DEVELOPMENT OF MACHINE LEARNING ALGORITHMS TO SEGMENT AND STUDY IMAGES OF ASTROMATERIAL SAMPLES. A.W. Needham[1,2], M.D. Lambert[1,2], J.I. Simon[2], D.S. Ebel[3], [1]Jacobs (andrew.w.needham@nasa.gov), [2]NASA Johnson Space Center, [3]American Museum of Natural History

Introduction: Micrometer-scale chemical analyses of chondritic meteorites and mission-returned asteroid samples can reveal details of the physical and chemical processes operating in the early solar system, including processes that gave rise to planets, moons, and minor bodies. These primitive astromaterials are comprised of chondrules, calcium- and aluminum-rich inclusions (CAI), and many other silicates, oxides, metals, sulfides, and fine-grained materials. The chemical and mineralogical complexity of these samples, vast populations of different components, and heterogeneity across mm to km scales, all limit our understanding of the origin and evolution of these materials.

Here, we describe recent efforts to use machine learning techniques to automate the segmentation of chemical maps of chondritic meteorites, designed to aid studies of asteroid samples returned by spacecraft. By automating the task of segmentation it will become possible to rapidly analyze and interpret the sizes, shapes, mineralogy, chemistry, and other properties of every chondrule, calcium- and aluminum-rich inclusion (CAI) and other clast within and between asteroid samples. Sample return missions significantly accelerate and heighten the need to develop such new data analysis techniques, and associated data repositories.

Techniques: Neural networks require abundant training data, i.e. images which have been segmented by a human user. We have manually segmented data available from previous petrologic and chemical work at NASA Johnson Space Center and the American Museum of Natural History [1-4]. These data were derived from energy- and wavelength-dispersive X-ray spectroscopy (EDS, WDS) mapping of samples from many chondrite groups.

The Deeplabv3+ [5] neural network architecture was trained on human-labeled masks and used to create machine-labeled masks. Several different algorithms were investigated, with inputs ranging from common RGB image formats through to hyperspectral datasets, with raw data comprising greyscale maps of Mg, Ca, and Al, with or without Si, Fe, Ti for both EDS and WDS data, and extending to other elements in EDS only. Each greyscale image was paired with a binary mask for each labelled particle type.

Results: The trained algorithms can segment (Fig 1), classify, and measure the dimensions of thousands of particles in chemical maps of a standard 1-inch round petrographic section in seconds to minutes, rather than many hours needed by a human. Accuracy of the algorithms varied from chondrite to chondrite and across particle types. Further results and details of the algorithms will be presented at the workshop.

Future directions: Machine learning has the potential to revolutionize our understanding of complex particle populations contained within primitive astromaterial, with segmentation being a critical first step. Example applications include better understanding of particle transport, nebular reservoirs, parent body accretion, and a deeper understanding of the relationships between particle populations and bulk rock elemental and isotopic compositions.

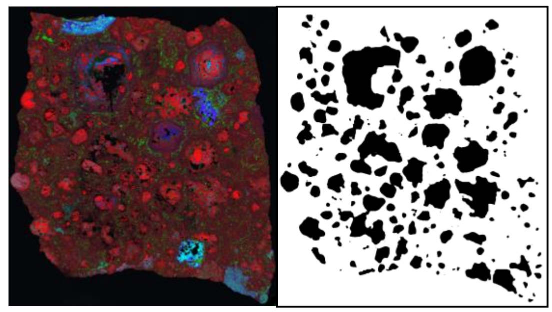

Figure 1. A false-color EDS map of Allende (left) with Mg-Ca-Al mapped to RGB respectively. The machine learning algorithm produced maps for each particle type, including the chondrule map (right).

In addition to benefits that machine learning can bring to individual researchers, building a community data repository of thousands to millions of particles across hundreds of samples will open up many other possibilities. For example, with a large enough dataset it will be possible to search for exceptionally closely matching particles across disparate samples. Such a capability would enable a single CAI from OSIRIS-REx or Hayabusa/II samples to be matched to chondritic CAIs that exhibit near-identical size, texture, and mineralogy, down to the level of similar core phenocrysts, zonation, and rim sequences. Such comparative analyses will help to disentangle precursor chemistry, chronology, gas/dust reservoirs during heating, and accretion. Such an endeavor would be impossible without machine learning and a large community data repository of astromaterial chemical/mineralogic maps.

References: [1] Ebel D.S. et al., (2016) *GCA 172*, 322-356. [2] Fendrich K.V. and Ebel D.S. (2020) *MAPS 56*, 77-95 [3] Barosch J. et al. (2020) *EPSL 542* 116286 [4] Simon J.I. et al., (2018) *EPSL 494*, 69-82. [5] Chen L.C., et al. (2018) *ECCV 801-818.*