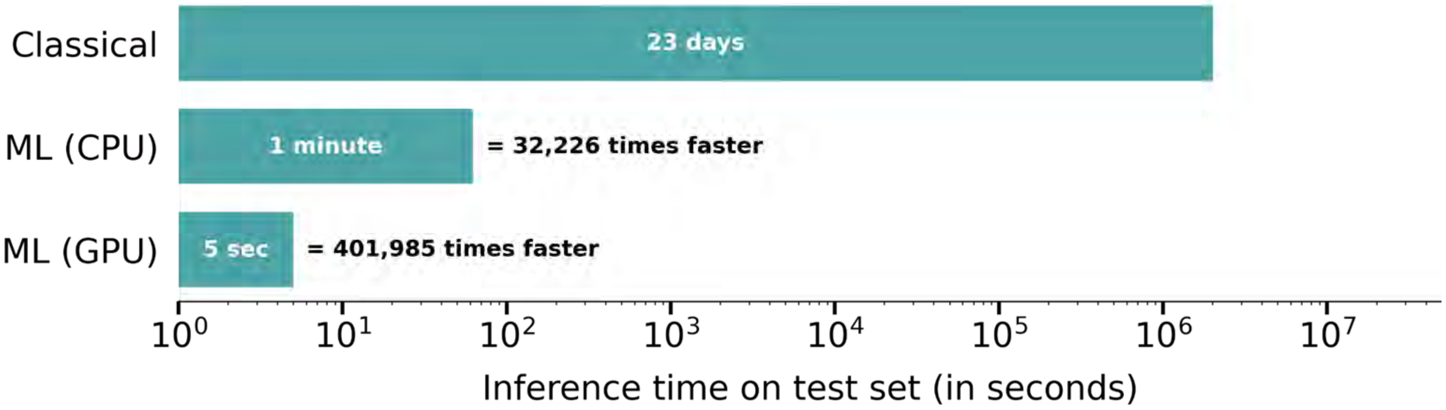
MACHINE LEARNING | **RESULTS:** *MASS-SPEC-TO-COMPLEXITY*





MACHINE LEARNING | **RESULTS:** *MOLECULE-TO-COMPLEXITY*

Test set: ~4000 molecules, mean prediction error: **9.8%**



Thank you for listening

Questions?

Selected references

[1] T. A. Le, A. G. Baydin, and F. Wood. Inference compilation and universal probabilistic programming. In International Conference on Artificial Intelligence and Statistics (AISTATS), 2017.
[2] A. Munk, A. Ścibior, A. G. Baydin, A. Stewart, G. Fernlund, A. Poursartip, and F. Wood. Deep probabilistic surrogate networks for universal simulator approximation. In PROBPROG, 2020.
[3] A. G. Baydin, L. Heinrich, W. Bhimji, L. Shao, S. Naderiparizi, A. Munk, J. Liu, B. Gram-Hansen, G. Louppe, L. Meadows, P. Torr, V. Lee, Prabhat, K. Cranmer, and F. Wood. Efficient probabilistic inference in the quest for physics beyond the standard model. In NeurIPS, 2019.
[4] A. G. Baydin, L. Shao, W. Bhimji, L. Heinrich, L. F. Meadows, J. Liu, A. Munk, S. Naderiparizi, B. Gram-Hansen, G. Louppe, M. Ma, X. Zhao, P. Torr, V. Lee, K. Cranmer, Prabhat, and F. Wood. Etalumis: Bringing probabilistic programming to scientific simulators at scale. In SC19, 2019.
[5] K. Cranmer, J. Brehmer, and G. Louppe. The frontier of simulation-based inference. Proceedings of the National Academy of Sciences, 117(48):30055–30062, 2020.
[6] B. Gram-Hansen, C. Schroeder, P. H. Torr, Y. W. Teh, T. Rainforth, and A. G. Baydin. Hijacking malaria simulators with probabilistic programming. In ICML workshop on AI for Social Good, 2019.
[7] B. Gram-Hansen, C. S. de Witt, R. Zinkov, S. Naderiparizi, A. Scibior, A. Munk, F. Wood, M. Ghadiri, P. Torr, Y. W. Teh, A. G. Baydin, and T. Rainforth. Efficient bayesian inference for nested simulators. In AABI, 2019.
[8] B. Poduval, A. G. Baydin, and N. Schwadron. Studying solar energetic particles and their seed population using surrogate models. In MML for Space Sciences workshop, COSPAR, 2021.
[9] G. Acciarini, F. Pinto, S. Metz, S. Boufelja, S. Kaczmarek, K. Merz, J. A. Martinez-Heras, F. Letizia, C. Bridges, and A. G. Baydin. Spacecraft collision risk assessment with probabilistic programming. In ML4PS (NeurIPS 2020), 2020.
[10] F. Pinto, G. Acciarini, S. Metz, S. Boufelja, S. Kaczmarek, K. Merz, J. A. Martinez-Heras, F. Letizia, C. Bridges, and A. G. Baydin. Towards automated satellite conjunction management with bayesian deep learning. In AI for Earth Sciences Workshop (NeurIPS), 2020.
[11] G. Acciarini, F. Pinto, S. Metz, S. Boufelja, S. Kaczmarek, K. Merz, J. A. Martinez-Heras, F. Letizia, C. Bridges, and A. G. Baydin. Kessler: a machine learning library for space collision avoidance. In 8th European Conference on Space Debris, 2021.
[12] S. Shirobokov, V. Belavin, M. Kagan, A. Ustyuzhanin, and A. G. Baydin. Black-box optimization with local generative surrogates. In NeurIPS, 2020.
[13] H. S. Behl, A. G. Baydin, R. Gal, P. H. S. Torr, and V. Vineet. Autosimulate: (quickly) learning synthetic data generation. In 16th European Conference on Computer Vision (ECCV), 2020.
[14] A. G. Baydin, B. A. Pearlmutter, A. A. Radul, and J. M. Siskind. Automatic differentiation in machine learning: a survey. Journal of Machine Learning Research (JMLR), 18(153):1–43, 2018.
[15] A. G. Baydin, B. A. Pearlmutter, and J. M. Siskind. DiffSharp: An AD library for .net languages. In 7th International Conference on Algorithmic Differentiation, 2016.
[16] A. G. Baydin, R. Cornish, D. M. Rubio, M. Schmidt, and F. Wood. Online learning rate adaptation with hypergradient descent. In ICLR, 2018.
[17] H. Behl, A. G. Baydin, and P. H. Torr. Alpha maml: Adaptive model-agnostic meta-learning. In AutoML (ICML), 2019.
[18] A. G. Baydin, K. Cranmer, M. Feickert, L. Gray, L. Heinrich, A. Held, A. Melo, M. Neubauer, J. Pearkes, N. Simpson, N. Smith, G. Stark, S. Thais, V. Vassilev, and G. Watts. Differentiable programming in high-energy physics. In Snowmass 2021 Letters of Interest (LOI), Division of Particles and Fields (DPF), American Physical Society, 2020.
[19] A. G. Baydin, K. Cranmer, P. de Castro Manzano, C. Delaere, D. Derkach, J. Donini, T. Dorigo, A. Giammanco, J. Kieseler, L. Layer, G. Louppe, F. Ratnikov, G. C. Strong, M. Tosi, A. Ustyuzhanin, P. Vischia, and H. Yarar. Toward machine learning optimization of experimental design. Nuclear Physics News International (Submitted), 2020.
[20] L. F. Guedes dos Santos, S. Bose, V. Salvatelli, B. Neuberg, M. Cheung, M. Janvier, M. Jin, Y. Gal, P. Boerner, and A. G. Baydin. Multi-channel auto-calibration for the atmospheric imaging assembly using machine learning. Astronomy & Astrophysics (in press), 2021.
[21] A. D. Cobb, M. D. Himes, F. Soboczenski, S. Zorzan, M. D. O'Beirne, A. G. Baydin, Y. Gal, S. D. Domagal-Goldman, G. N. Arney, and D. Angerhausen. An ensemble of bayesian neural networks for exoplanetary atmospheric retrieval. The Astronomical Journal, 158(1), 2019.
[22] C. Schroeder de Witt, B. Gram-Hansen, N. Nardelli, A. Gambardella, R. Zinkov, P. Dokania, N. Siddharth, A. B. Espinosa-Gonzalez, A. Darzi, P. Torr, and A. G. Baydin. Simulation-based inference for global health decisions. In ICML Workshop on Machine Learning for Global Health, Thirty-seventh International Conference on Machine Learning (ICML 2020), 2020.