Applying Machine Learning to MOMA Science Data for Scientific Autonomy. V. Da Poian\textsuperscript{1,2}, R. N. Lewis\textsuperscript{3}, J. Cirillo\textsuperscript{1,3}, E. Lyness\textsuperscript{1,3}, M. G. Trainer\textsuperscript{1}, X. Li\textsuperscript{1,4}, A. Grubisic\textsuperscript{1}, R. Danell\textsuperscript{5}, NASA Goddard Space Flight Center, Planetary Environments Laboratory, Greenbelt, MD 20771 (victoria.dapoian@nasa.gov)\textsuperscript{2}Southeastern Universities Research Association, Washington, DC 20005, \textsuperscript{3}Microtel LLC, \textsuperscript{4}University of Maryland, Baltimore County, Baltimore, MD 21250, \textsuperscript{5}Danell Consulting, Inc., Winterville, NC 28590.

Introduction: Planetary missions are restricted by three major parameters: mass, power, and data. As humanity ventures further into the solar system and beyond, these parameters become more precious and the challenges to scientists and engineers increases. Our goal is to automate science decision-making so spacecraft and scientific instruments can immediately analyze science data, perform on-board analysis of science data, and select the next operations to be run without the ground in the loop. Thereby simultaneously increasing the science return and decreasing the data volume. Data science (application of scientific method to discovery from data) and machine learning (mathematical algorithms trained by fitting data to patterns or clusters from previous experience or training) can greatly improve scientific autonomy in current and future interplanetary missions.

A primary focus of interplanetary missions is to search for life and abiotic compounds through the use of mass spectrometry. These missions face many challenges, which include having to withstand harsh radiation environments as well as the need to transmit data great distances back to Earth. Both can lead to low-quality or lost data. For missions such as those to the Jupiter system or beyond, the current process of manual data review and subsequent decision making with ground-in-the-loop significantly slows the mission operations. In order to expand our scientific autonomy and increase mission efficiency, we must intensify our use of on-board artificial intelligence.

To enable autonomous decision-making during flight missions, we are using data from the Mars Organic Molecule Analyzer (MOMA) instrument to develop mass spectrometry-focused machine learning techniques. We expect to find specific clustering patterns from different unsupervised algorithms, allowing us to identify an optimal algorithm for MOMA’s scientific goals. The optimal algorithm will separate the bulk data into distinct clusters for further analysis of mass spectrometry operations such as SWIFT and MSMS on the MOMA instrument. This will allow scientists, or the spacecraft and instruments themselves, to make real-time instrument adjustments on interplanetary operations as we continue to search for life in our solar system and beyond.

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