TOWARDS SCIENCE AUTONOMY FOR PLANETARY MISSION: MACHINE LEARNING APPLICATION FOR EXOMARS MISSION. V. Da Poian[1,2], E. I. Lyness[1,3], R. Danell[5], X. Li[1,4], M. G. Trainer[1], W. B. Brinckerhoff[1], [1]NASA Goddard Space Flight Center, Planetary Environments Laboratory (8800 Greenbelt Road, Greenbelt, MD 20771, victoria.dapoian@nasa.gov), [2]Southeastern Universities Research Association (Washington DC 20005), [3]Microtel LLC, [4]University of Maryland (Baltimore County, Baltimore, MD 21250), [5]Danell Consulting, Inc. (Winterville, NC 28590).

Introduction: The majority of NASA's robotic space missions return only one thing: data. The amount of data that science instruments produce is rapidly increasing, with large proportions of collected data left unstudied in significant depth. Earth science investigations, such as those on satellites observing the terrestrial climate at high resolution, have already confronted this overwhelming data management challenge. However, for remote planetary missions, while the data produced by science instruments continues to grow with mission ambitions, the investigations are still limited by insufficient bandwidth to transmit data back to Earth. Regardless of the target – the Earth, planets in our solar system, the sun, or deep space – new science instruments will continue to generate more data, requiring more efficient processing approaches that enable advanced mission operations and speed scientific progress.

Artificial intelligence (AI), and more precisely machine learning (ML), have revolutionized the world in the past decades. Massive amounts of collected data and development of more powerful computing and processing devices have been critical to the ubiquitous growth of AI applications.

To maximize the value of each bit, instruments need to be highly selective about which data are prioritized for return to Earth, as increasingly compression and transmission of the full data volume is not feasible. The fundamental goal is to enable the concept of *science autonomy*, where instruments perform selected onboard science data analyses and then act upon those analyses through self-adjustment and tuning of instrument parameters. Indeed, the selection of the next operation(s) to be run following preliminary measurements, without requiring ground-in-the-loop, could allow missions to transmit the most compelling or time-critical data yielding a more efficient and productive scientific investigation overall.

We present a first step toward this vision of science autonomy for space science missions. As a case study, we present a machine learning approach for analyzing data from the Mars Organic Molecule Analyzer (MOMA) instrument, [1], which will land on Mars within the ExoMars rover *Rosalind Franklin* planned to land in 2023. MOMA is a dual-source (laser desorption and gas chromatograph) mass spectrometer that will search for past or present life on the Martian surface and subsurface through analysis of soil samples.

We use data collected from the MOMA flight-like engineering model to develop mass-spectrometry-focused machine learning techniques. We apply unsupervised and supervised algorithms designed for MOMA's scientific goals in order to provide information to the scientists about the likely content of the sample [2]. This will help the scientists with their analysis of the sample and decision-making process regarding subsequent operations.

We also discuss motivations, related work, and the challenges and limitations of this implementation, as well as lessons learned and approaches that could be used for future space science missions.

References: [1] F. Goesmann, W. B. Brinckerhoff, F. Raulin, W. Goetz, R. M. Danell et al., "The Mars Organic Molecule Analyzer (MOMA) Instrument: Characterization of Organic Material in Martian Sediments," International Journal of Astrobiology 17, 2017. [2] X. Li, R. M. Danell, V. T. Pinnick et al., "Mars Organic Molecule Analyzer (MOMA) laser desorption/ionization source design and performace characterization," International Journal of Mass Spectrometry 422, 2017.