MINERALOGY OF THE MOON USING UNSUPERVISED CLUSTERING OF THE MOON MINERAL MAPPER (M3) SPECTRAL DATA.

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Introduction: Recent efforts in the space community have been focused on exploring and understanding the mineralogy of the Moon's south pole. Mapping the pole and researching areas of interest, as well as developing technologies for in-situ resource utilization (ISRU), are key goals of these efforts.

Hyperspectral imaging (HSI) provides information on the surface of the Moon by spectral absorption features. The hyperspectral images can be used to estimate the mineral composition in the image. The Moon Mineral Mapper (M3) is a spectrometer from the Chandrayaan-1 mission, which provides HSI in a wide range of wavelengths [1]. The M3 has a wide range in spectral dimension, which is only surpassed by the Imaging Infrared Spectrometer (IIRS) from the Chandrayaan-2 mission. M3 is a spectrometer that operates in the solar-dominated portion of the electromagnetic spectrum with wavelengths from 430 nm to 3000 nm (0.43 to 3.0 microns). The M3 was chosen for this analysis since it has a wide range in spectral wavelengths and a good coverage of the Moon.

Traditionally, an empirical equation is used when determining if a mineral is present in a spectral dataset. However, in recent years machine learning methods have shown to be useful for mineral classifications.

Dimensionality reduction techniques effectively preserve the data's features, making them crucial for clustering high-dimensional data. Autoencoders, in particular, has been demonstrated to be effective in representing distributions in latent space and reconstructing images from the same latent space. Recent studies have also shown the usefulness of variational autoencoders for clustering high-dimensional data, and in some cases, convolutional autoencoders have also been used.

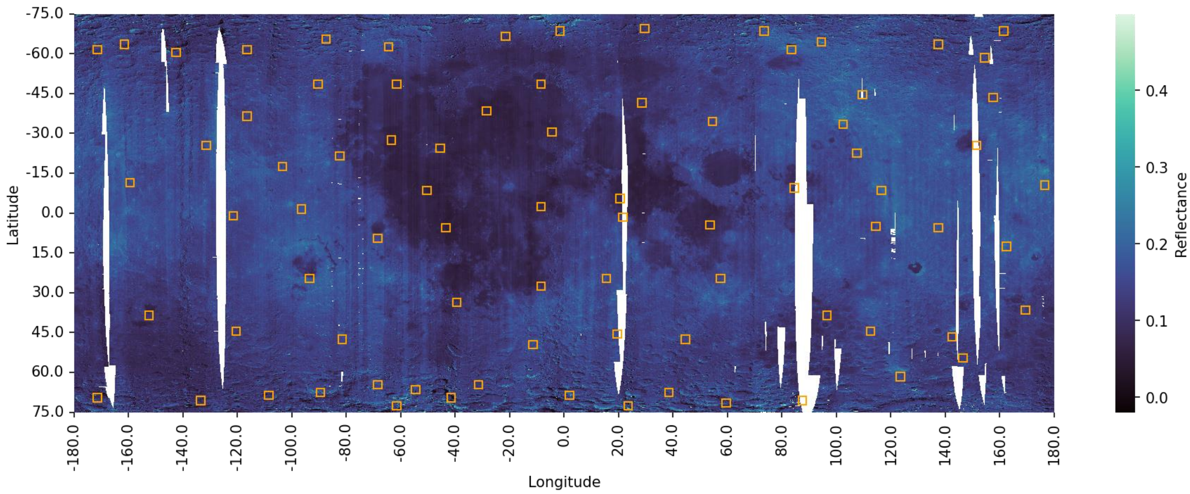

Figure 1: The Moon Mineralogy Mapper (M3) reflection data of the Moon is shown in the figure. The orange squares highlight the areas of the dataset used to train the convolutional variational autoencoder. The upper map is displayed in an equidistant cylindrical projection with a maximum latitude of 75 degrees.

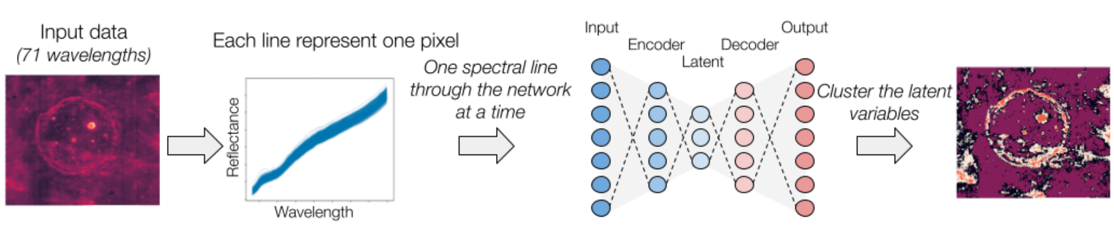

Figure 2: The Moon Mineralogy Mapper (M3) reflection data of the Moon is shown in the figure. The orange squares highlight the areas of the dataset used to train the convolutional variational autoencoder. The upper map is displayed in an equidistant cylindrical projection with a maximum latitude of 75 degrees. The bottom left and right show the Moon's south and north poles, respectively, in a stereographic projection with a minimum of 60 degrees

Data: The data selection included a cut on the sensor azimuth angle and observation angles. The cuts were chosen to be as tight as possible while not compromising the data coverage. The published M3 reflectance data was used, not including wavelengths over 2.5 microns, since additional corrections would be needed to correct thermal additions [2]. The data preprocessing steps include binning each M3 image to the highest resolution without losing coverage. After each image is binned, they are combined by an average. The data is normalized, and the continuum is removed before being passed to the neural network. The training data was selected by hand for the first 20 images, with a particular interest in high weight percentages and different mineral selections, as seen in Figure 1, and the rest were chosen at random.

Method: The approach is depicted in Figure 2. The spectra are passed through a symmetric convolutional autoencoder and reconstructed. The difference between the original spectra and the reconstructed spectra is minimized. The encoded latent variables contain the relevant features needed to reconstruct the spectra. Therefore the latent variables are used as a representation of the spectra in low-dimensional space. After the latent variables are obtained for each pixel, they are clustered by kmeans.

Results: Preliminary results of the mineral clusters of the poles are in Figure 3. The same clusters are also quantified for the entire Moon. The main mineralogy of the clusters is determined by comparison to the minerals maps from Kaguya [3] and the spectra from the PANGAEA mineral database [4]. Interestingly, the yellow cluster, which is shown to be prominent in Figure 3, is also found in areas of the Moon's mare with the highest amount of olivine. The light blue cluster in Figure 3 is present on the Moon in regions dominated by plagioclase. The bright orange is in the same cluster as the Moon's Mare region consisting of ilmenite, olivine, FeO, orthopyroxene, and clinopyroxene. The pink cluster is in other areas dominated by mostly orthopyroxene but also clinopyroxene. The grey cluster may be picking up the noise of the data and cannot precisely be determined.

Conclusion: An unsupervised learning algorithm is made to cluster spectra from the Moon Mineral Mapper (M3). The clusters correspond to mineral features on the Moon, and by quantifying the clusters, they are compared to spectra from the PANGAEA mineral database and mineral maps from Kaguya.

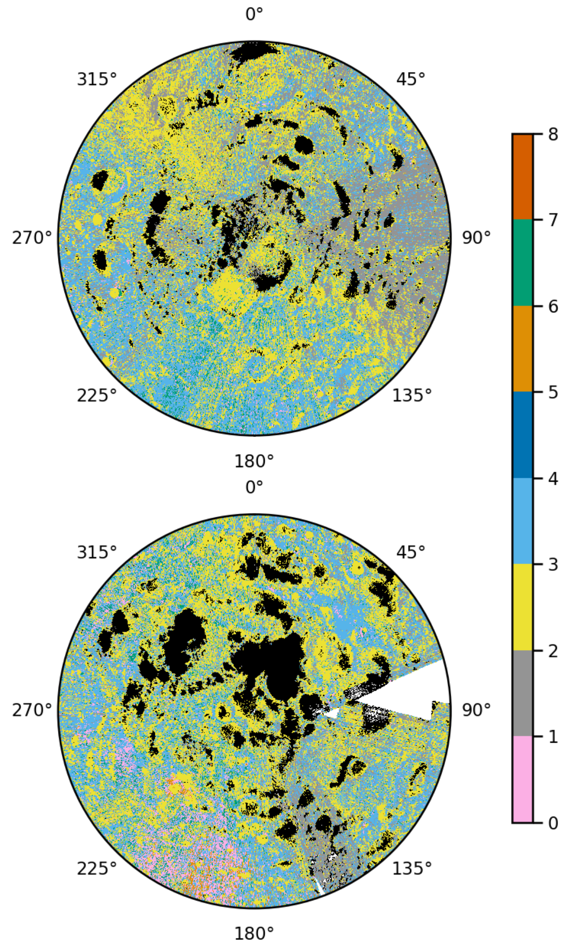

Figure 3: Clusters at the poles. Top: North pole from 80-90 degrees, bottom: South pole from -90 to -80 degrees. The black regions correspond to very low signals in the PSR, and the white regions are no data.

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References: [1] Pieters, C. et al. (2009), *The Moon Mineralogy Mapper (M3) on Chandrayaan-1*, Current Science 96, 500-505. [x] Li, S., & Milliken, R. E. (2016). *An empirical thermal correction model for Moon Mineralogy Mapper data constrained by laboratory spectra and Diviner temperatures.* Journal of Geophysical Research: Planets, 121(10), 2081–2107. [x] Lemelin, M. et. al. (2019). *The compositions of the lunar crust and upper mantle: Spectral analysis of the inner rings of lunar impact basins.* Planetary and Space Science, 165, 230–243. [x] Drozdovskiy, I. et. al. (2020). *The PANGAEA mineralogical database.* Data in Brief, 31